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## Master Thesis

Major: Computer Modeling of Knowledge and Reasoning

### Theme

AgriTechly Part 2: AI Solutions for  
Veterinary Diagnosis and Pest Management

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# Dedication

To my loving **parents**, whose endless love, support, and encouragement have been my greatest strength. Their unwavering belief in me has been my constant source of motivation and **hope**.

To my **sisters**, for their unwavering faith in me and their constant source of joy and inspiration. Their understanding and patience have helped me overcome the most challenging **obstacles**.

To my beloved **grandparents**, whose wisdom and love have guided me, and whom I dearly wish could be present to share this special moment. Their memory and values continue to be a guiding light in my **upliftment**.

To all my **friends and mentors** who have supported me throughout this journey, your guidance and belief in my abilities have been invaluable. Your optimism and dedication have profoundly influenced my personal and professional **development**.

To my **future self**, may you always remember the hard work and dedication that brought you here, and may you continue to strive for excellence in all your endeavors. Your achievements are a testament to your determination and **ambition**.

- *Mohamed Said*

# Dedication

We wholeheartedly dedicate this work to our cherished **family**. To our **parents**, whose unwavering love, sacrifices, and prayers have provided the foundation for our success, and to our **siblings**, whose encouragement and support have been a continuous source of motivation.

This dedication also extends to our respected **teachers**, whose commitment to education and nurturing our intellectual growth have greatly influenced our research journey. Their dedication to teaching has significantly shaped our academic path.

Lastly, we dedicate this work to **everyone** who has offered their support, whether big or small. Your contributions, both tangible and intangible, have played a crucial role in the completion of this dissertation.

- *Ahmed*

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# Acronym List

<b>AI</b>	Artificial Intelligence
<b>NN</b>	Neural Network
<b>DL</b>	Deep Learning
<b>RNN</b>	Recurrent Neural Network
<b>V-RNN</b>	Vanilla Recurrent Neural Network
<b>Bi-RNN</b>	Bidirectional Recurrent Neural Network
<b>CNN</b>	Convolutional Neural Network
<b>VGG</b>	Visual Geometry Group
<b>ResNet</b>	Residual Neural Network
<b>DenseNet</b>	Densely-connected-convolutional networks
<b>RELU</b>	Rectified Linear Unit
<b>SGD</b>	Stochastic Gradient Descent
<b>Tanh</b>	Hyperbolic tangent
<b>Lasso</b>	Least Absolute Shrinkage and Selection Operator
<b>MFCC</b>	Mel Frequency Cepstral Coefficients
<b>RMSprop</b>	Root Mean Square Propagation
<b>YOLO</b>	You Only Look Once
<b>NLP</b>	Natural Language Processing
<b>RAG</b>	Retrieval Augmented Generation
<b>BERT</b>	Bidirectional Encoder Representations from Transformers
<b>LLM</b>	Large Language Model
<b>LSTM</b>	Long Short-Term Memory
<b>GRU</b>	Gated Recurrent Unit
<b>GAI</b>	General Artificial Intelligence
<b>GPT</b>	Generative Pre-trained Transformer
	...

# **Chapter 1:**

## General introduction

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# Chapter 1

## General Introduction

### 1.1 Context

Accurately identifying diseased animals is crucial in the fields of veterinary care and animal husbandry. Veterinarians have traditionally diagnosed animal ailments by manual examination and observational methods. These approaches, however, are time-consuming, arbitrary, and prone to mistakes. The advent of deep learning technologies has presented encouraging approaches to tackle these difficulties. Both recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have shown to be remarkably adept in processing complicated data, including temporal data sequences and medical images, improving the efficiency and accuracy of diagnosis.

### 1.2 Motivation and problematic

The urgent need for rapid animal disease identification drives this research. Timely diagnosis and treatment are crucial in veterinary medicine to maintain both animal and public health. Traditional diagnostic methods are often slow and error-prone, leading to treatment delays and complications. This issue is compounded by the lack of scalable, objective diagnostic tools, especially in large-scale farming and disease surveillance. In Saïda, the absence of intelligent diagnostic services exacerbates these problems. This research addresses these gaps by utilizing deep learning models, such as CNNs and RNNs, to enhance the accuracy and efficiency of disease diagnosis in animals. Additionally, chatbots are employed to assist individuals with limited technical skills, making the technology accessible to a broader audience.

Specific contributions include advanced pest management solutions and the detection of diseases in chickens and cattle, which are critical to preventing outbreaks and ensuring animal welfare. The research also focuses on identifying queenlessness in beehives, which is vital for maintaining healthy bee populations and ecological balance. The integration of chatbots further facilitates user interaction with diagnostic tools, providing immediate and user-friendly support. Overall, this work aims to implement scalable, effective solutions to improve animal health management in Saïda and beyond.

## 1.3 Objectives

The primary goal of this research is to develop and evaluate advanced computational approaches for the detection of animal diseases, leveraging deep learning algorithms and diagnostic analysis techniques. The specific objectives of this study are as follows:

1. **Analyze and Understand Animal Diseases:** The research seeks to analyze and comprehend the distinct attributes of various animal diseases, encompassing their symptoms, transmission patterns, and the influence of diverse environmental and genetic factors on disease progression.
2. **Explore and Apply Deep Learning Algorithms:** To explore and apply deep learning algorithms, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for accurate and robust disease detection and classification.
3. **Investigate Diagnostic Analysis Models:** To investigate the effectiveness of diagnostic analysis models, employing state-of-the-art techniques like image recognition and natural language processing (NLP) models such as Mistral and Llama, in capturing and interpreting diagnostic data related to animal health.
4. **Develop Integrated Models:** To develop integrated models that combine deep learning algorithms and diagnostic analysis techniques to enhance the accuracy of disease detection and provide valuable insights for veterinary decision-making.
5. **Test Retrieval-Augmented Generation (RAG):** This research aims to test the RAG model to augment the efficiency of large language models with deep learning models. By doing so, we intend to extract valuable insights from the developed models, enabling veterinarians and farmers to make informed decisions regarding animal health management.
6. **Facilitate User Interaction with Technology:** By employing chatbots, this research aims to facilitate tasks for individuals who may not be proficient in technology, allowing them to interact with the system more easily.

By analyzing and understanding the patterns and trends identified by the models, individuals can make more informed choices when it comes to diagnosing, treating, and preventing diseases in animals.

## 1.4 Organization of The dissertation

### 1.4.1 Chapter 1: General Introduction

In this foundational chapter, the dissertation begins by contextualizing the overarching theme of leveraging AI in veterinary diagnosis and pest management within the agricultural domain. It articulates the motivation behind exploring this area, primarily driven by the pressing need to address disease and pest outbreaks that pose significant challenges to agricultural productivity and sustainability. By elucidating the problematic, which revolves around the limitations of traditional disease detection methods and the escalating threats posed by pest infestations, the chapter underscores the urgency of adopting innovative approaches. The objective of the dissertation is clearly delineated: to harness the power of AI to mitigate these challenges and contribute to more effective disease and pest management practices in agriculture.

### 1.4.2 Chapter 2: Deep Learning

A comprehensive understanding of deep learning serves as the cornerstone for the subsequent exploration of AI applications in agriculture. This chapter serves as a primer on deep learning techniques, offering insights into their underlying principles and architectures. Beginning with an overview of deep learning, it delves into the specifics of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), transformers, and RAG models. By elucidating the capabilities and potential applications of these advanced neural network architectures, the chapter lays a robust theoretical foundation for their subsequent deployment in disease detection, pest identification, and other agricultural challenges.

### **1.4.3 Chapter 3: AI in Agriculture**

The transition from traditional disease detection methods to AI-driven approaches marks a paradigm shift in agricultural practices. This chapter critically examines the shortcomings of conventional techniques and elucidates how AI holds the promise of overcoming these limitations. By leveraging vast datasets and advanced algorithms, AI has the potential to revolutionize disease and pest management in agriculture by enabling early detection, accurate diagnosis, and targeted interventions. Real-world applications of AI in agriculture are reviewed, providing insights into successful implementations and lessons learned. Additionally, the chapter offers a synthesis of existing research in the field, highlighting gaps and proposing avenues for future investigation and innovation.

### **1.4.4 Chapter 4: Contribution**

Building upon the theoretical framework established in previous chapters, this section showcases the original contributions of the dissertation to the field of AI in agriculture. Each proposed solution, ranging from chicken disease detection to the identification of queenlessness in bee hives using RNNs, is meticulously presented and contextualized within the broader landscape of agricultural challenges. Furthermore, the development of a veterinary specialist chatbot and the implementation of pest detection algorithms underscore the interdisciplinary nature of the research, bridging the gap between AI and veterinary medicine.

### **1.4.5 Chapter 5: Result Discussion and Experimentation**

The empirical validation of AI-driven solutions forms the crux of this chapter, where the results of extensive experimentation are analyzed and interpreted. Through rigorous evaluation and comparative analysis, the efficacy and performance of different models and algorithms are assessed, shedding light on their strengths, weaknesses, and potential areas for optimization. Special attention is paid to contextual factors and real-world applicability, ensuring that the findings are not only scientifically robust but also practically relevant. By engaging in a nuanced discussion of experimental results, this chapter provides valuable insights into the feasibility and viability of AI-based approaches in agricultural contexts.

### **1.4.6 Chapter 6: Agritechly**

A tangible manifestation of the research findings, Agritechly represents the culmination of efforts to translate theoretical insights into practical solutions. This chapter offers a comprehensive overview of the web platform, delineating its various features and functionalities designed to facilitate efficient disease and pest management in agriculture. From data collection and analysis tools to decision support systems and interactive interfaces, Agritechly embodies the fusion of cutting-edge AI technologies with domain-specific expertise. By showcasing the tangible impact of AI in agricultural settings, this chapter underscores the transformative potential of technology-driven innovation in addressing complex agricultural challenges.

### **1.4.7 Chapter 7: General Conclusion**

As the dissertation draws to a close, this final chapter provides a synthesis of key findings, insights, and contributions, culminating in a comprehensive conclusion. By reflecting on the journey undertaken and the lessons learned along the way, the chapter offers a holistic perspective on the role of AI in veterinary diagnosis and pest management within the broader agricultural landscape. Moreover, it outlines avenues for future research and development, identifying emerging trends, unresolved challenges, and opportunities for further innovation. By articulating a vision for the continued advancement of AI in agriculture, the chapter underscores the enduring significance of interdisciplinary collaboration and technological innovation in shaping the future of food security and sustainability.

# **Chapter 2:**

## Deep learning

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# Chapter 2

## Deep learning

### 2.1 Introduction to Deep learning

Deep learning is a powerful subset of machine learning that is inspired by the structure and function of the human brain. It involves the use of artificial neural networks, which are composed of interconnected nodes (neurons) that learn to perform specific tasks by adjusting the strength (weights) of the connections between them.[1]

Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are particularly effective at extracting and learning complex features from data, making them useful for a wide range of applications, including image recognition, natural language processing, and speech recognition.[2]

One example of how deep learning can be applied is in the detection of animal health issues. By training a deep learning model on a large dataset of images of healthy and unhealthy animals, the model can learn to identify subtle patterns and features that distinguish between healthy and unhealthy individuals. This can be used to develop automated systems for early detection of diseases or other health problems in livestock or wildlife, allowing for more timely and effective interventions. [3]

### 2.2 Neural Network Architecture and Components

#### Layers

1. **Input Layer:** This layer receives the input data and passes it to the next layer. The number of neurons in the input layer depends on the dimensionality of the input data.
2. **Hidden Layers:** These layers are responsible for complex feature extraction and transformation of the input data. They are composed of neurons that apply non-linear transformations to the input data.
3. **Output Layer:** This layer generates the final output of the neural network based on the transformations performed by the hidden layers

#### Neurons

1. **Artificial Neurons:** These are the basic computing units in a neural network. Each neuron receives input from other neurons, applies an activation function, and then sends the output to other neurons.
2. **Activation Functions:** These are mathematical functions that introduce non-linearity to the neural network, allowing it to learn complex representations from data. Common activation functions include sigmoid, ReLU, and tanh.

## Activation Functions

1. **Sigmoid**: Maps the input to a value between 0 and 1, often used in binary classification problems.
2. **ReLU (Rectified Linear Unit)**: Maps all negative values to 0 and all positive values to the same value, commonly used in deep neural networks.
3. **Tanh (Hyperbolic Tangent)**: Maps the input to a value between -1 and 1, often used in recurrent neural networks.

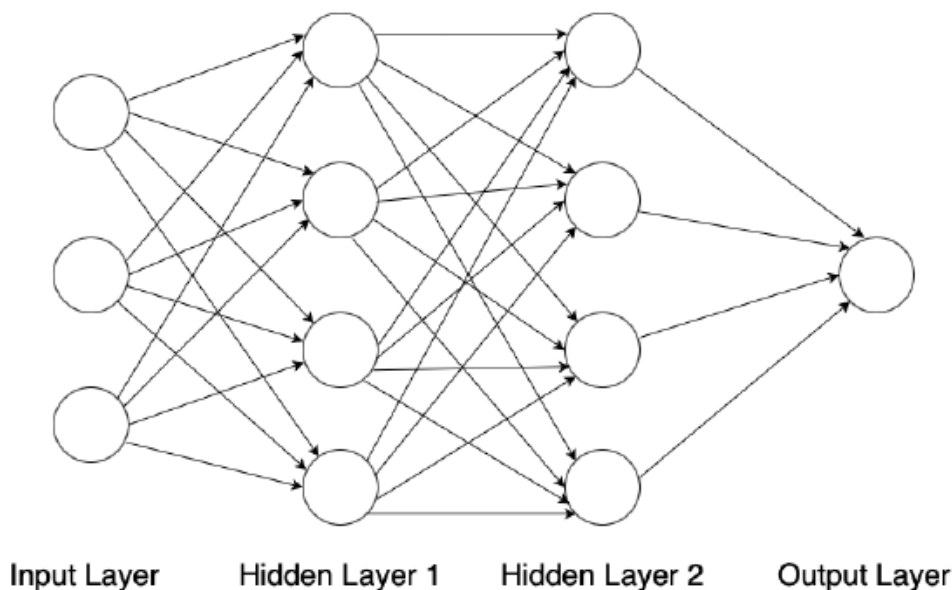


Figure 2.1: A typical Artificial Neural Network with two hidden layers and a single output[4]

### 2.2.1 Role of Neural Networks in Learning Complex Representations from Data

Neural networks are particularly effective in learning complex representations from data due to their ability to:

1. **Extract Features**: Neural networks can automatically extract relevant features from the input data, which can be difficult to define manually.
2. **Transform Data**: Neural networks can transform the input data in complex ways, allowing them to learn non-linear relationships between inputs and outputs.
3. **Generalize**: Neural networks can generalize well to new, unseen data by learning patterns and relationships in the training data.

### 2.2.2 Regularization Techniques in Neural Networks

Regularization techniques prevent overfitting and improve model generalization. Overfitting occurs when a model fits training data too closely, performing poorly on unseen data. Regularization adds a penalty term to the loss function to discourage unnecessary complex predictions[5].

## L2 Regularization (Ridge)

L2 regularization adds a penalty term proportional to the square of model weights:

$$\mathcal{L}(\theta) = \frac{1}{2} \sum_{i=1}^n (y_i - f(x_i; \theta))^2 + \frac{\lambda}{2} \sum_{j=1}^m \theta_j^2$$

where:

- $\mathcal{L}(\theta)$  is the loss function,
- $\theta$  are model weights,
- $y_i$  are target values,
- $x_i$  are input values,
- $n$  is the number of samples,
- $m$  is the number of parameters,
- $\lambda$  is regularization strength.

L2 regularization reduces weight magnitudes to prevent overfitting[6].

## Impact on Loss Function and Training

During training, L2 regularization penalizes large weight updates, stabilizing the model and improving generalization[6].

## L1 Regularization (Lasso)

L1 regularization adds a penalty term proportional to the absolute value of weights:

$$\mathcal{L}(\theta) = \frac{1}{2} \sum_{i=1}^n (y_i - f(x_i; \theta))^2 + \lambda \sum_{j=1}^m |\theta_j|$$

where:

- $\mathcal{L}(\theta)$  is the loss function,
- $\theta$  are model weights,
- $y_i$  are target values,
- $x_i$  are input values,
- $n$  is the number of samples,
- $m$  is the number of parameters,
- $\lambda$  is regularization strength.

L1 regularization encourages sparsity and improves feature selection[5].

## 2.2.3 Dropout Regularization

### Concept and Motivation

Dropout is a regularization technique used in neural networks to prevent overfitting and improve model generalization. It involves randomly dropping units (along with their connections) from the network during training, which prevents units from co-adapting too much. This helps in reducing the complexity of the model and improving its performance on unseen data.[7]

### **Purpose of Dropout**

The primary purpose of dropout is to prevent overfitting by reducing the model's ability to fit the training data too closely. By randomly dropping units, dropout ensures that the model does not rely too heavily on any specific set of units, which helps in improving its generalization capabilities[8].

### **Implementation and Effects**

During the training phase, dropout randomly drops units from the network, effectively creating multiple "thinned" networks. This process is repeated multiple times, and the model is trained on each of these thinned networks. At inference time, the model uses a single unthinned network with smaller weights to approximate the effect of averaging the predictions of all the thinned networks[9].

### **Impact on Network Architecture and Learning Dynamics**

Dropout affects both the network architecture and the learning dynamics. By randomly dropping units, dropout introduces noise into the network, which helps in reducing the model's ability to fit the training data too closely. This noise also helps in improving the model's robustness to overfitting and its ability to generalize to unseen data[7].

## **2.2.4 Optimization Algorithms**

Optimizers play a crucial role in training neural networks by minimizing the loss function and updating the model's parameters iteratively. Popular optimizers such as Stochastic Gradient Descent (SGD), Adam, and RMSprop employ different strategies to adjust the learning rate and update weights efficiently during training. SGD iteratively updates parameters based on the gradients computed from a subset of training data, making it computationally efficient for large datasets [10]. Adam combines the advantages of adaptive learning rates and momentum to converge faster and handle noisy gradients effectively [10]. RMSprop adapts the learning rate for each parameter based on the magnitude of recent gradients, often improving convergence in non-convex optimization problems [11]. Choosing the right optimizer depends on the specific problem, dataset characteristics, and computational resources available [12].

## 2.3 Convolutional neural network(CNN)

### 2.3.1 Introduction to CNN

Convolutional Neural Networks (CNNs) are a type of Artificial Neural Network (ANN) designed to reduce the complexity of image-based pattern recognition. They are a popular contemporary trend in machine learning, particularly in image processing tasks such as object detection and image segmentation. CNNs work by applying multiple layers of convolutional and pooling operations to extract features from images, followed by fully connected layers for classification. This process enables them to learn hierarchical representations of images, which are essential for tasks like image recognition and object detection[13].

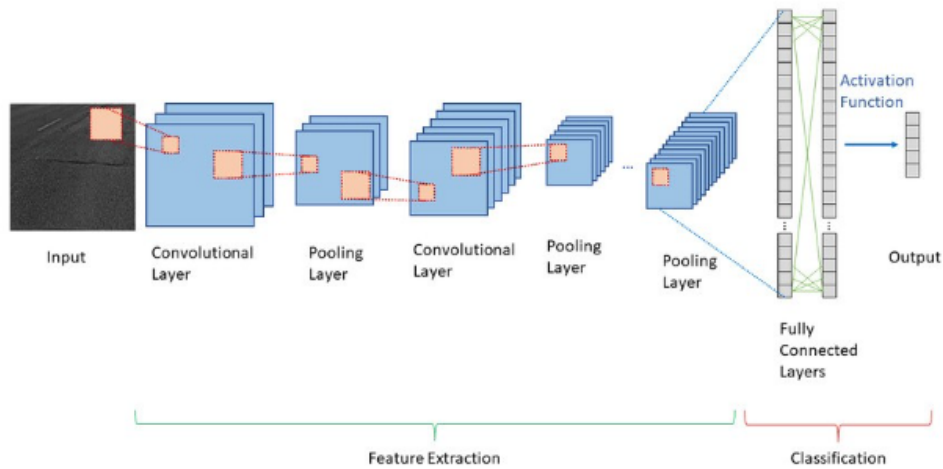


Figure 2.2: CNN architecture

### 2.3.2 ResNet

ResNet, also known as Residual Network, is a ground-breaking deep learning architecture that transformed computer vision and was first presented by He et al. The main idea behind ResNet is to solve the vanishing gradient issue in very deep network training by using residual connections or bypass pathways. With ResNet, a feed-forward network with residual connections is used. Each layer's output is the result of applying different operations, such as activation, batch normalization, and convolution, to the layer before it. This speeds up deep network training and permits unrestricted information flow. With depths of up to 1202 layers, ResNet was able to achieve state-of-the-art performance—much deeper than earlier architectures like VGG and AlexNet [14]

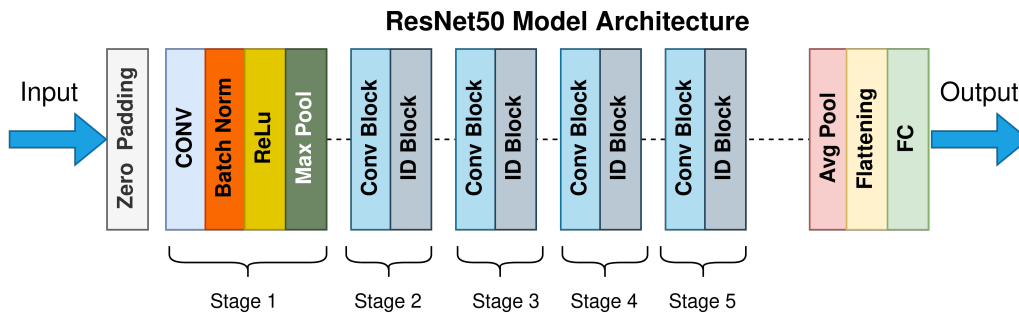


Figure 2.3: ResNet50 Architecture [15]

### 2.3.3 VGG

The Visual Geometry Group (VGG) architecture, proposed by Simonyan and Zisserman, introduced a simple and efficient design principle for Convolutional Neural Networks (CNNs). With 19 extra layers than previous architectures like ZefNet and AlexNet, VGG’s multilayer model enhances the network’s depth representational capacity. In contrast to its predecessors, VGG proved that smaller filters could produce comparable results while requiring less computational power by using a stack of 3x3 filters rather than larger 5x5 and 11x11 filters. Through the use of 1x1 convolutions between convolutional layers, VGG was able to learn linear combinations of feature maps and control network complexity. Its simplicity, uniform structure, and greater depth won it praise; however, the primary disadvantage was the high computational cost resulting from its roughly 140 million parameters. [14]

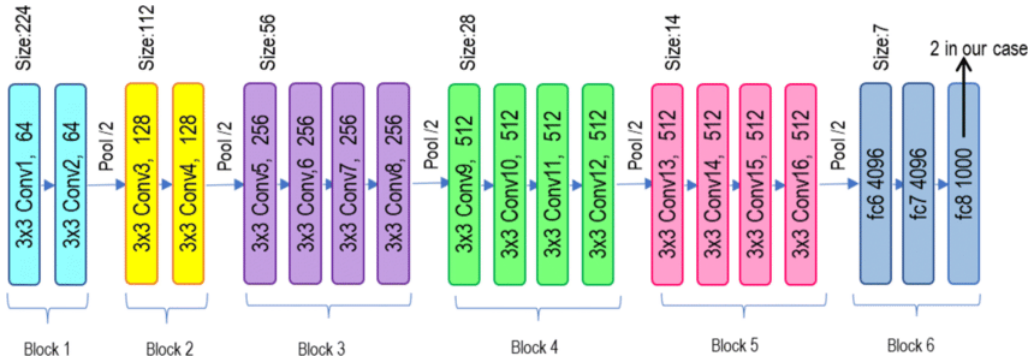


Figure 2.4: VGG19 Architecture [16]

### 2.3.4 DenseNet

DenseNet, proposed by Huang et al. in 2017, Is a collection of effective convolutional neural network models created specifically for embedded and mobile vision applications. These models are lightweight deep neural networks constructed with depth-wise separable convolutions. By introducing direct connections from every layer to every subsequent layer, the DenseNet architecture accelerates the flow of information across layers and increases the capacity of the network to learn intricate features. Because of the network’s deep interconnectedness, every layer may access the feature-maps of every layer that came before it, making full use of the network’s collective knowledge. To attain state-of-the-art results on different datasets, one critical hyperparameter that may be modified is the network’s growth rate, which controls the amount of new information each layer adds to the global state.[17]

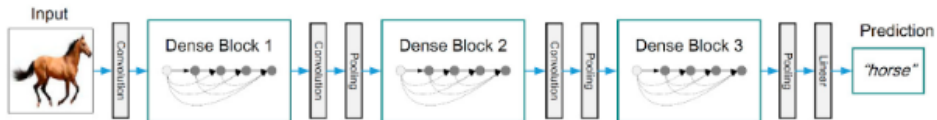


Figure 2.5: DenseNet General Architecture [17]

### 2.3.5 AlexNet

The innovative deep CNN architecture known as AlexNet, which was put forth by Krizhevsky et al., produced novel outcomes in image recognition and classification. It made it possible for AlexNet to model deeper representational capacity for a variety of image categories by increasing the depth of earlier models, such as LeNet, from five to seven feature extraction stages. AlexNet used two NVIDIA GTX 580 GPUs simultaneously for training in order to get around hardware constraints. Using ReLU as a non-saturating activation function to improve convergence, applying dropout to guarantee robust learned features, and utilizing big 5x5 and 11x11 filters in the early layers were some of the key improvements. Although overfitting resulted from AlexNet’s depth, it heralded a new era in CNN research and applications. [14]

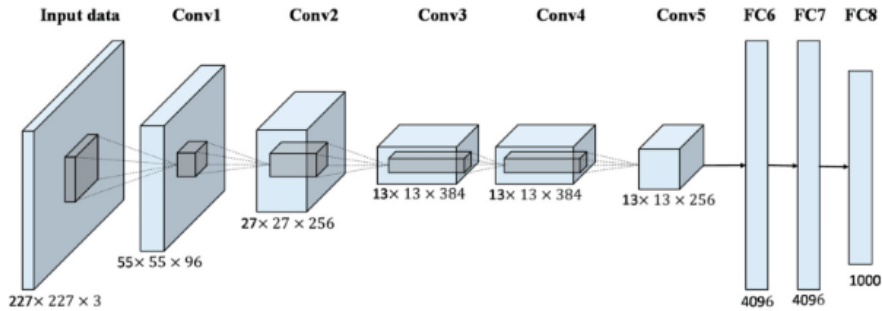


Figure 2.6: AlexNet Architecture [18]

### 2.3.6 Inception

Inception v3 reduces the computational cost while optimizing a network’s performance. Applications with limited processing power and memory can benefit from it. The experimental findings show that Inception v3 is a potent network with an overall accuracy of 93% for using transfer learning to identify cassava illnesses. An additional version of GoogLeNet, called Inception v4, takes the place of the filter concatenation step. The Inception architecture is combined with residual connections to expedite the training of Inception networks. This model achieves a 98% accuracy rate.[14]

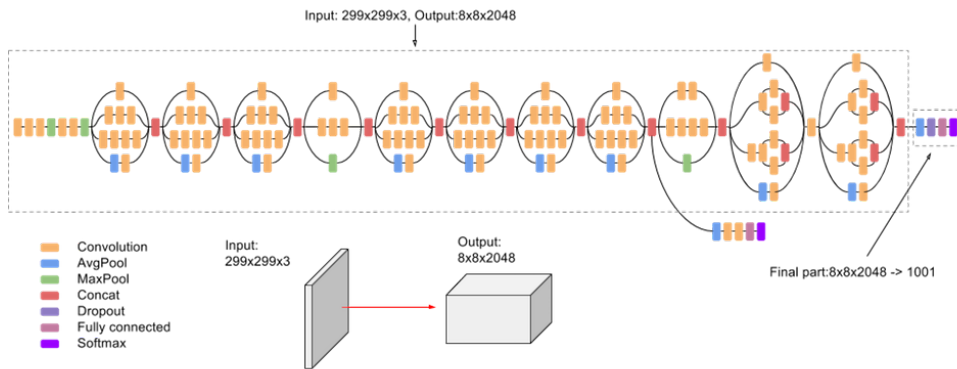


Figure 2.7: InceptionV3 Architecture [19]

### 2.3.7 Xception

Xception, proposed by Chollet, is an extreme version of the Inception architecture that employs depthwise separable convolutions. The main idea of Xception is to swap out the conventional Inception module with one that uses pointwise convolutions first, then depthwise convolutions. Due to the ability to decouple channel-wise and spatial correlations, the model’s computational

efficiency is increased. After mapping the input to an embedding space using  $1 \times 1$  convolutions, Xception executes  $k$  spatial transformations, where  $k$  is the cardinality or width of the model. To capture cross-channel correlations,  $1 \times 1$  pointwise convolutions are applied after the spatial convolutions, which are applied independently to each channel. Xception's distinct architecture allows for improved performance and learning efficiency even though it keeps the same number of parameters as Inception. [20]

### 2.3.8 MobileNet

In order to minimize computing costs and retain accuracy, MobileNets employ depthwise separable convolutions, which are efficient convolutional neural networks tailored for mobile and embedded vision applications. Two hyperparameters that allow for trade-offs between latency and accuracy are the width multiplier ( $\alpha$ ) and resolution multiplier ( $\rho$ ). These parameters reduce the number of input/output channels and input resolution, respectively, and are important characteristics. The 28-layer design consists of a fully linked layer for classification, batch normalization, depthwise and pointwise convolutions, and ReLU nonlinearity. Because mobile networks are smaller in size, they require less regularization. They are trained using RMSprop and asynchronous gradient descent. Offering a strong mix between accuracy and efficiency, they excel in applications such as facial traits, object detection, large-scale geo-localization, and fine-grain categorization. When compared to other models, MobileNets are more accurate than GoogleNet and nearly as accurate as VGG16, but they are 32 times smaller and 27 times less computationally demanding. This makes them perfect for compressing big systems. [21]

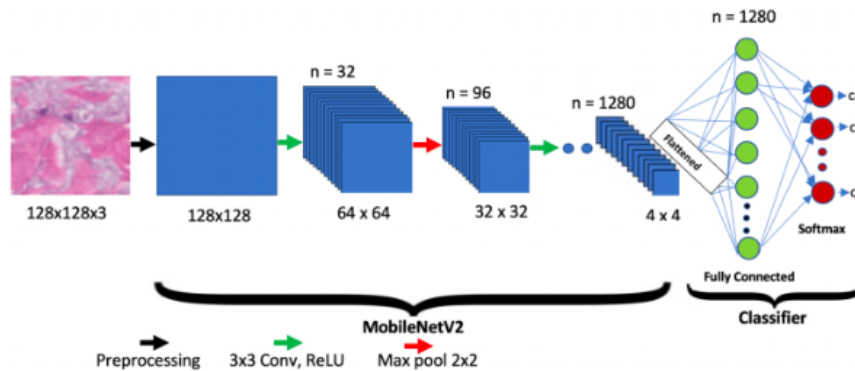


Figure 2.8: MobileNetV2 Architecture [22]



### 2.3.9 EfficientNet

Proposed by Tan et al in 2019, Efficient-Net uses a multi-objective neural architecture search, much like MnasNet, to maximize both accuracy and FLOPS. The objective is to balance accuracy and FLOPS in order to maximize both. The baseline, EfficientNet-B0, has squeeze-and-excitation optimization and mobile inverted bottleneck (MBConv) layers. With fixed coefficients ( $w$ ,  $d$ ,  $r$ ) and a small grid search, the model is scaled using a compound technique that simultaneously modifies network width, depth, and resolution. Experiments on the ImageNet dataset show that the EfficientNet models, ranging from B0 to B7, dramatically reduce FLOPS and parameters without sacrificing accuracy. Every model is a scaled-down version of the one before it, demonstrating the effectiveness of the compound scaling technique.[23]

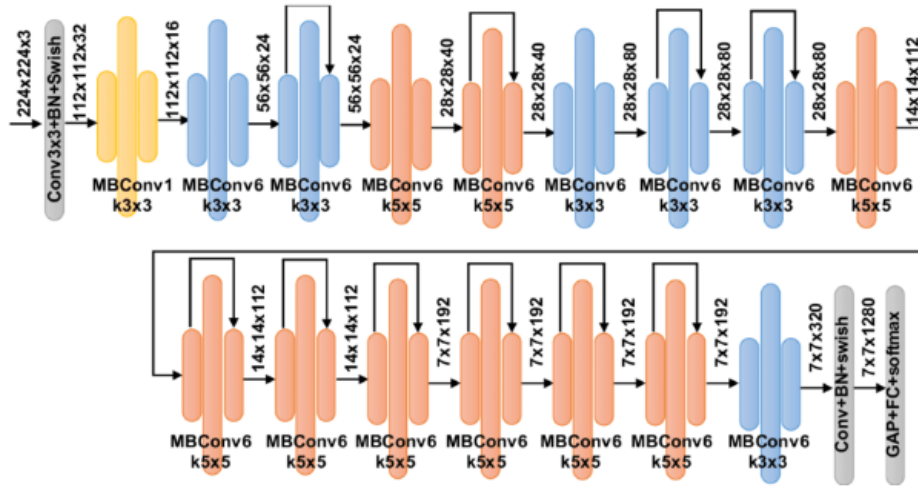


Figure 2.9: EfficientNetB0 Architecture [23]

### 2.3.10 Object detection using CNN:

#### You Only Look Once (YOLO):

The You Only Look Once (YOLO) object detection model has been extensively used in many different domains, such as traffic sign identification, automated vehicle counting, e-waste management, and real-time slug flow monitoring in subsea pipes. YOLO is a real-time object detection method that use deep learning to achieve high accuracy and speed. YOLOv5 and YOLOv3, which have been trained on annotated photos to enhance their detection ability, are two of the versions that have utilized it. For instance, it has been demonstrated that YOLOv5n can detect gas slugs and dense bubbles in slug flow images with a comprehensive detection performance of 67.94% and a high precision of 93.5%. In a similar vein, YOLO has demonstrated exceptional accuracy and speed in detecting and identifying traffic signs, pedestrians, and automobiles. Furthermore, YOLO has been used in agricultural contexts to identify the pineapple ripening phase with a 98.26% recognition accuracy. YOLO is a widely used tool in various industries, such as traffic control, e-waste management, and agricultural productivity, due to its versatility and effectiveness.

## 2.4 Transfer Learning in Deep Learning

Transfer learning is a technique in deep learning where a model trained on one task is used as a starting point for another task. This approach leverages the knowledge gained from the initial task to improve the performance on the new task, often with less data and computational resources required. Transfer learning has been widely applied across various domains, including computer vision, natural language processing, and audio processing.

### 2.4.1 Key Concepts of transfer learning:

1. **Feature Hierarchy:** Transfer learning relies on the concept of a feature hierarchy, where lower-level features learned from the initial task can be reused for the new task. This hierarchy is often represented by the layers in a deep neural network, where early layers learn general features and later layers learn task-specific features[24].
2. **Domain Adaptation:** Transfer learning involves adapting the model to the new task by fine-tuning the weights of the pre-trained model. This adaptation process is crucial to ensure that the model generalizes well to the new task, especially when the tasks have different distributions or domains[25].

### 2.4.2 Applications of transfer learning:

1. **Computer Vision:** Transfer learning has been highly successful in computer vision tasks such as image classification, object detection, and segmentation. For example, pre-trained convolutional neural networks (CNNs) have been used for tasks like facial recognition, medical image analysis, and autonomous driving[24].
2. **Natural Language Processing:** Transfer learning has been applied in NLP tasks such as language modeling, text classification, and machine translation. For instance, pre-trained language models like BERT have been used for tasks like sentiment analysis, named entity recognition, and question answering[26].
3. **Audio Processing:** Transfer learning has been used in audio processing tasks such as speech recognition, music classification, and audio classification. For example, pre-trained models have been used for tasks like speech-to-text systems and music genre classification[27].

### 2.4.3 Challenges and Limitations:

1. **Overfitting:** Fine-tuning a pre-trained model can lead to overfitting if the new task has a different distribution or if the model is not regularized properly. Techniques like dropout and early stopping can help mitigate this issue[28].
2. **Domain Shift:** Transfer learning assumes that the new task has a similar distribution to the initial task. However, if there is a significant domain shift, the model may not generalize well. Techniques like domain adaptation and data augmentation can help address this issue[25].

### 2.4.4 Future Directions:

1. **Meta-Learning:** Meta-learning is a subfield of transfer learning that focuses on learning how to learn from a few examples. This approach has the potential to further improve the efficiency and effectiveness of transfer learning[26].
2. **Explainability:** As transfer learning becomes more widespread, there is a growing need for explainability and interpretability of the models. Techniques like feature importance and attention mechanisms can help provide insights into the decision-making process of the model[27].

### 2.4.5 Conclusion:

Transfer learning is a powerful technique in deep learning that allows models to leverage knowledge gained from one task to improve performance on another task. By understanding the key concepts, applications, challenges, and future directions of transfer learning, researchers and practitioners can effectively apply this technique to a wide range of problems and domains.

## 2.5 Recurrent Neural Networks (RNNs)

### 2.5.1 Definition of RNNs

Recurrent Neural Networks (RNNs) are a powerful class of artificial neural networks specifically designed to handle sequential data. Unlike traditional feedforward neural networks, RNNs incorporate a feedback loop that allows them to process information from previous steps in a sequence, enabling them to capture temporal dependencies within the data [29]. In this chapter we will dive into the fundamentals of RNNs, exploring their definition, different models, and their unique capabilities in various applications. List of common keywords used in RNNs:

- **Sequential Processing:** RNNs process data one step at a time, allowing them to capture the temporal relationships within the sequence.
- **Internal Memory:** The loop in the RNN architecture acts as a form of internal memory, enabling the network to store information about previous inputs and utilize it for processing subsequent elements in the sequence.
- **Parameter Sharing:** RNNs share a set of weights across all time steps. This allows the network to learn a single set of rules for processing the sequence, promoting efficiency and generalization.

### 2.5.2 RNN Architectures

While the core concept of RNNs remains consistent, different architectures have been developed to address specific challenges and improve performance. Here are some prominent RNN models:

#### Vanilla RNN:

The simplest RNN architecture, VRNNs suffer from the vanishing gradient problem, where gradients become very small or large during backpropagation, hindering training for long sequences [30].

#### Long Short-Term Memory:

The vanishing gradient problem is addressed by LSTM (Long Short-Term Memory), a kind of Recurrent Neural Network (RNN) that enhances the learning of long-term sequential dependencies in data. This is accomplished by adding memory cells, which have the capacity to store information for extended periods of time, and by utilizing gates to regulate the information that enters and exits these cells[31].

##### 1. Essential Elements of LSTM:

- **Memory Cells:** The network can learn long-term dependencies thanks to these cells' ability to store information for extended periods of time. Gates that manage information flow into and out of the cells are in charge of them[1].
- **Gates:**
  - **Input Gate (i):** Regulates the movement of fresh data into the memory cell.
  - **Forget Gate (f):** Establishes the appropriate amount of prior time step data to be forgotten.
  - **Output Gate (o):** Regulates the information transfer from the memory cell to the LSTM unit's output[31].

##### 2. Benefits of LSTM:

- **Enhanced Long-Term Dependency Learning:** Compared to basic RNNs, LSTMs are more effective at learning long-term dependencies in data.
- **Robustness to Vanishing Gradients:** LSTMs can withstand vanishing gradients that can happen in basic RNNs during backpropagation[31].

### 3. Drawbacks of LSTM:

- **Higher Memory Requirements:** Compared to simple RNNs, LSTMs require more memory to hold the additional memory cells and gates.
- **Higher Computational Complexity:** The extra gates and memory cells in LSTMs make them more computationally complex[31].

### 4. LSTM Variations:

- **Stacked LSTM:** The network's ability to learn long-term dependencies can be enhanced by stacking multiple LSTM layers.
  - **Bidirectional LSTM:** This variant may collect context from both the past and the future by processing input sequences in both forward and backward directions.
  - **Multidimensional LSTM:** This variant uses connections from earlier stages along various dimensions to handle multidimensional sequences, including images.
  - **Grid LSTM:** This variant links LSTM cells along spatial dimensions. It is a particular kind of multidimensional LSTM.
  - **Differential RNN:** This variant finds and records significant spatiotemporal sequences in data by applying differential operators[31].
5. **Conclusion:** Long-term dependencies in sequential data can be effectively handled by LSTM, a strong model. It is more efficient than basic RNNs because it can manage the flow of information through gates and maintain information for extended periods of time. But the computational complexity and memory needs are higher. To handle particular activities and data types, LSTM variants have been created, providing greater application flexibility[31].

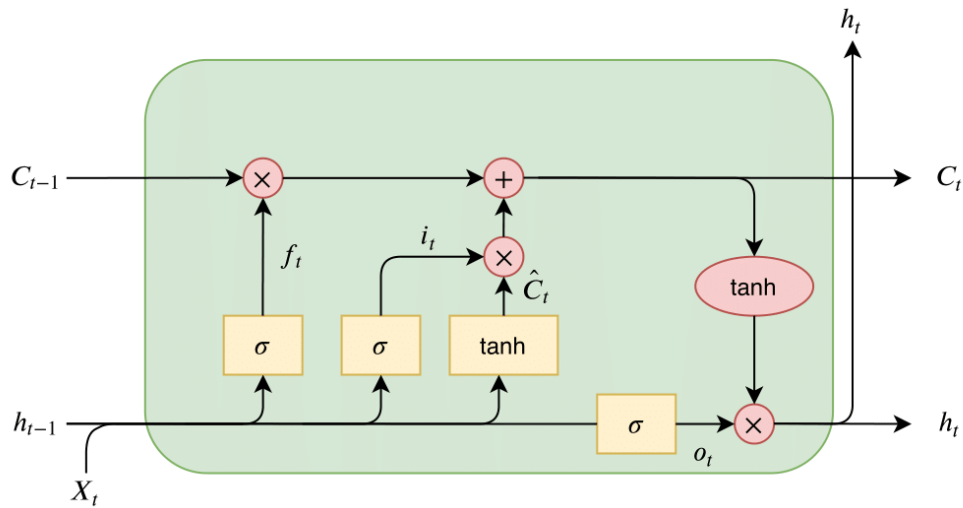


Figure 2.10: Long Short-term Memory [32]

### Gated Recurrent Unit:

The Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) unit that was proposed by *Cho et al.* in 2014. It is designed to adaptively capture dependencies of different time scales by using gating units to modulate the flow of information inside the unit[33].

The GRU has two main components:

- **Update Gate (z):** This gate decides how much the unit updates its activation. It is computed by

$$z_j^t = \sigma(W_z x^t + U_z h_j^{t-1})$$

- **Reset Gate (r):** This gate determines how much the unit forgets its previous state. It is computed by

$$r_j^t = \sigma(W_r x^t + U_r h_j^{t-1})$$

The GRU's activation at time  $t$  is a linear interpolation between the previous activation  $h_j^{t-1}$  and the candidate activation  $\tilde{h}_j^t$ :

$$h_j^t = (1 - z_j^t)h_j^{t-1} + z_j^t \tilde{h}_j^t$$

The candidate activation  $\tilde{h}_j^t$  is computed by:

$$\tilde{h}_j^t = \tanh(W_x x^t + U(r_j^t \odot h_j^{t-1}))$$

The GRU does not have a separate memory cell like the LSTM unit, but it still maintains the ability to capture long-term dependencies by using the update gate to control the flow of information[33].

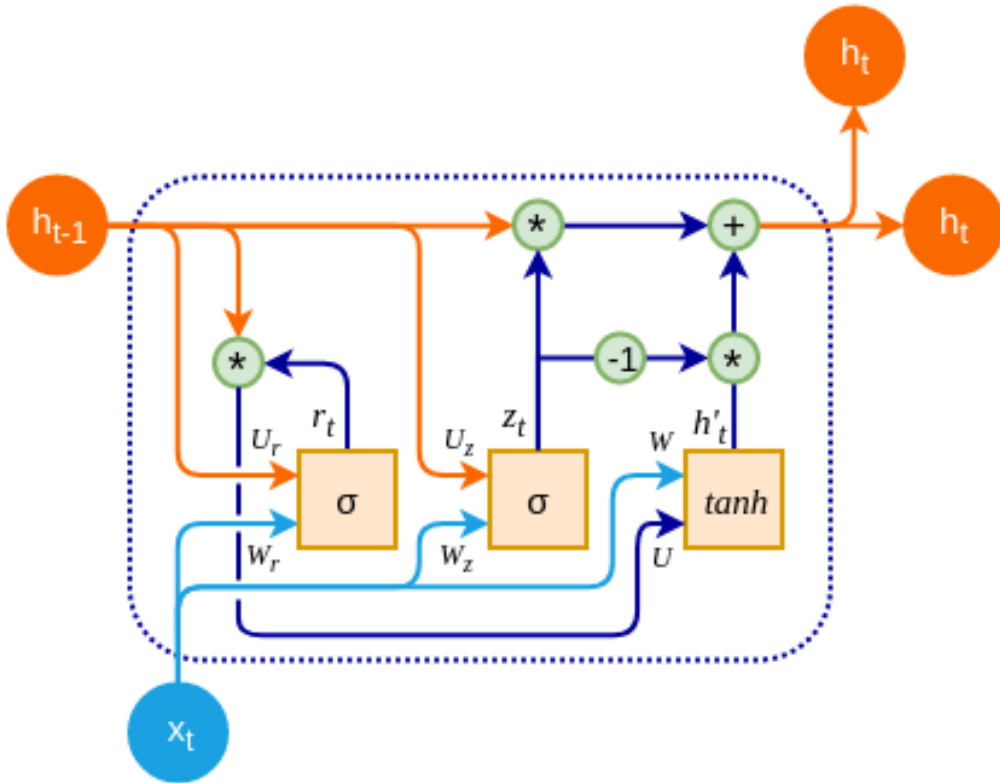


Figure 2.11: Gated Recurrent Unit [34]

## Bidirectional RNN:

One kind of recurrent neural network architecture that can process input sequences both forward and backward is the bidirectional RNN (Recurrent Neural Network). This makes it possible for the model to represent each input element's context from the past as well as the future, which can be very helpful for jobs involving the analysis of long-range dependent sequences.

Information only moves in one direction in a standard RNN: from the past to the future. This can be restrictive when working with sequences in which an element's context is determined by both its previous and subsequent elements. This restriction is overcome by bidirectional RNNs, which process the input sequence both forward and backward, efficiently capturing each element's past and future context.

Bidirectional RNNs are typically employed for the following tasks:

1. **Sentiment Analysis:** Bidirectional RNNs can enhance the accuracy of sentiment analysis models by capturing the context of each word in a phrase by processing the input sequence in both forward and backward orientations.[35].
2. **Sequence Alignment:** Bidirectional RNNs are beneficial for tasks like sequence alignment, where each element's context depends on both its past and future elements, by modeling sequences and their long-range relationships.[36].
3. **Human Activity Recognition:** By capturing the context of each movement in a series, bidirectional RNNs can be utilized to identify human activities, which can increase the accuracy of activity recognition models[37].

All things considered, bidirectional RNNs are an effective method for modeling long-range dependencies in sequences and have a plethora of applications where context is crucial.

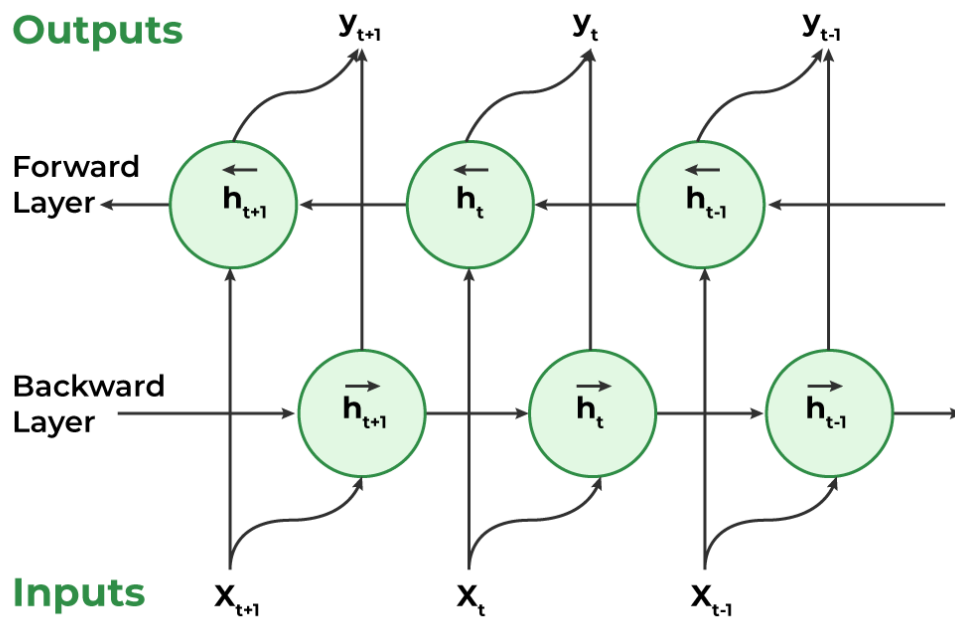


Figure 2.12: Bi-directional Recurrent Neural Network [38]

## 2.6 General AI Applied to Specific Problems

### 2.6.1 Overview of General AI

General Artificial Intelligence (GAI), often referred to as Strong AI, aims to create machines capable of performing any intellectual task that a human can do. While narrow AI is made to accomplish particular tasks, general artificial intelligence (GAI) aims to comprehend, acquire, and apply knowledge in a broad range of fields. This wider reach entails combining several AI approaches to create resilient and adaptable systems.

### 2.6.2 Application of General AI to Specific Problems

The application of General AI to specific problems involves leveraging its broad capabilities to address complex, real-world issues across different fields. This approach ensures that AI systems can adapt and provide solutions that are not limited to a narrow set of predefined tasks [39].

#### Case Studies

**Healthcare Disease Diagnosis and Treatment:** GAI systems are revolutionizing healthcare by improving diagnostic accuracy and personalizing treatment plans. For example, GAI can integrate data from medical imaging, patient history, and genomic information to provide comprehensive diagnostics. Systems like IBM's Watson have been used to recommend treatment options for cancer patients, analyzing vast amounts of medical literature and patient data to suggest personalized therapies [39].

**Agriculture Precision Farming:** In agriculture, GAI is applied to optimize crop yields and manage resources efficiently. By analyzing data from satellite imagery, weather patterns, soil sensors, and historical crop performance, GAI can provide actionable insights for farmers. This includes recommendations on irrigation, fertilization, and pest control, tailored to specific plots of land [40].

**Finance Fraud Detection:** GAI systems are employed in the financial sector to detect and prevent fraudulent activities. By analyzing transaction data, user behavior, and external factors, GAI can identify unusual patterns and flag potentially fraudulent transactions. These systems continuously learn and adapt to new fraud tactics, improving their detection capabilities over time [39].

### 2.6.3 Benefits of General AI

The benefits of applying General AI to specific problems are vast and transformative. Some of the key advantages include:

#### Enhanced Decision-Making

GAI systems can process and analyze large amounts of data to support more informed decision-making. In healthcare, this means better diagnostics and treatment plans. In finance, it leads to more accurate risk assessments and fraud detection [39].

#### Increased Efficiency

By automating complex tasks and providing actionable insights, GAI systems significantly increase efficiency. This is particularly evident in industries like agriculture and manufacturing, where GAI can optimize production processes and resource management [40].

#### Personalization

GAI enables highly personalized services and recommendations. In sectors such as healthcare and education, this means tailoring treatments and learning plans to individual needs, leading to better outcomes and user satisfaction [39].

## 2.6.4 Challenges and Considerations

While the potential of GAI is immense, there are several challenges and considerations that need to be addressed:

### **Ethical and Social Implications**

The deployment of GAI systems raises important ethical and social questions. Issues such as privacy, security, and the potential for job displacement need to be carefully managed to ensure that the benefits of GAI are widely shared and do not exacerbate existing inequalities [39].

### **Bias and Fairness**

Ensuring that GAI systems operate fairly and without bias is a significant challenge. Research is ongoing to develop techniques that can identify and mitigate biases in AI models, ensuring that these systems provide equitable outcomes across diverse populations [39].

### **Explainability and Transparency**

Developing methods to make GAI systems more transparent and understandable is crucial for their widespread adoption. Explainable AI (XAI) aims to provide insights into how AI systems make decisions, which is essential for trust and accountability, especially in critical fields like healthcare and finance [39].

## 2.6.5 Future Directions

The future of General AI involves further integration of advanced AI techniques to solve increasingly complex and interdisciplinary problems. Key areas of focus include:

### **Improved Adaptability**

Future GAI systems will need to be more adaptable, learning from fewer examples and generalizing better to new, unseen tasks. Techniques such as transfer learning and meta-learning are at the forefront of this research, aiming to make AI systems more flexible and capable of quickly adapting to new environments and problems [39].

### **Human-AI Collaboration**

Enhancing the collaboration between humans and AI systems is another critical area. Developing interfaces and interaction models that allow humans to work seamlessly with AI can leverage the strengths of both, leading to more effective problem-solving and decision-making [39].

### **Scaling Up**

As computational power and data availability continue to grow, GAI systems will be scaled up to tackle even larger and more complex problems. This includes addressing global challenges such as climate change, pandemics, and large-scale economic planning [39].



## 2.7 Transformers

Natural language processing (NLP) is a field of artificial intelligence that focuses on human-computer interaction. It has grown significantly due to the growing availability of textual data and the need for more sophisticated communication. NLP aims to develop accurate and natural algorithms for understanding and manipulating human language, revolutionizing industries like healthcare, education, and customer service.

Transformers, a significant NLP architecture, is based on a multi-head self-attention mechanism and a fully connected feedforward network. This mechanism enables the model to focus on different parts of the input sequence, weighing their importance in prediction. It also allows for parallel processing, making it more versatile than traditional models. The feedforward network, a multi-layer perceptron, applies linear transformations and activation functions to output the final representation, making it permutation-equivariant and suitable for sequence processing.

BERT, a pre-trained model, is effective for sentiment analysis, named entity recognition, and question answering. It learns rich contextual representations of words through contrastive tasks. GPT, a generative model trained on a large text corpus, is effective for text generation, language modeling, and question-answering. Both models have shown success in diverse and complete language representations.[41]

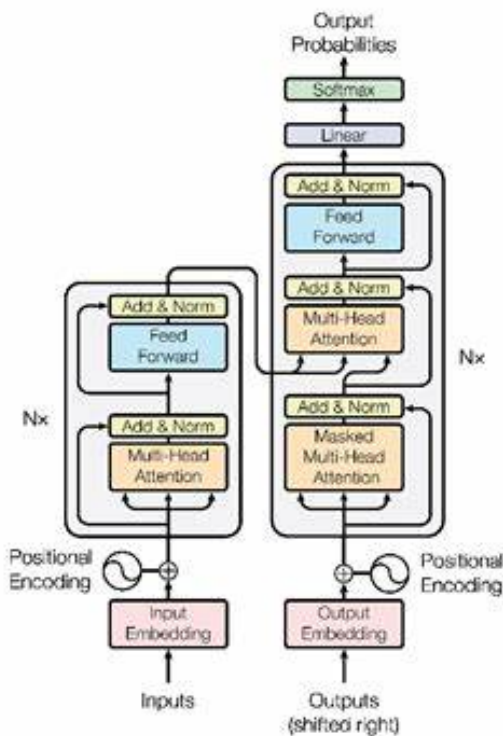


Figure 2.13: Transformers Architecture[42]

## 2.8 Large Language Models (LLMs)

### 2.8.1 Introduction

Large Language Models (LLMs) have revolutionized the field of natural language processing (NLP). They represent a significant leap in how machines understand and generate human language, enabling applications ranging from automated chatbots and virtual assistants to sophisticated text analysis and content creation tools[43]. In this section, we will explore the principles behind LLMs, their development, underlying technologies, and the impact they have had on various industries.

### 2.8.2 What are Large Language Models?

Large Language Models are advanced neural network models specifically designed for processing and generating human language. These models are characterized by their vast number of parameters, often running into billions, which allow them to capture complex patterns in language[44]. The fundamental idea behind LLMs is to predict the next word in a sentence, given a sequence of preceding words. By training on large datasets, these models learn the intricacies of grammar, context, and even the subtle nuances of meaning and tone[45].

### 2.8.3 Historical Development

#### Early NLP Techniques

The journey to modern LLMs began with simpler models such as n-grams and early neural networks. N-gram models predict the next word based on the previous 'n' words, but they struggle with capturing long-range dependencies in text[46]. Early neural networks, including feedforward and recurrent neural networks (RNNs), improved on n-grams by allowing for more complex pattern recognition.

#### The Transformer Model

The transformative moment in NLP came with the introduction of the Transformer model by Vaswani et al. in 2017. Unlike RNNs, which process sequences sequentially, Transformers leverage an architecture that processes words in parallel, using a mechanism called self-attention. This innovation allowed Transformers to capture long-range dependencies more effectively and train on much larger datasets within feasible timeframes[43].

#### Emergence of LLMs

Building on the Transformer architecture, researchers developed increasingly larger models. OpenAI's GPT (Generative Pre-trained Transformer) series exemplifies this progression. GPT-3, one of the most well-known LLMs, has 175 billion parameters and is trained on diverse datasets encompassing a vast range of human knowledge. Such models have demonstrated unprecedented capabilities in understanding and generating text that is contextually relevant and coherent[43].

## 2.8.4 How LLMs Work

### Training Process

Training an LLM involves several key steps:

1. **Data Collection:** Amassing a large and diverse corpus of text data[46].
2. **Tokenization:** Breaking down text into tokens (words or subwords) that the model can process[45].
3. **Pre-training:** Using unsupervised learning to allow the model to predict the next token in a sequence, thereby learning language patterns[44].
4. **Fine-tuning:** Adjusting the model on specific tasks or domains to enhance its performance in those areas.

### Architecture

LLMs rely on the Transformer architecture, which includes:

- **Encoder-Decoder Structure:** Though primarily used in translation tasks, many LLMs use just the decoder part for generating text[44].
- **Self-Attention Mechanism:** Enables the model to weigh the importance of different words in a sequence relative to each other[43].
- **Positional Encoding:** Since Transformers process all words in parallel, positional encodings help the model understand the order of words[43].

## 2.8.5 Applications of LLMs

### Text Generation

LLMs can generate human-like text, making them valuable for applications like content creation, story writing, and even generating programming code[43].

### Language Translation

Models like GPT-3 and BERT have been adapted for translation tasks, providing high-quality translations that often rival traditional systems.

### Chatbots and Virtual Assistants

LLMs power advanced chatbots and virtual assistants, enabling them to understand and respond to user queries with high accuracy and contextual relevance[43].

### Sentiment Analysis

Businesses use LLMs to analyze customer feedback, social media posts, and reviews to gauge public sentiment and improve their services[43].

## 2.8.6 Ethical Considerations and Challenges

### Bias and Fairness

LLMs can inadvertently perpetuate biases present in their training data, leading to unfair or harmful outputs. Ensuring fairness and mitigating bias is a critical area of ongoing research[43, 46].

### Misinformation

The ability of LLMs to generate convincing text raises concerns about their potential use in spreading misinformation and fake news[46].

### Privacy

Training on large datasets often involves scraping publicly available data, which can include sensitive or personal information. Ensuring data privacy is a significant concern[46].

### Environmental Impact

Training large models consumes significant computational resources, leading to a considerable carbon footprint. Efforts are ongoing to make training processes more energy-efficient[46].

## 2.8.7 Future Directions

### Model Efficiency

Research is focused on making LLMs more efficient, both in terms of computational resources required for training and inference[46].

### Multimodal Models

Integrating text with other forms of data, such as images and audio, to create more holistic AI systems.

### Personalization

Developing techniques to personalize LLMs for individual users while maintaining privacy and data security.

### Ethical AI

Creating frameworks and guidelines to ensure the ethical use of LLMs, addressing issues like bias, fairness, and accountability[43, 46].

## 2.8.8 Conclusion

Large Language Models represent a remarkable advancement in AI, transforming how machines interact with human language. While they offer immense potential, it is crucial to address the accompanying ethical and practical challenges. As research continues to evolve, LLMs will likely become even more integrated into our daily lives, driving innovation across multiple domains. Understanding their workings, applications, and implications is essential for leveraging their capabilities responsibly and effectively[43].

## 2.9 Retrieval-augmented generation (RAG)

### 2.9.1 Introduction

Retrieval-Augmented Generation (RAG) is a fine-tuning strategy that combines pre-trained parametric and non-parametric memory to generate language. For parametric memory, RAG models employ a pre-trained sequence-to-sequence model, and for non-parametric memory, they use a dense vector index accessible by a pre-trained neural retriever. There are two RAG formulations: RAG-Token, which can use different passages for each token, and RAG-Sequence, which uses the same retrieved passages for the entire created sequence.[47]

### 2.9.2 Model Architecture

RAG is made up of two primary parts:

- **Retriever:** Using a bi-encoder architecture, retrieves the top-K text passages in response to a query.[47]
- **Generator:** Text is produced using a pre-trained sequence-to-sequence transformer model using the retrieved passages as input.[47]

Training and Decoding

- **Training:** By considering the recovered documents as latent variables, the generator and retriever are trained in tandem.[47]
- **RAG-Sequence Decoding:** Generates the entire sequence from the same retrieved document, utilizing a beam search for each document and scoring hypotheses.[47]
- **RAG-Token Decoding:** Predicts each token by utilizing a variety of documents, operating similarly to a normal autoregressive sequence generator.[47]

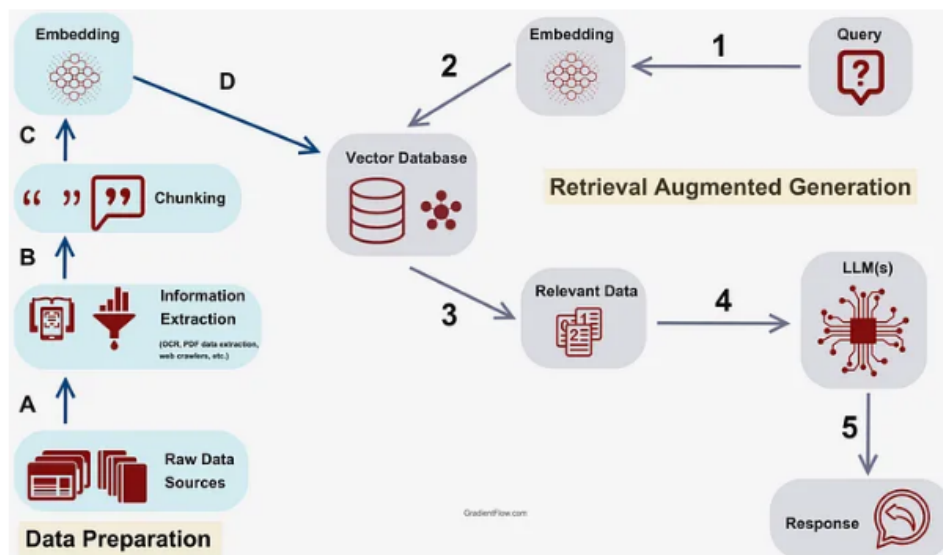


Figure 2.14: RAG Architecture [48]

# **Chapter 3:**

## AI in Agriculture

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## Chapter 3

# AI in Agriculture

### 3.1 Introduction :

Artificial intelligence (AI) has transformed livestock farming by improving animal health and welfare in intensive animal farms, resulting in economic benefits. However, the availability of references for study and farming is hampered by the notable dearth of literature reviews addressing AI applications across a variety of livestock species[49]. By giving a thorough overview of AI technology used in smart farming, outlining its potential for sophisticated, profitable, and environmentally friendly animal farming, and providing essential resources for researchers and engineers interested in smart animal farming, this review seeks to close this knowledge gap[49]. The review addresses application domain, research area, challenges, and future needs in animal farming in agriculture[49]. It offers insights into the potential of AI in enhancing animal health and welfare by discussing AI models used in a variety of animal species, research trends, and future requirements in agriculture and animal farming [49] [50].

### 3.2 The traditional way

The foundation of livestock healthcare has historically been based on traditional veterinary practices. These practices rely on the extensive knowledge and experience of Arab shepherds, particularly the Bedouins, who have a longstanding tradition of diagnosing and treating animal ailments[51]. Arab shepherds in the Near East region have a rich history of expertise in identifying and treating different illnesses, primarily through the use of plant combinations and the practice of fire branding[51].

Traditional animal healthcare practices are still relied upon by small-scale livestock farmers in many regions of the world for disease prevention and control[52]. A recent study revealed that the majority of herders independently performed the diagnosis and treatment of livestock diseases, while only a minority sought advice from veterinary professionals[52]. Although a few farmers employed both traditional and modern veterinary services, a considerable number relied exclusively on traditional methods to maintain the health of their animals[52].

### 3.3 Limitation of traditional way

Traditional veterinary practices have various drawbacks that restrict their widespread adoption and effectiveness. One major constraint is the lack of documentation and standardization of traditional techniques, making it impossible to evaluate their efficacy and safety[51]. Additionally, the reliance on plant-based cures and fire branding can be time-consuming and labor-intensive, which may not be feasible for large-scale farming operations[51]. Moreover, with time, diseases and parasites may become resistant to conventional treatments, making them ineffective.. The limited availability of qualified specialists and the necessity for specialized knowledge to prepare and administer traditional treatments can also be significant impediments to their use[53].

- **Lack of documentation and standardization:**Traditional techniques are generally passed down through generations orally, without written records, making it impossible to prove their

efficacy and safety[51].

- **Time-consuming and labor-intensive:** Plant-based cures and fire branding can be time-consuming and labor-intensive, which may not be practicable for large-scale farming operations[51].
- **Development of resistance:**Regular use of conventional treatments might cause illnesses and parasites to become resistant, eventually making them ineffective..
- **Limited availability of skilled experts:** Particularly in rural regions, there may be a shortage of skilled specialists who can administer and prepare traditional remedies[53].
- **specialist knowledge required:** A common obstacle to the use of traditional remedies is the need for specialist expertise in their preparation and administration[53].

### 3.4 Introduction AI

Recent advances have led to the adoption of AI and computer vision techniques, particularly deep learning models, as decision-making tools within the livestock industry[50]. These models have been employed for tasks like animal identification, tracking, body part recognition, and species classification[50]. In the past decade, there has been a growing interest in using these models to explore the connection between livestock behaviour and health issues[3]. While previous review studies have been rather generic, there is currently no review study specifically focusing on DL for livestock behaviour recognition.

Livestock welfare assessment helps monitor animal health status to maintain productivity, identify injuries and stress, and avoid deterioration[50]. It has also become an important marketing strategy since it increases consumer pressure for a more humane transformation in animal treatment[50]. Common visual welfare practices by professionals and veterinarians may be subjective and cost-prohibitive, requiring trained personnel[50]. Recent advances in remote sensing, computer vision, and artificial intelligence (AI) have helped developing new and emerging technologies for livestock biometrics to extract key physiological parameters associated with animal welfare[50].

### 3.5 How can AI help this field

AI can significantly enhance the livestock industry by addressing various challenges and improving animal health, welfare, and productivity. Here are some examples:

1. **Animal Identification and Tracking:** AI-powered sensors and cameras can be used to track and identify animals, enabling more efficient monitoring and management of herds. This can help reduce labor costs and improve animal welfare[54].
2. **Behavioral Analysis:** AI systems are able to examine animal behavior to identify early indicators of disease or stress, facilitating timely treatments that enhance production and general health..
3. **Genome-to-Phenome Analysis:** AI can help analyze the genetic makeup of animals and predict their traits, enabling more targeted breeding programs and improving the overall quality of livestock [54].
4. **Data Quality and Integration:** AI can help integrate and analyze large amounts of data from various sources, such as sensors and IoT devices, to provide more accurate insights and improve decision-making[54].
5. **Predictive Maintenance:** AI-powered predictive maintenance can help identify potential issues before they become major problems, reducing downtime and improving overall efficiency[54].
6. **Smart Farming Systems:**AI can be integrated into smart farming systems to optimize crop yields, reduce waste, and improve resource allocation, ultimately enhancing the overall sustainability of the livestock industry[54].



7. **Real-Time Monitoring:** Real-time tracking of animal behavior and health using AI can lead to more efficient interventions and an improvement in animal welfare overall..
8. **Personalized Medicine :** AI has the potential to advance animal personalized medicine by modifying care to meet each patient’s unique demands and enhancing overall health results..

These examples illustrate the potential of AI to transform the livestock industry, improving animal health, welfare, and productivity while reducing costs and enhancing sustainability.

### 3.6 Limitations of AI

Even though AI and IoT are transforming the dairy livestock export industry, there are several challenges in their integration. These challenges include:

1. **Individual animal customization:** AI and IoT technologies require precise data on individual animals, which can be difficult to obtain and manage, especially for large-scale operations[54].
2. **Economic analysis:** The cost-benefit analysis of integrating AI and IoT technologies into dairy livestock export operations can be complex and may not always be economically viable[54].
3. **Data security and privacy:** The integration of AI and IoT technologies generates vast amounts of data, which must be secured and protected to prevent unauthorized access and misuse[54].
4. **Technological adaptability:** The dairy livestock export industry is constantly evolving, and AI and IoT technologies must be adaptable to changing conditions and requirements[54].
5. **Training and stakeholder engagement:**The successful integration of AI and IoT technologies requires extensive training and engagement with stakeholders, including farmers, veterinarians, and other industry professionals[54].
6. **Sustainability concerns:**The environmental and social impacts of AI and IoT technologies in dairy livestock export operations must be carefully considered and managed to ensure sustainability[54].
7. **Animal welfare and treatment:**The integration of AI and IoT technologies must prioritize animal welfare and ensure that animals are treated with respect and care throughout the entire supply chain[54].
8. **Data quality and management:** The quality and management of data generated by AI and IoT technologies are critical to their effectiveness and must be carefully monitored and maintained[54].

### 3.7 Data problem

Data quality and management particularly are crucial aspects of integrating AI and IoT technologies in the dairy livestock export industry. The sheer volume and complexity of data generated by IoT sensors and AI algorithms require robust data management systems to ensure accuracy, integrity, and accessibility. Poor data quality can lead to inaccurate predictions, misinformed decisions, and compromised animal welfare. Therefore, it is essential to implement data quality control measures, such as data validation, cleaning, and normalization, to ensure that data is reliable and consistent.

Additionally, data management strategies, such as data warehousing, data lakes, and data visualization tools, must be employed to facilitate data analysis, reporting, and decision-making. Furthermore, data security and privacy measures must be implemented to protect sensitive information and prevent unauthorized access. By ensuring high-quality data and effective data management, the dairy livestock export industry can leverage the full potential of AI and IoT technologies to improve efficiency, reduce costs, and enhance animal welfare.[55].

### 3.8 Case of studies and real world applications

The integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies in the dairy livestock export industry has significant potential to transform the industry. Here are some case studies and real-world applications that demonstrate the transformative impact of AI and IoT:

1. **Livestock Enumeration and Identification:** AI-powered sensors and cameras can be used to track and identify animals, enabling more efficient monitoring and management of herds. This technology has been successfully implemented in several countries, including the United States and Australia, to improve animal welfare and reduce supply chain inaccuracies[54].
2. **Behavioral Analysis:** AI algorithms can analyze animal behavior to detect early signs of illness or stress, allowing for prompt interventions and improving overall health and productivity. Many researchers used AI-powered cameras to monitor the behavior of dairy cows and detect signs of mastitis, enabling early treatment and reducing the need for antibiotics[54].
3. **Real-Time Weight Monitoring:** AI-powered sensors can be used to monitor the weight of animals in real-time, enabling more accurate tracking and management of herds. This technology has been successfully implemented in several countries, including the United States and Canada, to improve animal welfare and reduce supply chain inaccuracies[54].
4. **Genome-to-Phenome Analysis:** AI algorithms can be used to analyze the genetic makeup of animals and predict their traits, enabling more targeted breeding programs and improving the overall quality of livestock. Many studies used AI-powered genome analysis to predict the genetic traits of dairy cows and improve their milk production[54].
5. **Smart Farming Systems:** AI-powered smart farming systems can be used to optimize crop yields, reduce waste, and improve resource allocation, ultimately enhancing the overall sustainability of the dairy livestock export industry. Recently, many research studies used AI-powered smart farming systems to optimize the growth of corn and soybeans, reducing waste and improving resource allocation[54].
6. **Animal Feed Formulation:** AI decision support systems can be used to optimize animal feed formulation, promoting animal health and environmental stewardship. Many studies used AI-powered decision support systems to optimize animal feed formulation, reducing waste and improving resource allocation.
7. **Electronic nose:** Electronic nose (E-nose) technology has emerged as a promising tool for rapid and objective analysis of complex odor profiles in various industries. E-noses mimic the human olfactory system to detect, discriminate, and classify odor samples. They are non-destructive intelligent electronic sensing instruments that can be used for quality control, optimizing blend formulations, monitoring processing conditions, and assuring the quality of finished products. E-noses have been applied in various sectors, including food and dairy industries, tobacco, and animal-source food, to detect adulteration, monitor shelf life, and predict physico-chemical and sensory parameters of products[56].

They have also been used for early disease detection by analyzing volatile organic compounds (VOCs) in exhaled breath and other samples[56]. The technology has the potential to revolutionize industries by ensuring consistent product quality, meeting changing consumer demands, and addressing public health concerns and regulatory requirements[56].

These case studies and real-world applications demonstrate the transformative potential of AI and IoT technologies in the dairy livestock export industry, highlighting the importance of integrating these technologies to improve animal welfare, reduce supply chain inaccuracies, and enhance sustainability.

### 3.9 Future Directions and Opportunities

1. **Digital Transformation and Integration:** The dairy livestock export sector could undergo a dramatic transformation if AI and IoT technology are integrated. By improving animal welfare, decreasing errors in the supply chain, and raising operational productivity, these technologies can eventually open up new markets and boost competitiveness internationally.

2. **AI and IoT Integration:** The dairy livestock export sector will continue to change as a result of the integration of AI and IoT technology, improving animal welfare, decreasing supply chain errors, and raising operational productivity. Additionally, this integration will improve global competitiveness and increase market access..
3. **Precision Farming:** Real-time weight monitoring and behavioral analysis are two examples of precision farming tools that will proliferate and improve animal wellbeing while cutting waste.. These innovations will also optimize crop yields, reduce waste, and improve resource allocation, enhancing the overall sustainability of the dairy livestock export industry[57].
4. **Data-Driven Decision Making:** AI-driven decision support tools will enhance animal feed formulation techniques, promoting animal health and environmental stewardship[57]. By leveraging AI decision support systems, producers can optimize feed composition to adapt to the evolving needs of livestock while ensuring environmentally sustainable practices amidst the challenges of climate change[57].
5. **Sustainability and Environmental Stewardship:**As the dairy livestock export industry faces growing demands and environmental pressures, a focus on sustainability and environmental stewardship has become increasingly crucial. Leveraging advanced technologies, such as AI-driven decision support systems, can promote animal health and environmental sustainability, contributing to the long-term resilience of the sector[54]
6. **Climate-Resilient Livestock Production:** Livestock production will focus on climate-resilient practices, such as optimizing animal feed formulation to promote animal health and environmental stewardship[57]. This will involve leveraging AI decision support systems to enhance formulation techniques, ensuring environmentally sustainable practices amidst the challenges of climate change[57].
7. **Efficient Resource Use:** The dairy livestock export industry will prioritize efficient resource use, reducing waste and improving resource allocation to enhance sustainability[57].
8. **Animal Welfare Standards:** The industry's main goals will be raising the bar for animal welfare, making sure that livestock is managed more sustainably, and supporting sustainable veterinarian and agricultural methods..
9. **Market Access and Global Competitiveness:**The dairy livestock export industry operates in a highly competitive global market, requiring strategic approaches to enhance market access and global competitiveness. Innovative technologies, diversified product portfolios, and strategic partnerships can play a pivotal role in positioning the industry for success in the international arena [54].
10. **Export-Oriented Production:** The export of dairy cattle will prioritize export-oriented production, utilizing AI and IoT technologies to boost worldwide competitiveness and increase market accessibility. .
11. **Diversified Product Portfolio:** The industry will diversify its product portfolio, including high-quality cheeses and meat products, to cater to global demand and enhance export opportunities[57].
12. **Strategic Partnerships:** The establishment of strategic collaborations among farmers, processors, and traders is important to augment market accessibility and global competitiveness, thereby guaranteeing the enduring viability of the dairy animal export sector..

Authors	Paper title	Year	URL
Xin Du, Jun Zhou	Application of biosensors to detection of epidemic diseases in animals	2018	<a href="https://www.sciencedirect.com/science/article/abs/pii/S0034528817312341">https://www.sciencedirect.com/science/article/abs/pii/S0034528817312341</a>
M. Sakova, P. Jurik, P. Galajda and M. Sokol	Bee Hive Acoustic Monitoring and Processing Using Convolutional Neural Network and Machine Learning	2024	<a href="https://ieeexplore.ieee.org/abstract/document/10524087">https://ieeexplore.ieee.org/abstract/document/10524087</a>
Rai, G., Naveen, Hussain, A., Kumar, A., Ansari, A., & Khanduja.	A deep learning approach to detect lumpy skin disease in cows	2021	<a href="https://link.springer.com/chapter/10.1007/978-981-16-0965-7_30">https://link.springer.com/chapter/10.1007/978-981-16-0965-7_30</a>
Vidic, J., Manzano, M., Chang, C. M., & Jaffrezic-Renault	Advanced biosensors for detection of pathogens related to livestock and poultry	2017	<a href="https://link.springer.com/article/10.1186/s13567-017-0418-5">https://link.springer.com/article/10.1186/s13567-017-0418-5</a>
Yazdanbakhsh, O., Zhou, Y., & Dick, S	An intelligent system for livestock disease surveillance	2017	<a href="https://www.sciencedirect.com/science/article/abs/pii/S0020025516312658">https://www.sciencedirect.com/science/article/abs/pii/S0020025516312658</a>
Fernández-Carrión, E., Martínez-Avilés, M., Ivorra, B., Martínez-López, B., Ramos, Á. M., & Sánchez-Vizcaíno, J. M.	Motion-based video monitoring for early detection of livestock diseases: The case of African swine fever	2017	<a href="https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0183793">https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0183793</a>

Table 3.1: Overview of AI Applications in the Veterinary Field

## 3.10 Conclusion

AI has the potential to revolutionize animal disease detection and management by improving efficiency, productivity, and sustainability. However, several challenges need to be addressed, including data quality and availability, interpretability and explainability, and cost and accessibility. Further research is needed to overcome these challenges and fully realize the benefits of AI in this field.

## 3.11 Recommendations for Future Research and Development in Deep Learning for Disease Detection in Animals

### 3.11.1 Enhance Data Collection and Quality

#### 1. Integration and Standardization of Data :

- To guarantee consistency, create uniform procedures for gathering data on different animal species and geographical areas.
- To guarantee consistency, create uniform procedures for gathering data on different animal species and geographical areas.

#### 2. Enhancing Data Quality

- Make investments in superior methods for data annotation and curation.
- Accurate and up-to-date data on animal behavior and health can be gathered in real time with IoT devices and sophisticated sensors.

### 3.11.2 Algorithm Development and Optimization

#### 1. Advanced Deep Learning Models

- Create and refine deep learning models that are especially suited to various animal diseases and species.
- Examine the application of hybrid models that combine conventional statistical techniques with deep learning to increase prediction accuracy.

#### 2. Explainable AI

- Make an effort to develop AI models that are comprehensible and interpretable so that they can shed light on the decision-making process.
- Provide visualization tools to aid in the understanding of AI diagnostics and predictions by researchers and veterinarians.

### 3.11.3 Robustness and Generalizability

#### 1. Cross-Species and Cross-Region Generalization

- Train models on a variety of datasets to improve their generalisation across many animal species and geographic areas.
- Cross-validate models to evaluate AI model robustness under different environments.

#### 2. Dealing with Data Scarcity

- Make an effort to develop AI models that are comprehensible and interpretable so that they can shed light on the decision-making process.
- Provide visualization tools to aid in the understanding of AI diagnostics and predictions by researchers and veterinarians.

### **3.11.4 Integration with Field Operations**

#### 1. Real-Time Monitoring and Response

- Build artificial intelligence-driven systems that can track and warn about disease outbreaks in real time.
- Create intuitive user interfaces and mobile applications to enable farmers and veterinarians to use AI tools in the field.

#### 2. Automated Diagnostic Tools

- Invest in the development of automated diagnostic tools, such as AI-powered imaging systems for early disease detection.
- Integrate AI diagnostics with existing veterinary diagnostic workflows to enhance efficiency and accuracy

### **3.11.5 Ethical, Legal, and Social Considerations**

#### 1. Ethical AI Development

- Establish moral standards for the creation and application of AI in animal health to guarantee data privacy and animal welfare.
- To win over stakeholders, encourage responsibility and openness in AI systems.

#### 2. Regulatory Frameworks

- Collaborate with regulatory agencies to create precise rules and specifications for the application of AI to the treatment of animal diseases.
- Check that data protection laws and international animal health standards are being followed.

### **3.11.6 Interdisciplinary Collaboration**

#### 1. Collaboration Between Veterinarians and Data Scientists

- Inspire multidisciplinary cooperation among epidemiologists, data scientists, veterinarians and other interested parties.
- Plan conferences and training courses to improve knowledge of and use of AI technologies in animal health.

#### 2. Public-Private Partnerships

- Promote collaborations to support R&D projects among government agencies, business, and academic institutions.
- Open up funding sources for joint initiatives that want to progress AI applications in animal disease detection.

### **3.11.7 Evaluation and Validation**

#### 1. Clinical Trials and Field Testing

- Undertake comprehensive clinical trials and field testing to verify the efficiency and dependability of AI-driven instruments in practical environments.
- Create performance standards and evaluation criteria to measure the usefulness, speed, and accuracy of AI models.

#### 2. Continuous Improvement

- Use feedback and continuous monitoring systems to improve AI models with fresh information and understanding.
- Encourage an attitude of ongoing education and adjustment to new problems and technical developments.

# **Chapter 4:**

## Contribution

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# Chapter 4

## Contribution

### 4.1 Introduction

Advanced AI-based solutions are becoming more and more necessary in modern agriculture to manage agricultural pests and detect diseases in animals. The complexity and magnitude of these difficulties make traditional techniques inadequate. AI technology helps farmers and veterinarians identify diseases and pests more accurately and efficiently, giving them important information.

Our contribution processes and analyzes massive datasets using deep learning techniques, looking for patterns and irregularities that point to the presence of pests or health problems. This project specifically focuses on a number of important areas, including the use of feces image analysis to detect diseases in poultry, the identification of Lumpy Skin Disease in cattle, the use of audio signals to recognize queenlessness in beehives, the use of classification and object detection techniques to detect agricultural pests, and the implementation of a veterinary specialist conversational agent.

In order to help farmers and veterinarians make better decisions and raise the productivity and health of their crops and livestock, this project aims to develop a strong system that improves disease and pest detection capacities. Our approach tackles the major issues in veterinary diagnostics and agricultural pest management by fusing state-of-the-art deep learning models with a perceptive conversational agent.

### 4.2 Classification models

#### 4.2.1 Agritechly's chicken disease detection

Image analysis of excrement is used to identify illnesses in chickens. Using cutting-edge deep learning algorithms, this method carefully inspects feces for signs of illnesses like salmonella, coccidiosis, and Newcastle disease. These models can detect tiny symptoms of diseases that may not be visible using conventional approaches by evaluating the photos of feces. Poultry producers can benefit from a number of advantages with this non-invasive and effective diagnostic technology, including fast and accurate illness detection—a critical component of effective disease management and treatment.

Farmers can prevent disease outbreaks and take early action by using this technology to continually and real-time monitor the health of their flocks. In order to minimize financial losses, improve flock health overall, and slow the spread of infectious diseases within chicken populations, early detection is essential. Additionally, this approach lessens the need for more intrusive diagnostic techniques, which can cause discomfort in the animals and take time for the farmers.

The fecal image analysis challenge is suited for a variety of deep learning models, including ResNet50, EfficientNetB4, DenseNet169, and MobileNetV3. These models guarantee great accuracy and dependability in disease identification because they are made to manage the intricate patterns and variations present in fecal matter. They are perfect for usage in a farm scenario where quick decisions are frequently needed due to their capacity to process and analyze massive volumes of data rapidly and effectively.



Moreover, on-site diagnoses are made possible by the integration of these models into mobile and edge devices, giving farmers the resources they need to make educated decisions without the need for specialist laboratory equipment. This mobility makes it possible for farms with low resources or in remote locations to take use of state-of-the-art disease detection equipment, thereby encouraging improved animal health practices throughout the chicken sector.

## Pre-trained Models

We trained a number of pre-trained models, such as ResNet50, EfficientNetB4, DenseNet169, and MobileNetV3, in order to attain high accuracy in disease identification. These models were selected because their efficacy in picture classification tasks has been demonstrated.

To enhance the performance of these models and prevent overfitting, we incorporated layers of batch normalization, regularization, and dropout into the architecture. These additions help stabilize and generalize the models, ensuring they perform well on unseen data.

### 1. ResNet50:

Residual Networks with 50 layers, also known as ResNet50, are well-known for their skip connections and deep architecture, which lessen the issue of disappearing gradients in deep networks. Gradients can pass straight through the network thanks to these skip connections, guaranteeing efficient training even for extremely deep designs. The architecture of this model is illustrated in Figure 2.3, demonstrating its intricate design.

ResNet50 is particularly adept at identifying small disease indicators in chicken feces because of its exceptional capability to extract finely detailed features from images. By examining fecal pictures for signs of sickness, its capacity to detect minute patterns and anomalies is essential for early disease identification and control in chicken farms, thereby protecting the flock's health and productivity.

### 2. EffectiveNetB4:

The depth, width, and resolution of the network's scalability are all balanced by the EfficientNet family, which includes EfficientNetB4. EfficientNetB4 is perfect for real-time illness identification using feces photos because it delivers great accuracy with fewer parameters and cheaper processing costs. Because of its efficiency, the model can operate at a high level without consuming a lot of computational power, which makes it appropriate for use in settings with constrained processing capacity.

In chicken farms, where prompt and precise disease detection via fecal analysis is essential, it is especially helpful for on-site veterinary assessments and mobile health diagnostics.

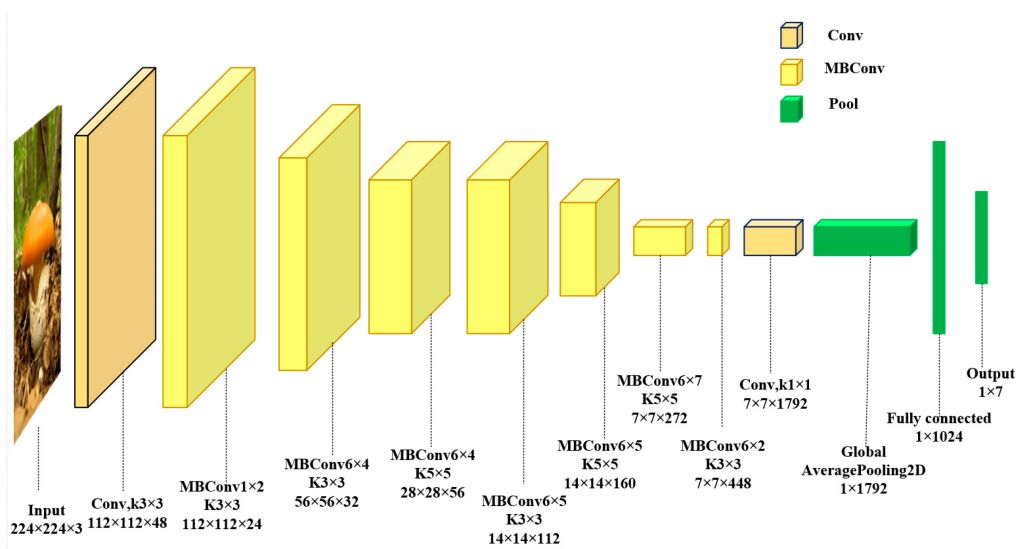


Figure 4.1: EfficientNetB4 Architecture [58]

### 3. DenseNet169:

DenseNet169, a member of the Densely Connected Convolutional Networks family, connects each layer feed-forward to each other using dense blocks. Because of the optimal information flow between layers provided by this connection design, the model is able to learn rich feature representations.

The capacity of DenseNet169 to retain and leverage data from all earlier layers improves the system's performance in identifying minute illness signs in chicken excrement. Because of this, it works especially well in applications like as fecal image analysis, where identifying complex patterns and correlations in the data might yield important information for the early diagnosis of diseases in chickens.

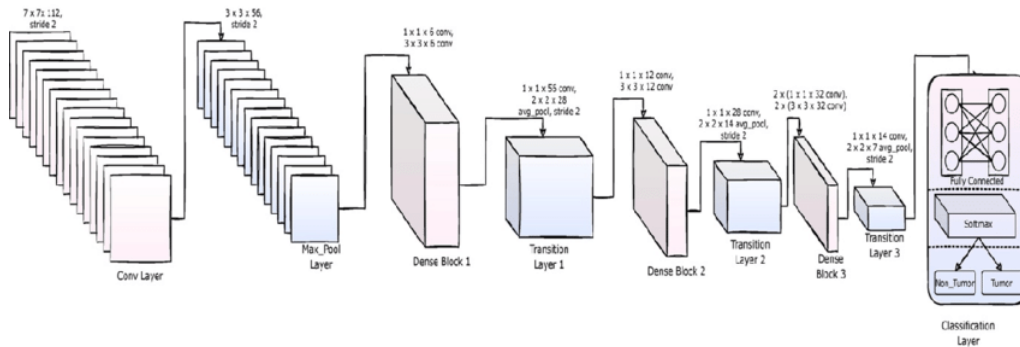


Figure 4.2: DenseNet169 Architecture [59]

### 4. MobileNetV3:

MobileNetV3, which offers a trade-off between latency, precision, and computing efficiency, is intended for mobile and edge applications. It achieves great accuracy with low processing needs by utilizing streamlined architecture and effective convolutional techniques. Because of this, MobileNetV3 is perfect for using on mobile devices to detect diseases in chicken poop in real time.

Farmers and veterinarians can conduct on-site diagnostics without expensive equipment because to its capacity to execute advanced detection algorithms on devices with little computing power. By making it possible to identify diseases by fecal analysis quickly, this improves the welfare and production of chickens by enabling shorter response times and proactive health management methods.

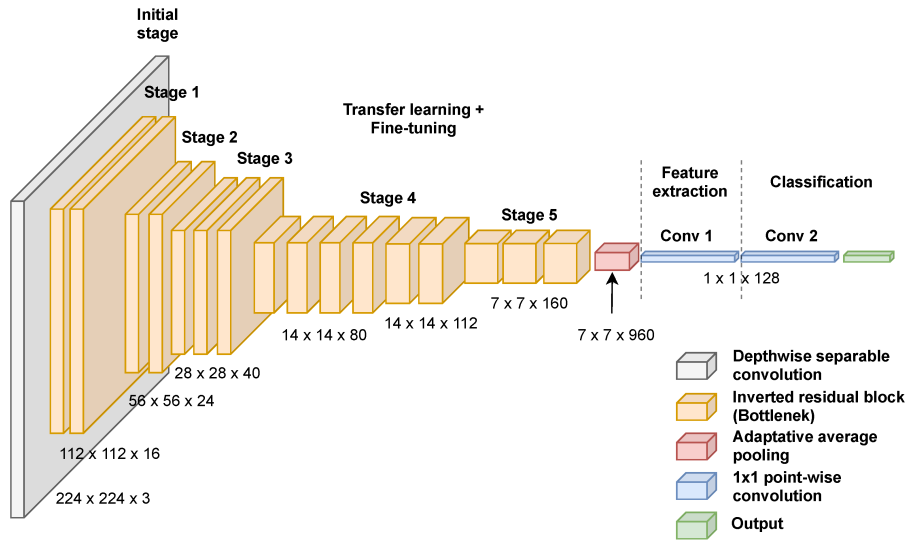


Figure 4.3: MobileNetV3 Architecture [60]

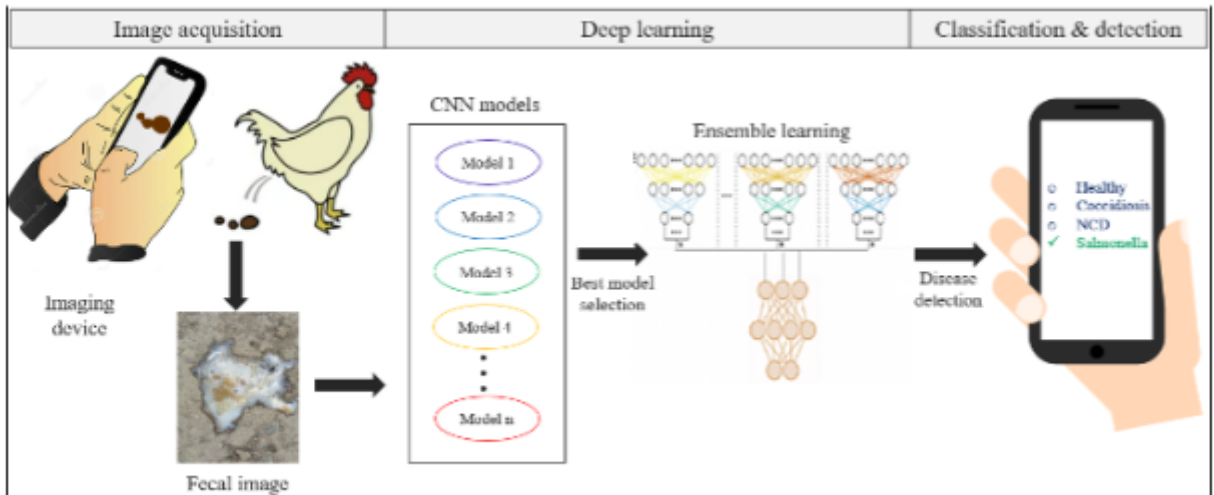


Figure 4.4: Representation of Agritechly's Chicken disease detection[61]

#### 4.2.2 Agritechly's Lumpy Skin Disease in Cattle detection

Following a similar approach to the chicken disease detector, we developed a system to detect Lumpy Skin Disease (LSD) in cattle using image analysis. This system aims to provide accurate and timely diagnosis of LSD, enabling effective management and treatment of the disease.

##### 1. EffectiveNetB3:

EfficientNetB3, a member of the EfficientNet family, is meticulously developed to provide a pleasing harmony between resolution, breadth, and depth scaling. Its simplified architecture has a limited number of parameters and excellent accuracy, which makes it especially good at spotting faint signs of Lumpy Skin Disease in cattle. By utilizing its accuracy and efficiency, EfficientNetB3 proves to be a vital instrument in veterinary diagnostics, facilitating the prompt identification and control of this infectious virus in cow populations.

The strength of EfficientNetB3 is its rapid and accurate picture analysis of cattle, which enables timely intervention and stops the disease from spreading. Through the analysis of fine-grained traits, this model offers farmers and vets a dependable way to diagnose this disease, enabling quick treatment and containment strategies. EfficientNetB3's sophisticated

features enable stakeholders to quickly identify impacted animals, reducing the disease's impact on individual animals as well as the overall health of the herd.

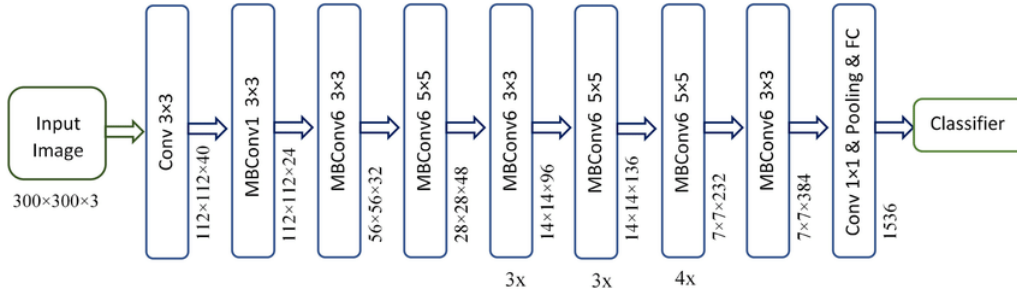


Figure 4.5: EfficientNetB3 Architecture [62]

## 2. VGG19:

VGG19, with its 19 weight layers, is proof of the simplicity and effectiveness of deep architecture. This model, which is well-known for its capacity to extract minute details from photos, is helpful in recognizing the unique lesions that are indicative of lumpy skin disease. The architecture of this model is illustrated in Figure 2.4, demonstrating its ability to extract fine-grained features, making it a dependable diagnostic tool for farmers and veterinarians, enabling timely treatment and containment measures.

Through the use of VGG19's capabilities, stakeholders may quickly identify animals that are afflicted, reducing the impact of the disease on the health of individual animals as well as the larger herd. The efficacy of VGG19 in detecting indications of Lumpy Skin Disease in photos is guaranteed by its deep design and ease of use, which facilitates prompt interventions and proactive approaches to disease treatment.

## 3. Xception:

Xception, which stands for "Extreme Inception," uses depthwise separable convolutions to present a revolutionary architecture for deep convolutional neural networks. Because of its novel architecture, Xception is incredibly good at identifying complex patterns in images, which makes it a great tool for diagnosing Lumpy Skin Disease in cattle. Veterinarians can promptly undertake containment tactics and interventions by utilizing Xception's strong feature extraction capabilities, which facilitate accurate diagnosis of disease-related signs.

Xception is a useful tool for diagnosing lumpy skin disease because of its remarkable capacity to identify complex patterns in photographs. Thanks to its creative architecture, cattle photos can be thoroughly analyzed, which makes it easier to identify diseases and take timely action. By enabling stakeholders to handle Lumpy Skin Disease outbreaks efficiently, Xception protects both agricultural output and animal welfare.

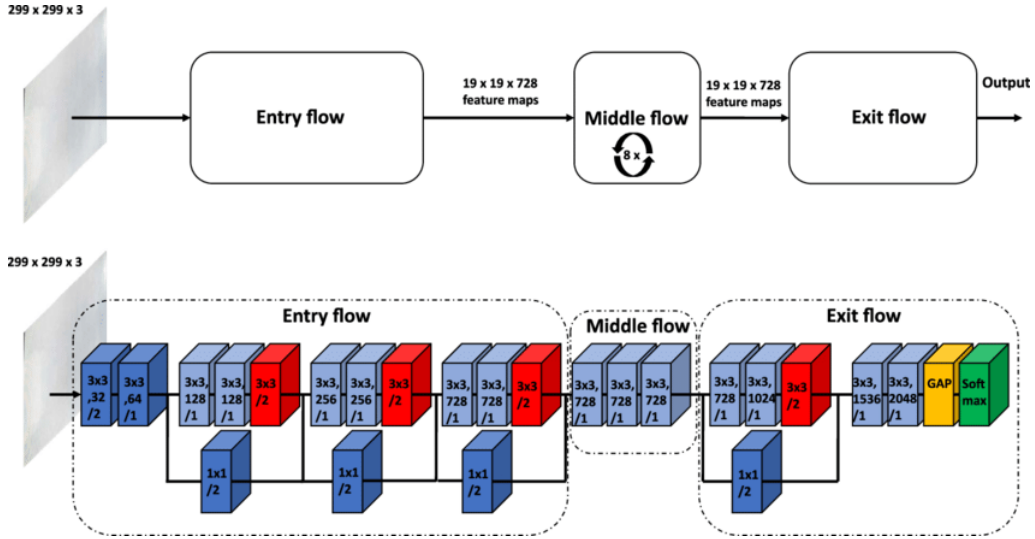


Figure 4.6: Xception Architecture [63]

#### 4. MobileNetV2:

MobileNetV2 positions itself as the best option for mobile and edge applications by providing a special trade-off between computation accuracy and efficiency. This approach, which is well-suited for a variety of real-world applications, bridges the gap between performance and resource limits by being designed to function flawlessly on devices with limited computational resources. The architecture of this model is illustrated in Figure 2.8, showcasing its efficient design. Because of its effective architecture, computing resources are used as efficiently as possible to minimize processing costs and maintain acceptable levels of accuracy. This balance is especially important for applications like disease detection, where fast and affordable diagnostics depend on computing efficiency.

The model of choice for Lumpy Skin Disease detection is MobileNetV2, particularly for devices with constrained resources. Because of its compatibility with mobile and edge devices, cattle images may be analyzed on-device, which makes disease screening in remote or resource-constrained locations quick and affordable. Farmers and veterinarians may now perform real-time diagnostics in the field without the need for costly infrastructure or specialist equipment thanks to MobileNetV2's computing efficiency. This feature enables proactive approaches to disease control, guaranteeing prompt intervention and containment strategies to stop the disease from spreading. By democratizing access to sophisticated diagnostic tools, MobileNetV2's deployment on mobile and edge devices promotes wider adoption and strengthens disease surveillance initiatives within agricultural communities.

#### 4.2.3 Agricultural pest

In this section, we go over the creation of a sophisticated image-analysis system for agricultural pest detection. This technology correctly detects a wide range of pests that might damage crops, allowing for prompt management and action.

The method uses deep learning models that have been trained on large datasets of pest images to identify various insect life stages and crop types. It uses mobile devices, field cameras, and drones to capture high-resolution photos for real-time alerts and ongoing monitoring. This lessens the need for human inspections, increasing pest management's precision and efficiency and, eventually, raising crop health and output.

## Pre-trained Models

To achieve high accuracy in detecting agricultural pests, we used a variety of complex pre-trained models such as InceptionV3, EfficientNetV2S, ConvNeXtBase, and NASNetMobile. These models were chosen for their shown efficacy in handling difficult image classification problems, with each having distinct strengths in feature extraction and scalability.

To improve performance and assure strong generalization to fresh data, we added layers of batch normalization, regularization, and dropout to these models. This strategy reduces overfitting, improves model stability, and ensures good accuracy across a wide range of pest pictures.

### 1. Inception V3:

As a member of the prestigious Inception architectural family, InceptionV3 is well-known for its deep network architecture and use of various filter sizes. It is quite successful in a variety of visual identification tasks because of its distinctive design, which allows it to extract a wide range of information from images. The architecture of this model is illustrated in Figure 2.7, showcasing its ability to work with various image sizes and resolutions. InceptionV3 is particularly adept at identifying a variety of pests, providing significant benefits to agricultural stakeholders by guaranteeing reliable performance across diverse pest detection scenarios. This support is crucial for pest management operations.

Because of its advanced architecture, InceptionV3 can detect pests with accuracy and dependability by capturing minute features and subtle fluctuations in their photos. This model improves pest detection systems' accuracy by utilizing its extensive feature extraction capabilities, offering farmers and other agricultural professionals timely insights for pest control and mitigation measures. Due to its adaptability and efficiency, InceptionV3 is a vital tool in the battle against pests, protecting crop harvests and promoting sustainable farming methods.

### 2. EfficientNetV2S:

As a member of the EfficientNet family, EfficientNetV2S is designed to maximize efficiency and accuracy by balancing depth, width, and resolution scaling. Because of this model's remarkable efficiency, real-time pest detection applications in agricultural settings can benefit greatly from its use. EfficientNetV2S facilitates proactive pest control techniques in the field by enabling fast and accurate pest identification through the utilization of its efficient design.

Because of its effective architecture, EfficientNetV2S can function reliably even on devices with minimal processing power, which makes it a great option for deployment in contexts with limited resources. Farmers are given efficient instruments for early pest identification and action thanks to its capacity to achieve high accuracy at low computing cost, which also improves the accessibility and scalability of pest detection systems. Through the use of EfficientNetV2S, stakeholders can minimize crop damage and ensure sustainable agricultural practices for increased food security by implementing timely pest management methods.

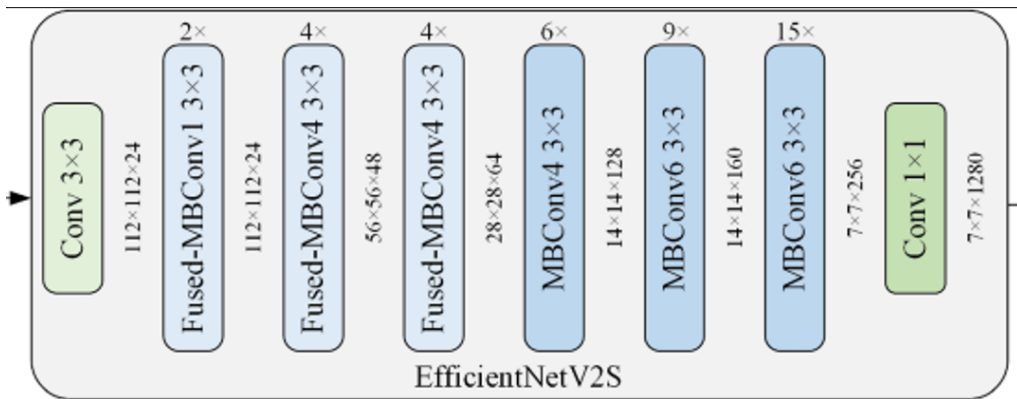


Figure 4.7: EfficientNetV2S Architecture [64]

### 3. ConvNeXtBase:

A modern convolutional neural network architecture tailored for image classification applications is represented by ConvNeXtBase. Its creative architecture is designed to be very good at catching subtle details in pest images, improving the precision and dependability of pest detection systems. ConvNeXtBase’s innovative architecture allows it to perform exceptionally well in pest recognition, making it possible to accurately identify and classify pest species with impressive efficiency.

Because of ConvNeXtBase’s sophisticated feature extraction capabilities, it can evaluate pest photos with previously unheard-of accuracy, enabling proactive pest management tactics and reducing losses to agriculture. Its capacity to identify minute details in pest morphology guarantees reliable results in a variety of pest detection situations, giving agricultural stakeholders vital assistance in managing pests. Farmers may apply focused pest management strategies with ConvNeXtBase, maximizing resource utilization and encouraging sustainable farming methods for long-term crop health and yield.

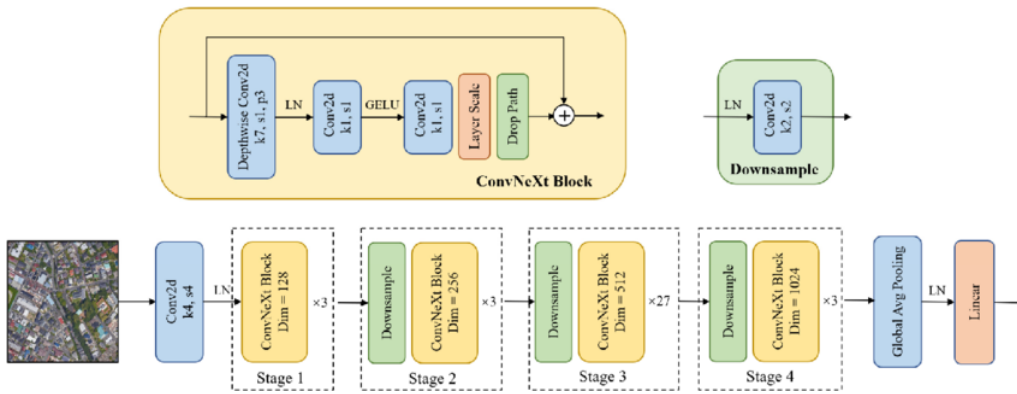


Figure 4.8: ConvNeXtBase Architecture [65]

### 4. NASNetMobile:

NASNetMobile is a specialized architecture that uses neural architecture search (NAS) techniques to improve efficiency and lower computing costs. It is intended for effective deployment on mobile devices. This model provides great performance in a resource-constrained environment and is designed to fulfill the specific needs of mobile pest detection systems. Using its effective design, NASNetMobile gives farmers timely information for pest management and control by enabling real-time pest detection on mobile devices.

Because of its lightweight design, NASNetMobile works seamlessly on mobile devices, making it possible to monitor and control pests while on the road. Its effective use of computing power reduces processing overhead, allowing for quick analysis of pest photos without sacrificing precision. Using NASNetMobile, agricultural stakeholders may better safeguard their crops, encourage sustainable farming methods, and manage pests with the help of mobile technology.

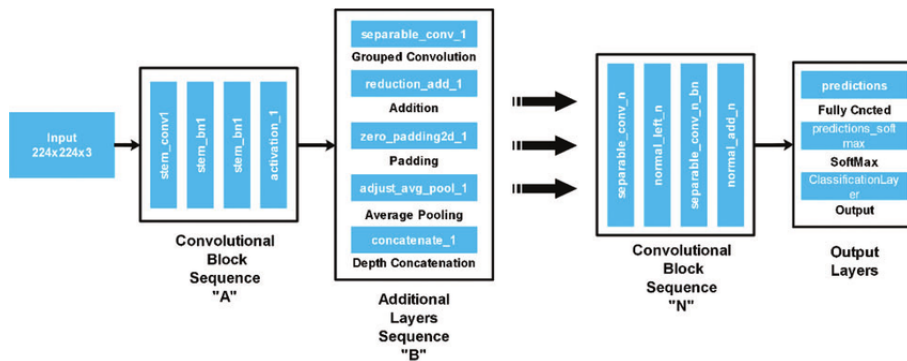


Figure 4.9: NASNetMobile Architecture [66]

Architecture	Depth	Parameters (Millions)	Size
DenseNet169	338	14.3	57MB
MobileNetV3Small	-	2.9	9.8MB
ResNet50	107	25.6	98MB
EfficientNetB4	258	19.5	75MB
EfficientNetB3	210	12.3	48MB
MobileNetV2	105	3.5	14MB
VGG19	19	143.7	549MB
Xception	81	22.9	88MB
InceptionV3	189	23.9	92MB
NASNetMobile	389	5.3	23MB
EfficientNetV2S	-	21.6	88MB
ConvNeXtBase	-	88.5	338.58MB

Table 4.1: Summary of all the architectures used in this research

## 4.3 CNN Object Detection Algorithms

### 4.3.1 Agricultural pest detection

We used YOLOv5, a cutting-edge object identification model well-known for its remarkable speed and accuracy in real-time object detection tasks, to improve our agricultural pest detection capabilities. With the help of YOLOv5’s sophisticated features, we can effectively identify and locate pests in photos, enabling accurate identification and focused intervention techniques. The capacity of this model to pinpoint the exact location of pests on crops enables agricultural stakeholders to promptly and efficiently execute pest management strategies, hence reducing crop damage and augmenting overall yield.

A major development in agricultural technology, the incorporation of YOLOv5 into our pest detection system allows for the quick and precise identification of pests in a variety of agricultural environments. Our method significantly improves pest management efficiency by quickly and accurately recognizing many pests in a single image. This enables farmers to take immediate action against infestations and minimize potential crop losses. This breakthrough transforms pest management techniques by giving farmers the means to efficiently control insect infestations and protect crop yields.

Additionally, using YOLOv5 makes it easier to respond quickly and accurately to pest outbreaks, giving farmers the opportunity to take preventative action to safeguard their crops. Farmers are able to preserve crop health and maximize agricultural productivity when they are able to respond promptly and efficiently to pest infestations. By providing agricultural stakeholders with actionable information through the integration of YOLOv5 into our pest detection system, they are better equipped to make educated decisions and carry out targeted pest control methods, which ultimately promotes sustainable agricultural practices and ensures food security.



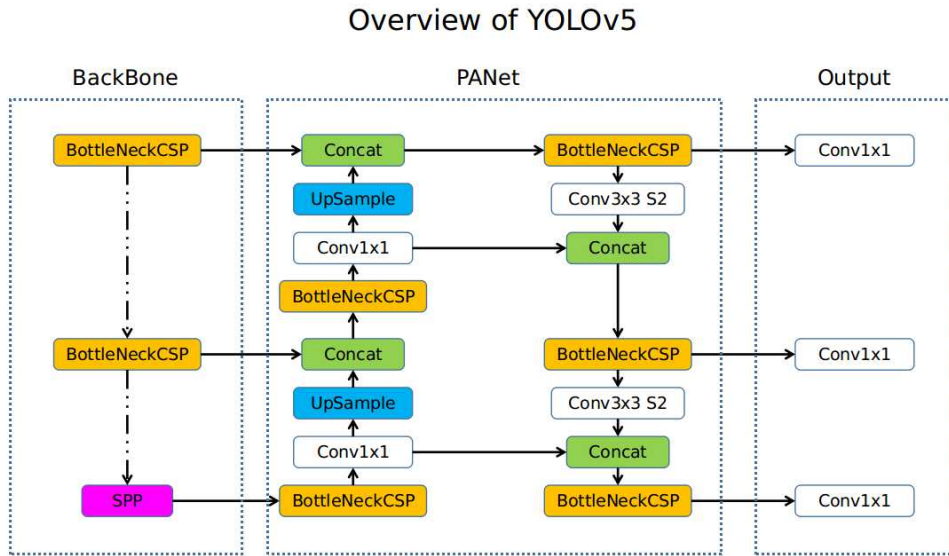


Figure 4.10: the structure of YOLOv5[67]

## 4.4 Queenlessness detection using audio

### 4.4.1 Recurrent Neural Networks

RNNs are essential tools for analyzing sequential data in diverse jobs. Recurrent Neural Networks (RNNs) are highly proficient in analyzing sequences of data, making them extremely helpful for tasks that heavily rely on temporal patterns. RNNs have the ability to capture temporal dependencies by studying previous data, allowing them to detect intricate patterns within sequential data[68]. Nevertheless, recurrent neural networks (RNNs) may encounter difficulties in preserving long-term context, hence restricting their efficacy in capturing complex patterns that extend over prolonged durations[68].

### 4.4.2 Bidirectional Recurrent Neural Networks

Bi-RNNs provide an effective approach for overcoming the constraints of conventional RNNs. Bidirectional recurrent neural networks (Bi-RNNs) improve upon regular RNNs by concurrently processing data in both the forward and backward directions. This bidirectional processing allows the model to incorporate context from both past and future timestamps, providing a more comprehensive interpretation of sequential data[69]. By leveraging the bidirectional feature of Bi-RNNs, we may efficiently capture complicated patterns inherent in sequential data, increasing the model's overall performance[69].

### 4.4.3 Long Short-Term Memory

LSTM networks have developed into a powerful tool for sequential data analysis. One particular kind of Recurrent Neural Network (RNN) designed to address the challenges of capturing long-term dependencies is the Long Short-Term Memory (LSTM) network. Long-term information retention is a capability of long-term storage transistors, or LSTMs. They are able to preserve crucial context from earlier data pieces as a result. Because of this, LSTMs work especially well in situations where a grasp of temporal dynamics is essential. We may extract complex patterns from sequential data by leveraging the memory capacity of LSTMs, which will enable more precise and trustworthy analysis..

#### 4.4.4 Gated Recurrent Units

GRUs are another way to sequential data analysis, offering a simpler alternative to LSTMs. Like LSTMs, GRUs have gating mechanisms that regulate information flow throughout the network. However, GRUs attain comparable performance with fewer parameters, making them more computationally efficient[68]. This efficiency makes GRUs well-suited for tasks where rapid processing of sequential data is required. By utilizing the effectiveness and efficiency of GRUs, we may evaluate sequential data with greater speed and accuracy, providing rapid insights and actions[68] .

#### 4.4.5 Agritechly's LSTM architecture

A sequential model with multiple bidirectional long short-term memory (LSTM) layers makes up the model architecture. To improve model stability and avoid overfitting, Batch Normalization and Dropout layers are added after each Bidirectional LSTM layer. Beginning at 256 units and ending at 16 units in the last layer, the LSTM layers gradually shrink in size. L2 regularization is used in every LSTM layer to prevent overfitting. To create the final binary classification output, a Dense layer with a single unit and a sigmoid activation function are added at the end. This architecture is specifically designed to produce precise predictions for the target variable and efficiently capture temporal dependencies within the input sequence.

#### 4.4.6 Agritechly's GRU architecture

The sole manner in which the GRU architecture differs from the LSTM configuration is that Bidirectional Gated Recurrent Unit (GRU) layers are used in place of bidirectional long short-term memory (LSTM) layers. This modification preserves architectural coherence while utilizing GRU's special qualities for efficient sequence modeling.

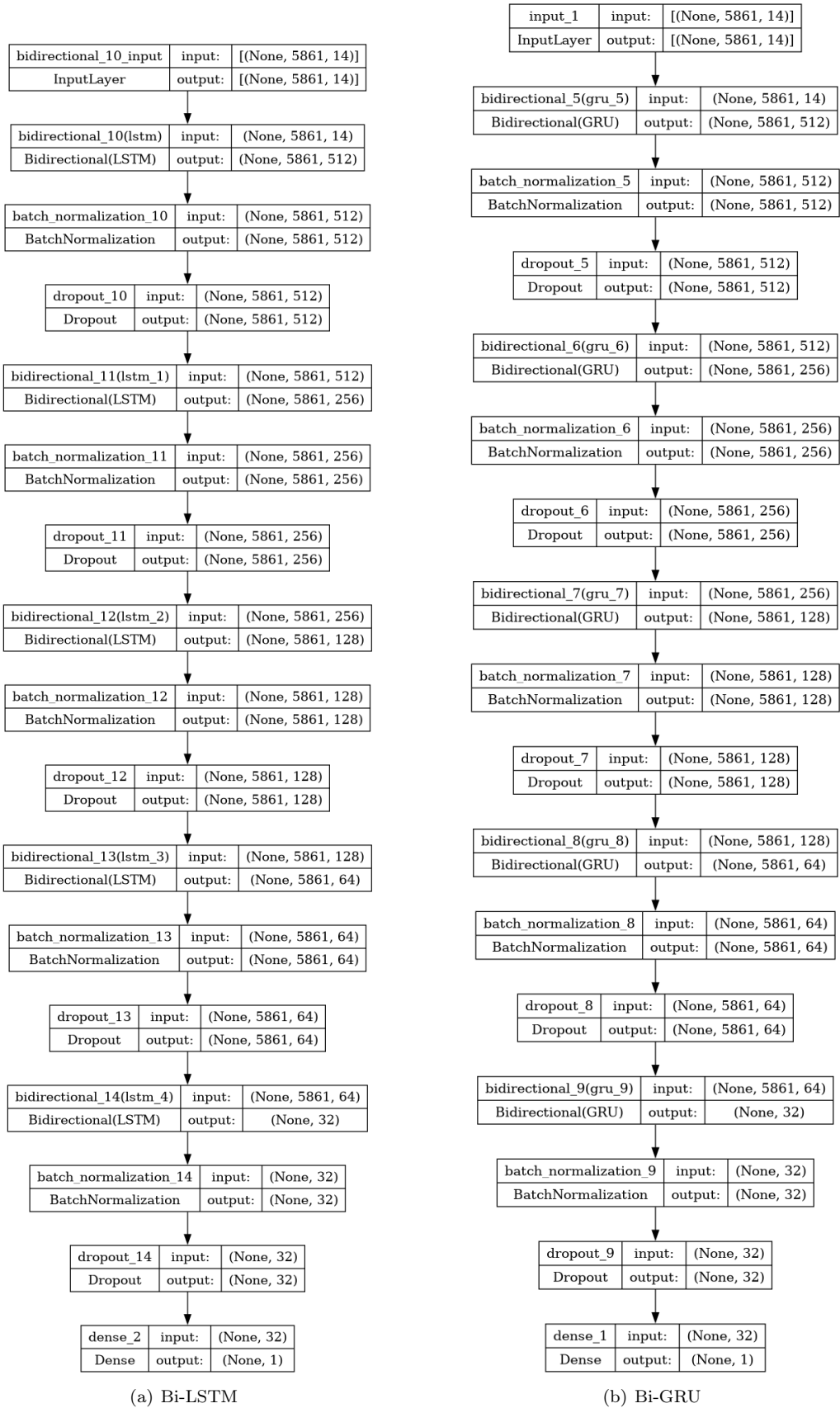


Figure 4.11: comparison between the architecture of LSTM and GRU.

## 4.5 Chatbot

In order to enable farmers to make wise decisions, our chatbot is a vital tool. Farmers can obtain vital information and insights through a dynamic interface provided by Retrieval-Augmented Generation (RAG) technology. Customized prompts, which offer focused advice and suggestions, improve the user experience even more. Our chatbot acts as a reliable advisor, providing farmers with the information they need to maximize their agricultural operations, from crop management to livestock care. As a useful ally on the path to agricultural excellence, our chatbot stands out for its smooth integration of RAG and customized prompts.

## 4.6 Self-Learning from Community Data

One of the significant contributions of this research lies in its integration of self-learning mechanisms facilitated by community engagement and the utilization of collected data. By harnessing feedback and insights from agricultural stakeholders, including farmers, veterinarians, and agricultural researchers, and analyzing collected data, our models continuously evolve and improve. This collaborative approach not only enhances the accuracy and applicability of our AI solutions but also fosters a community-driven ecosystem where knowledge sharing and continuous learning are paramount. Through ongoing interactions and partnerships with the agricultural community, we have refined our algorithms, adapted to local contexts, and developed tailored solutions that meet real-world challenges effectively. This iterative process of self-learning from the community, supported by robust data collection and analysis, underscores our commitment to bridging the gap between cutting-edge technology and practical agricultural applications, ultimately contributing to sustainable agricultural practices and enhanced food security.

## 4.7 Conclusion

To sum up, this chapter has covered a wide range of topics related to agricultural disease detection and pest management, emphasizing the need for a comprehensive strategy that is essential for good agricultural stewardship. Our research has shown how important modern technologies are to preserving the health of livestock, from the detection of diseases in poultry such as coccidiosis, salmonella, and Newcastle disease to the diagnosis of lumpy skin disease in cattle. Additionally, the need of taking early steps to minimize crop damage and guarantee sustainable agricultural practices has been underscored by our conversation on pest classification and object identification.

The complex dynamics of beekeeping and the need of early identification in hive management have also been clarified by our work into the detection of queenlessness in beehives. In conclusion, the incorporation of a chatbot that is outfitted with Retrieval-Augmented Generation (RAG) technology is evidence of our dedication to furnishing farmers with comprehensible and practical information to facilitate their decision-making procedures.

When taken as a whole, these observations highlight the complexity of agricultural problems and the necessity of using creative methods to solve them. Our goal is to create a more productive and resilient agricultural sector by utilizing cutting-edge technologies and interdisciplinary approaches, which will ultimately support sustainable food systems and lives.

# **Chapter 5:**

## Result discussion and Experimentation

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## Chapter 5

# Result Discussion and Experimentation

This chapter presents the outcomes of our model evaluations. We examine the efficacy of our models in agricultural disease diagnosis and pest control through thorough experimentation. We study a variety of topics, from chatbot interaction dynamics to algorithms for detecting poultry diseases, in order to gain understanding of the limitations and effectiveness of our models. Our results provide directions for further investigation and real-world implementation in improving farming methods.

### 5.1 Datasets description

#### 5.1.1 Chicken diseases dataset

The Chicken Diseases dataset <sup>1</sup> is a publicly available dataset comprising 8,067 images of poultry fecal samples distributed across four distinct classes: coccidiosis, salmonella, Newcastle disease, and healthy samples. These captioned photos are an invaluable tool for diagnosing poultry diseases, especially for small- to medium-sized poultry producers. The dataset was painstakingly assembled from chicken excrement samples that were gathered in Tanzania's Arusha and Kilimanjaro areas between September 2020 and February 2021. The Open Data Kit (ODK) software was used to make image capture easier, resulting in simpler data collecting and annotation processes. This dataset offers a comprehensive representation of common poultry diseases encountered in agricultural settings.

#### 5.1.2 Lumpy skin in cattle dataset

Our study's Lumpy Skin dataset is a composite of two publicly accessible sources: the "Lumpy Skin Images Dataset"<sup>2</sup> and the "Cow Lumpy Disease dataset."<sup>3</sup> The purpose of this consolidation was to provide strong model training and lessen the effects of class imbalance. This merged dataset, which has 1,260 photos in total, gives researchers and practitioners a thorough collection of lumpy skin disease samples. It also offers a representative and diversified group of images for tasks related to illness identification and classification. We hope to improve the efficacy and dependability of our algorithm in correctly detecting and diagnosing lumpy skin disease in cattle by combining datasets from various sources.

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<sup>1</sup><https://www.kaggle.com/datasets/allandclive/chicken-disease-1/>

<sup>2</sup><https://www.kaggle.com/datasets/warcoder/lumpy-skin-images-dataset>

<sup>3</sup><https://www.kaggle.com/datasets/shivamagarwal29/cow-lumpy-disease-dataset/data>

### 5.1.3 Agricultural pest

#### Classification model

The Agricultural Pest Image Dataset <sup>4</sup> that we utilized in our study is openly accessible and comprises a total of 5,494 images. It features twelve different types of agricultural pests, including wasps, weevils, ants, beetles, caterpillars, earthworms, earwigs, grasshoppers, and slugs. These photos, sourced from Flickr via the API, have been meticulously selected to ensure authenticity and relevance to real agricultural scenarios. Additionally, each image has been resized to a maximum width or height of 300 pixels, streamlining processing and enhancing convenience for model training and assessment. By leveraging this extensive collection, our research aims to advance agricultural pest management techniques through the development of robust classification and detection algorithms.

#### Object detection model

The publicly accessible Object Detection Dataset <sup>5</sup>, which comprises artificially generated photos, was utilized in our research. There are 1,000 photos in this collection for the following classes: moths, spiders, cicadas, dragonflies, butterflies, beetles, and grasshoppers. The backgrounds used in these pictures were obtained from websites that are well-known for providing free vector graphics without asking for permission: pexels.com, unsplash.com, and pixabay.com. This varied dataset is a useful tool for developing robust algorithms that accurately and efficiently identify and categorize agricultural pests. It is also a useful resource for training and assessing object identification models.

### 5.1.4 Beehive monitoring

We address the problem of using acoustic data to detect queenlessness in beehives in our Beehive Monitoring project. The dataset <sup>6</sup> that was used for this project is 7,100 samples long and is freely accessible. The INMP441 microphone module, which has a reputation for being functional even if it is not as high-quality as more expensive models, was used to record these audio files. Our research attempts to derive useful insights from the audio data in order to create efficient algorithms for detecting queenlessness in beehives, despite the constraints of the microphone. By guaranteeing the well-being and production of bee colonies, this innovative method has the potential to completely transform beekeeping techniques.

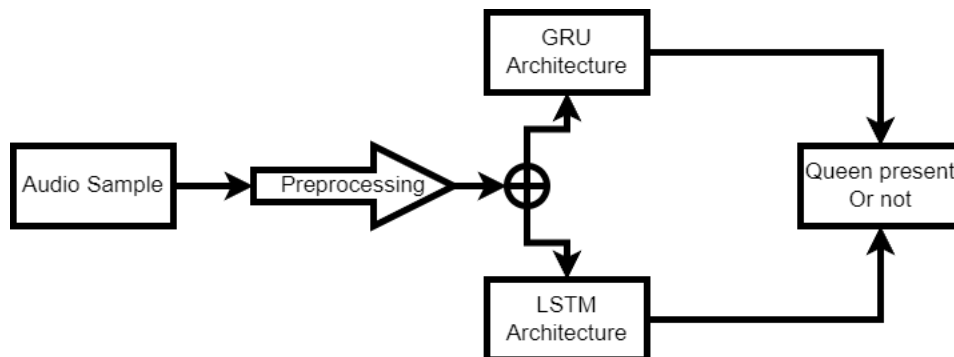


Figure 5.1: Representation of Agritechly's Bee monitoring approach

<sup>4</sup><https://www.kaggle.com/datasets/vencerlanz09/agricultural-pests-image-dataset>

<sup>5</sup><https://www.kaggle.com/datasets/vencerlanz09/insect-village-synthetic-dataset>

<sup>6</sup><https://www.kaggle.com/datasets/annajyang/beehive-sounds>

## 5.2 Implementation Tools

### 5.2.1 TensorFlow

TensorFlow<sup>7</sup> is an open-source library developed by the Google Brain team for numerical computation and machine learning. It is a flexible, scalable, and comprehensive ecosystem of tools, libraries, and community resources that allows researchers to push the state-of-the-art in machine learning and developers to easily build and deploy machine learning-powered applications.

### 5.2.2 Keras

Keras<sup>8</sup> is a high-level, user-friendly API for building and training deep learning models. It was initially developed as an independent project and later became part of the TensorFlow ecosystem. Keras emphasizes ease of use, modularity, and extensibility, making it accessible for beginners while being powerful enough for experts.

### 5.2.3 Scikit-Learn (sklearn)

Scikit-Learn<sup>9</sup> (often abbreviated as sklearn) is an open-source machine learning library for Python. It is built on top of SciPy and is designed to be simple and efficient for data mining and data analysis. It provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python.

Usage in Machine Learning:

### 5.2.4 PyTorch

PyTorch<sup>10</sup> is an open-source machine learning library developed by Facebook's AI Research lab (FAIR). It is widely used for applications in deep learning and provides a flexible and dynamic computational graph, which makes it easier to build and debug complex models. PyTorch emphasizes ease of use, dynamic computation, and strong GPU acceleration.

### 5.2.5 PIL (Python Imaging Library)

PIL<sup>11</sup> is a Python library for manipulating image files. It provides tools for opening, editing, and saving many different image file formats. PIL is widely used for tasks such as image processing, computer vision, and generating image thumbnails.

### 5.2.6 Pandas

Pandas<sup>12</sup> is an open-source data manipulation and analysis library for Python. It provides data structures and functions needed to manipulate structured data seamlessly. Pandas is built on top of NumPy and integrates well with other data science libraries in the Python ecosystem. Its primary data structures are Series (1-dimensional) and DataFrame (2-dimensional), which are flexible and easy to use for data cleaning, transformation, and analysis.

### 5.2.7 Numpy

numpy<sup>13</sup> is a fundamental package for scientific computing with Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays. numpy is essential for data manipulation and computation tasks in machine learning and scientific computing workflows.

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<sup>7</sup><https://www.tensorflow.org>

<sup>8</sup><https://www.keras.io>

<sup>9</sup><https://scikit-learn.org/stable/>

<sup>10</sup><https://pytorch.org>

<sup>11</sup><https://pillow.readthedocs.io>

<sup>12</sup><https://pandas.pydata.org>

<sup>13</sup><https://numpy.org>



## 5.2.8 Seaborn

seaborn<sup>14</sup> is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics. seaborn is particularly useful for exploring and visualizing relationships in complex datasets, offering built-in themes and color palettes to enhance plot aesthetics.

## 5.2.9 Matplotlib

matplotlib<sup>15</sup> is a comprehensive library for creating static, animated, and interactive visualizations in Python. It provides a MATLAB-like interface and supports a wide variety of plots and charts, including line plots, bar plots, histograms, scatter plots, and more. matplotlib is widely used for data visualization across various domains, from scientific research to business analytics.

## 5.2.10 Librosa

librosa<sup>16</sup> is a Python library for analyzing and extracting features from audio signals. It provides functionalities for spectral analysis, feature extraction, and audio playback, making it a valuable tool for tasks such as music information retrieval, speech processing, and sound classification.

## 5.2.11 Flask

Flask<sup>17</sup> is a lightweight, open-source web framework for Python. It is designed to be simple and flexible, allowing developers to build web applications quickly and easily. Flask follows the WSGI (Web Server Gateway Interface) standard and is classified as a microframework because it does not require particular tools or libraries. It includes a built-in development server and debugger, making it ideal for developing and testing web applications.

# 5.3 Programming languages:

## 5.3.1 Python

Python<sup>18</sup> is a high-level, interpreted programming language known for its readability, simplicity, and versatility. It is widely used in various domains, including web development, data science, artificial intelligence, machine learning, and deep learning. Python's extensive libraries and frameworks make it an ideal choice for implementing deep learning models.

## 5.3.2 Tailwind CSS

Tailwind CSS<sup>19</sup> is a highly customizable, low-level CSS framework that provides a set of utility classes for building custom user interfaces quickly. Unlike traditional CSS frameworks like Bootstrap, which come with pre-designed components, Tailwind CSS offers a utility-first approach, allowing developers to compose custom designs directly in their HTML by applying utility classes.

## 5.3.3 HTML

HTML<sup>20</sup> (HyperText Markup Language) is the standard markup language used to create web pages. It provides the structure of a webpage, allowing the inclusion of text, images, links, forms, and other elements to be displayed in web browsers. HTML uses tags to annotate text and define the roles of various parts of the document, such as headers, paragraphs, lists, links, and more.

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<sup>14</sup><https://seaborn.pydata.org>

<sup>15</sup><https://matplotlib.org>

<sup>16</sup><https://librosa.org>

<sup>17</sup><https://flask.palletsprojects.com/en/3.0.x/>

<sup>18</sup><https://www.python.org>

<sup>19</sup><https://tailwindcss.com>

<sup>20</sup><https://developer.mozilla.org/fr/docs/Web/HTML>

### 5.3.4 Javascript

JavaScript<sup>21</sup> is a versatile, high-level programming language commonly used in web development to create interactive and dynamic content on websites. It is an essential technology of the World Wide Web, alongside HTML and CSS. JavaScript enables developers to implement complex features on web pages, such as content updates, multimedia, animated graphics, and user interactions.

## 5.4 Evaluation measures:

### 5.4.1 Accuracy

**Definition:**

Accuracy measures the proportion of correctly classified instances out of the total instances evaluated, providing a general overview of a model's predictive performance. While it's a straightforward metric, it may not adequately represent performance nuances, especially in cases of class imbalance or varying misclassification costs.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

### 5.4.2 Loss

**Definition:**

Loss refers to the error rate between predicted and actual values in the training phase of machine learning models. It quantifies how well or poorly a model performs, with lower values indicating better performance.

### 5.4.3 F1 Score

**Definition:**

The F1 Score is the harmonic mean of precision and recall, offering a balanced measure of a model's performance in binary classification tasks.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

### 5.4.4 Precision

**Definition:**

Precision measures the proportion of true positive predictions out of all positive predictions, highlighting the model's ability to avoid false positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

### 5.4.5 Recall

**Definition:**

Recall quantifies the proportion of true positive predictions out of all actual positives, indicating the model's ability to capture relevant instances.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

---

<sup>21</sup><https://developer.mozilla.org/fr/docs/Web/JavaScript>

### 5.4.6 Confusion Matrix

**Definition:**

The Confusion Matrix is a tabular representation of a model’s performance, illustrating the counts of true positives, true negatives, false positives, and false negatives across different classes or categories.

	<b>Predicted Negative</b>	<b>Predicted Positive</b>
<b>Actual Negative</b>	True Negative (TN)	False Positive (FP)
<b>Actual Positive</b>	False Negative (FN)	True Positive (TP)

### 5.4.7 Response time

**Definition:**

Response time in deep learning models refers to the duration from input data processing to output prediction. It’s crucial for real-time applications like autonomous driving and natural language processing. Achieving low response times is essential for timely processing. Optimization methods include model optimization, hardware acceleration, and distributed computing to enhance efficiency and reduce inference latency.

### 5.4.8 mAP (Mean Average Precision)

**Definition:**

mAP is a metric used to evaluate the performance of object detection algorithms. It calculates the average precision for each class across a range of recall values and then averages these values to obtain the final mAP score. Higher mAP scores indicate better model performance in detecting objects across different categories.

$$\text{mAP} = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} \frac{1}{|G_c|} \sum_{g \in G_c} \text{AP}(g) \tag{5.1}$$

where:

- mAP denotes the mean Average Precision,
- $\mathcal{C}$  is the set of classes (categories),
- $G_c$  represents the set of ground truth instances for class  $c$ ,
- $\text{AP}(g)$  denotes the Average Precision for ground truth instance  $g$ .

## 5.5 Chicken disease detection:

### 5.5.1 Preprocessing and Results:

For chicken disease detection, we conducted experiments using four pretrained models—DenseNet169, MobileNetV3, ResNet50, and EfficientNetB4—enhanced with various combinations of hyperparameters. Each model underwent preprocessing, including resizing the images to 224 pixels by 224 pixels, and was augmented with data augmentation techniques, namely random rotation, width and height shifts, and random horizontal flips, to enrich the training dataset. The data was split into an 80:10:10 format for training, validation, and testing, respectively. Our objective was to evaluate the performance of these models in accurately identifying chicken diseases. To mitigate overfitting, we incorporated batch normalization, regularization, and dropout techniques. The results of these experiments are presented below:

### 5.5.2 Discussion:

The results of our experiments reveal notable performance variations among the pretrained models used for chicken disease detection, as shown in Table 5.1. DenseNet169 and EfficientNetB4 demonstrate the highest accuracy, precision, recall, and F1 score, indicating superior performance

Model	Accuracy	Precision	Recall	F1 Score
DenseNet169	0.9739	0.98	0.98	0.98
MobileNetV3	0.9677	0.97	0.96	0.96
ResNet50	0.9653	0.97	0.96	0.96
EfficientNetB4	0.9764	0.98	0.98	0.98

Table 5.1: Results of Chicken Disease Detection Models

compared to MobileNetV3 and ResNet50. The higher performance of DenseNet169 and EfficientNetB4 can be attributed to their deeper architectures and increased model capacity, enabling them to capture more intricate features in the input images. In contrast, MobileNetV3 and ResNet50, despite their shallower architectures, still exhibit commendable performance, albeit slightly lower than DenseNet169 and EfficientNetB4.

One interesting observation is the consistency in performance metrics across all models, particularly in terms of precision, recall, and F1 score. This consistency suggests that while accuracy may vary slightly, the models maintain a balanced trade-off between true positive and false positive rates, indicating robust performance in identifying chicken diseases.

The effectiveness of data augmentation techniques, including random rotation, width and height shifts, and random horizontal flips, is evident in the performance of all models. By artificially increasing the diversity of the training dataset, data augmentation helps improve the models' generalization ability and reduces overfitting, resulting in higher accuracy and robustness in real-world scenarios.

However, it's essential to acknowledge certain limitations and areas for improvement in our experiments. Firstly, while we explored various combinations of hyperparameters, there may be additional configurations that could further enhance model performance. Fine-tuning hyperparameters, such as learning rate, batch size, and dropout rate, could potentially yield even better results.

Secondly, the choice of pretrained models was limited to a subset of widely used architectures. Exploring other architectures specifically designed for medical imaging tasks or conducting model ensembling techniques could potentially improve overall performance.

Lastly, while we achieved high accuracy and other performance metrics on our validation and test sets, the real-world applicability and generalizability of our models require further validation and testing in diverse environmental conditions and datasets.

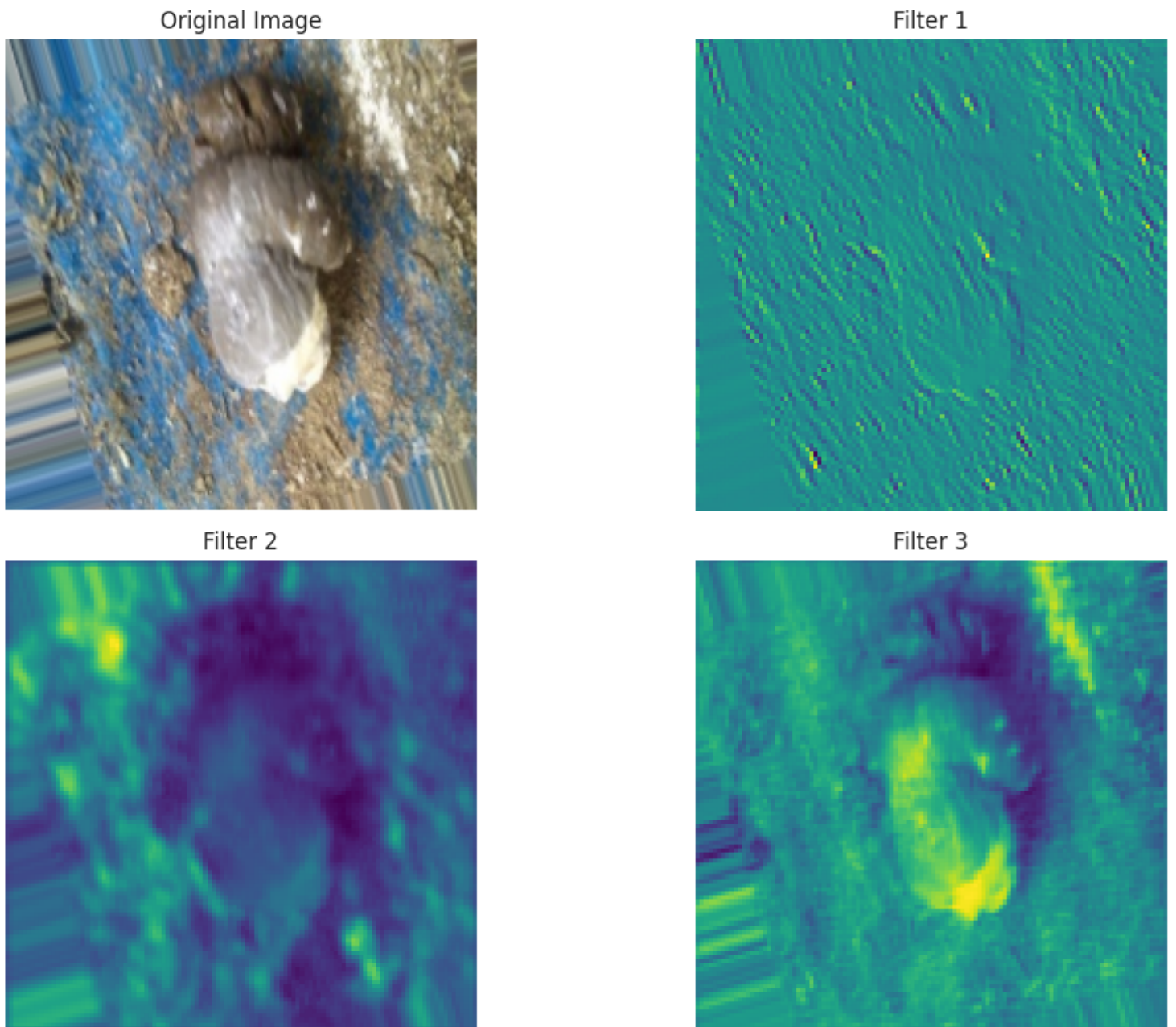


Figure 5.2: Visualization of a random image (top-left) from the dataset and feature maps extracted from the first convolutional layer of the ResNet50 model.

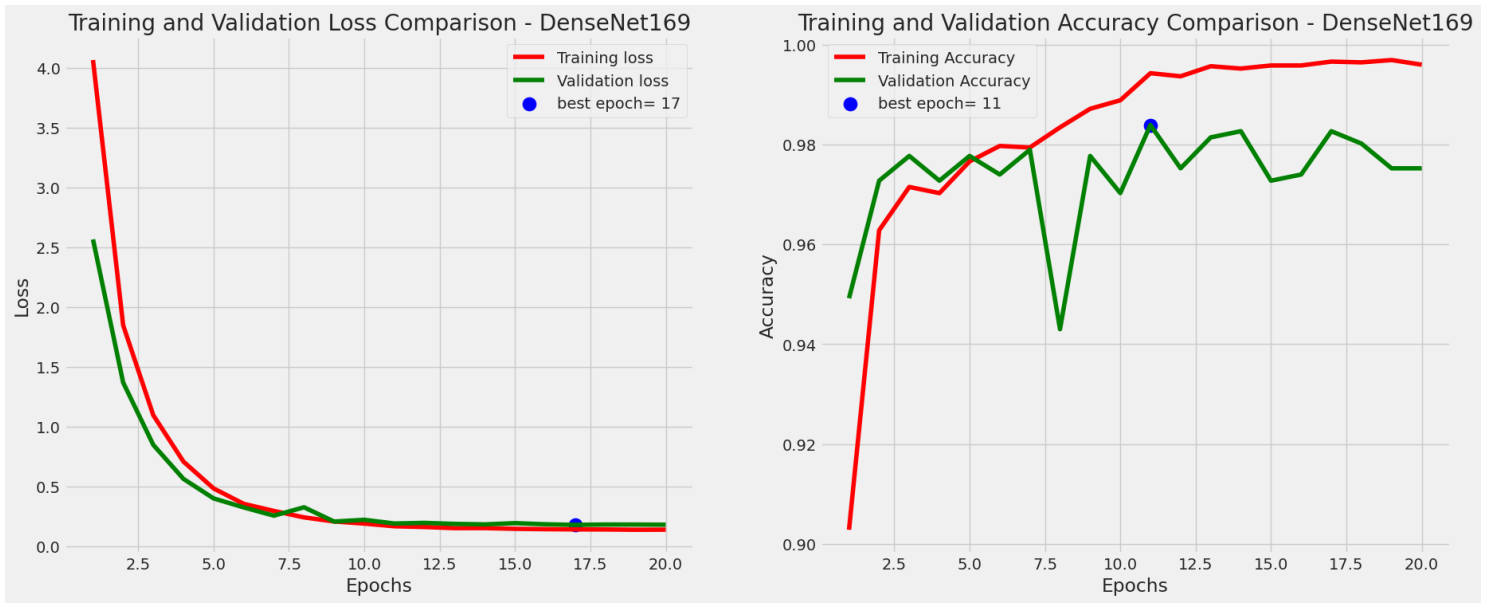


Figure 5.3: Accuracy and Loss Plot Of DenseNet169 Model

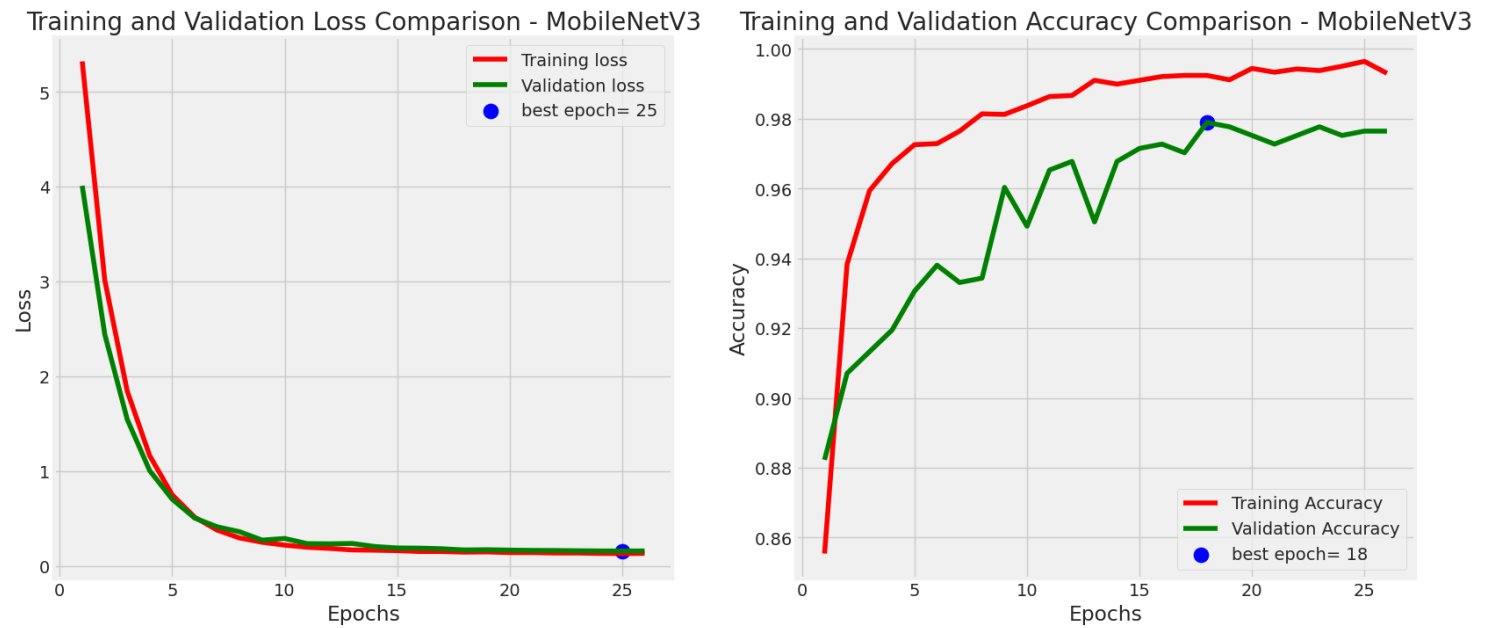


Figure 5.4: Accuracy and Loss Plot Of MobileNetV3 Model

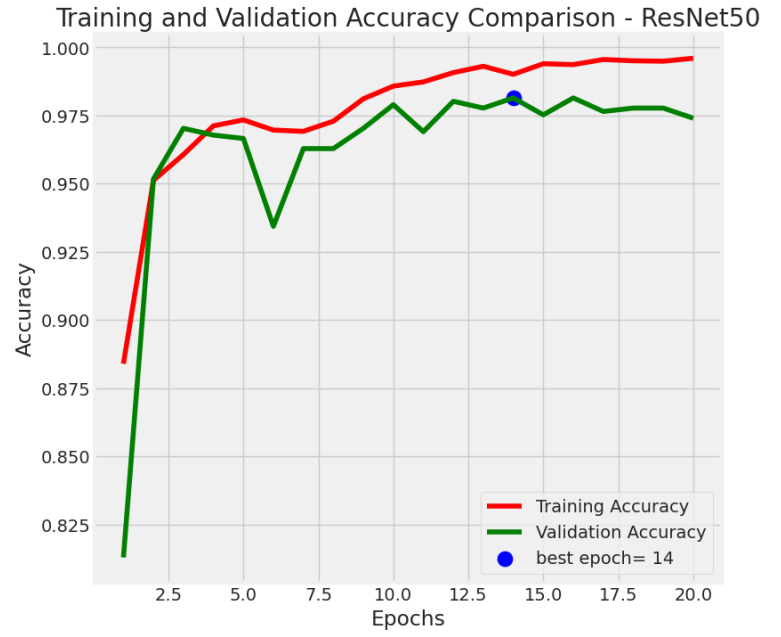
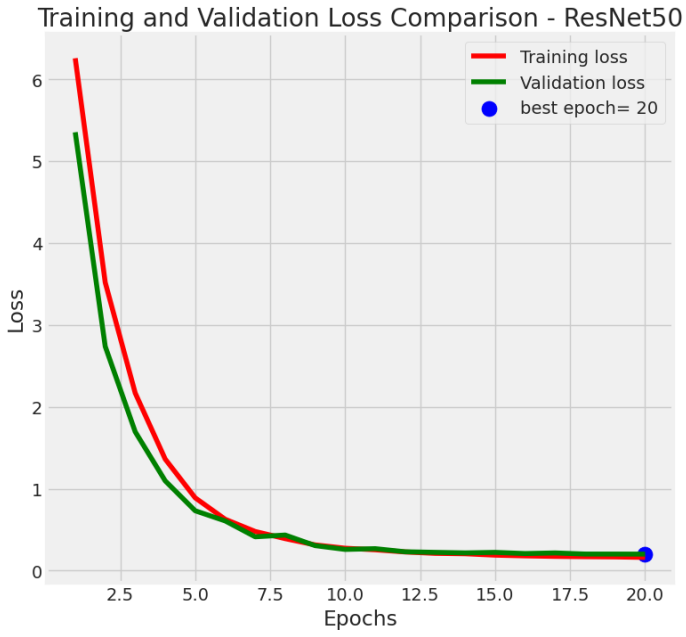


Figure 5.5: Accuracy and Loss Plot Of ResNet50 Model

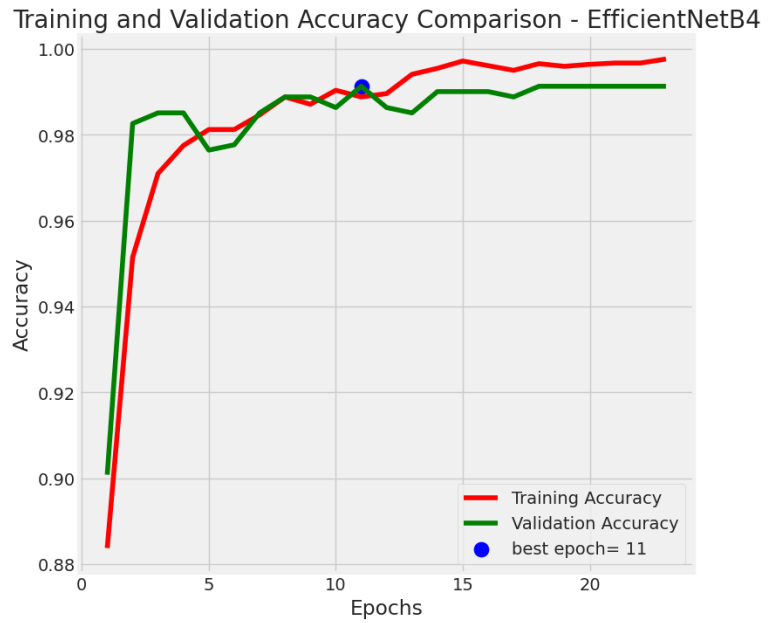
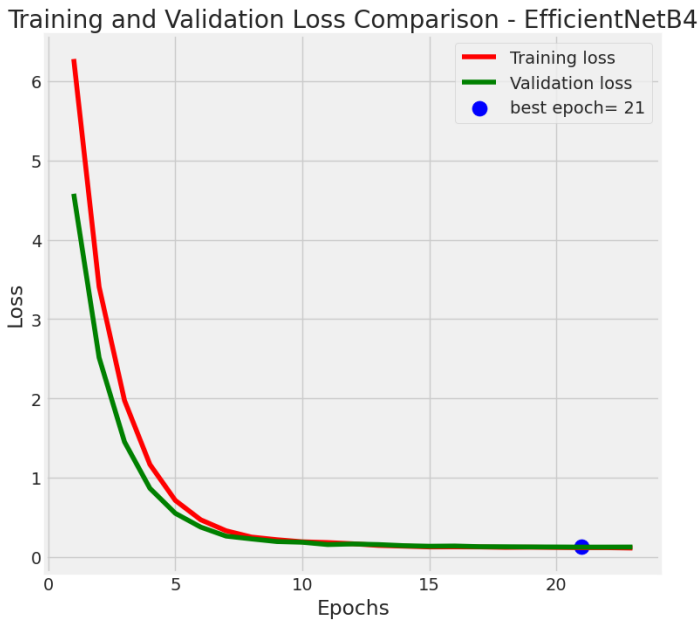


Figure 5.6: Accuracy and Loss Plot Of EfficientNetB4 Model

## 5.6 Lumpy skin disease in cattle detection:

### 5.6.1 Preprocessing and Results:

We conducted experiments to detect lumpy skin disease in cattle using four different pretrained models: EfficientNetB3, MobileNetV2, VGG19, and Xception. To improve model performance and minimize overfitting, we applied batch normalization, regularization, and dropout techniques. Multiple combinations of hyperparameters were tested, and the images were preprocessed to a fixed size of 224x224 pixels. The dataset was split into training, validation, and test sets in an 80:10:10 ratio, and data augmentation techniques such as random rotation, width and height shifts, and random horizontal flips were utilized to increase dataset diversity. Given the merge of data and the less-than-ideal dataset quality, we employed 10-fold cross-validation (K-fold) during model training. The results reported are from the best fold of each model.

Model	Accuracy	Precision	Recall	F1 Score
EfficientNetB3	0.9206	0.92	0.92	0.92
MobileNetV2	0.8333	0.84	0.85	0.83
VGG19	0.6904	0.70	0.70	0.69
Xception	0.9285	0.93	0.92	0.93

Table 5.2: Results of Lumpy Skin Disease Detection Models

### 5.6.2 Discussion:

The results of our experiments for lumpy skin disease detection in cattle, presented in Table 5.2, reveal distinct performance differences among the four pretrained models utilized: EfficientNetB3, MobileNetV2, VGG19, and Xception.

Among the models, Xception and EfficientNetB3 demonstrate superior performance with accuracies of 0.9285 and 0.9206, respectively. Both models also show high precision, recall, and F1 scores, indicating their effectiveness in identifying lumpy skin disease while minimizing false positives and negatives. Their deep and complex architectures likely contribute to their enhanced detection capabilities.

MobileNetV2, while slightly behind the top performers, still shows commendable results with an accuracy of 0.8333 and balanced precision (0.84), recall (0.85), and F1 score (0.83). This suggests that MobileNetV2 can effectively manage disease detection tasks, though with slightly lower performance compared to Xception and EfficientNetB3.

In contrast, VGG19 exhibits the lowest performance among the models with an accuracy of 0.6904, precision and recall of 0.70, and an F1 score of 0.69, indicating it struggles more with distinguishing between healthy and diseased samples.

A notable observation is the consistency in performance metrics across Xception and EfficientNetB3, highlighting their robustness in maintaining a balanced trade-off between true positive and false positive rates.

The effectiveness of data augmentation techniques, including random rotation, width and height shifts, and random horizontal flips, is evident across all models, enhancing their generalization ability and reducing overfitting. Additionally, using 10-fold cross-validation ensured reliable and unbiased results.

However, it is essential to acknowledge certain limitations and areas for improvement in our experiments:

Firstly, The merged dataset may contain inconsistencies or biases that affect the models' learning. Enhancing the dataset's quality and diversity could improve performance. Secondly, While multiple hyperparameter combinations were explored, further fine-tuning specific parameters might yield better results. Thirdly, The choice of pretrained models was limited. Exploring other architectures or employing model ensembling techniques could improve overall performance. Lastly, Although high performance was achieved on the validation and test sets, further validation in diverse environmental conditions and datasets is required to ensure real-world applicability and generalizability. By addressing these limitations, future work can enhance the effectiveness and reliability of deep learning models for lumpy skin disease detection in cattle.



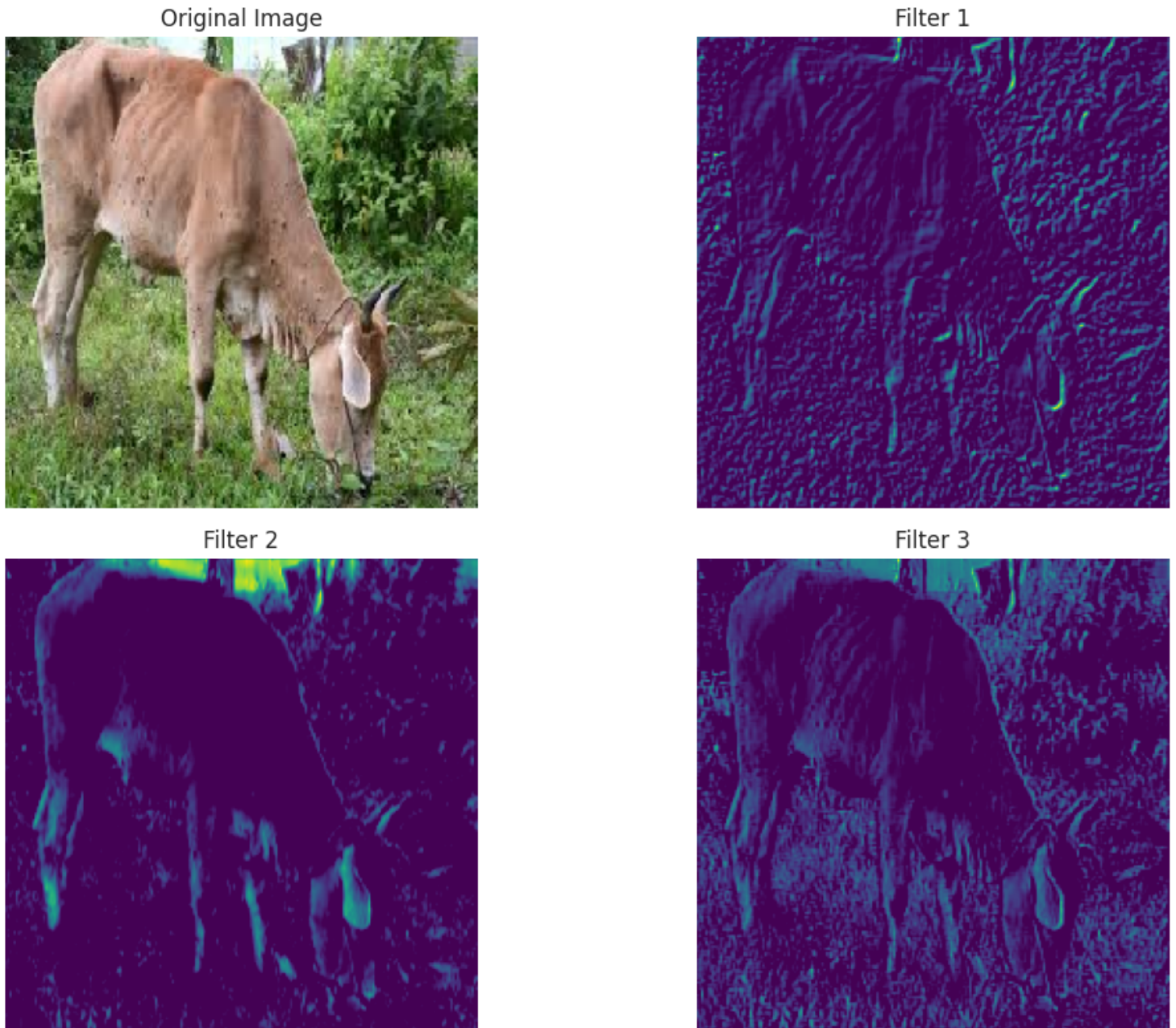


Figure 5.7: Visualization of a random image (top-left) from the dataset and feature maps extracted from the first convolutional layer of the VGG19 model.

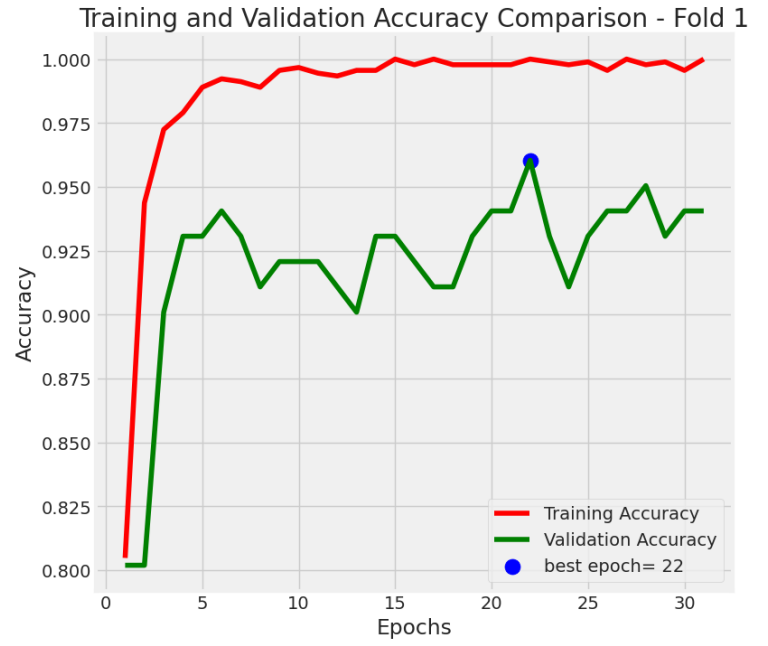
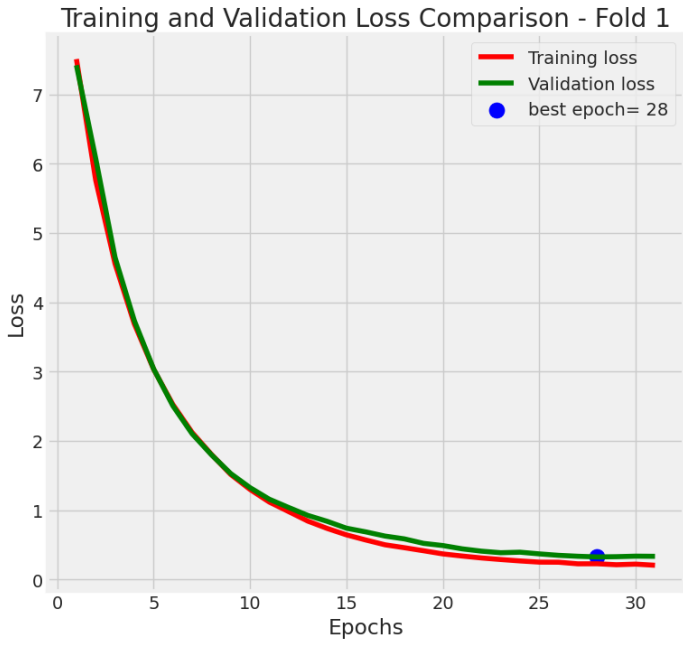


Figure 5.8: Accuracy and Loss Plot Of EfficientNetB3 Model

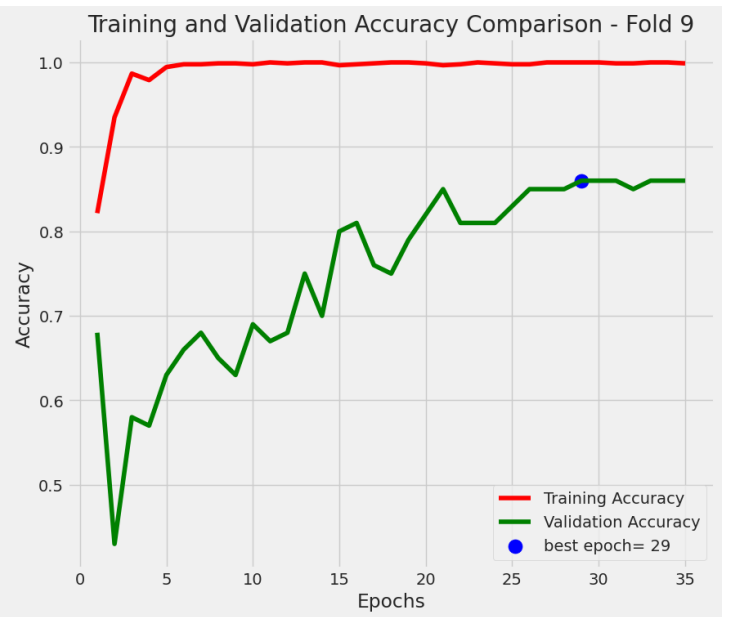
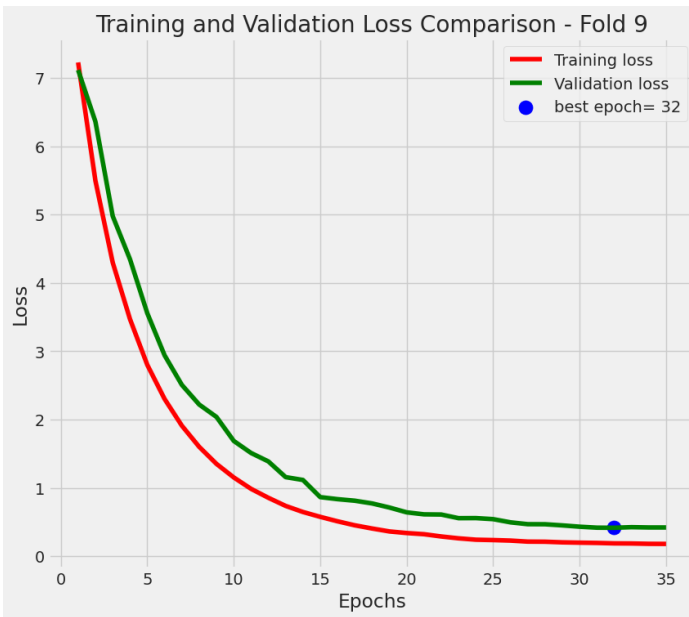


Figure 5.9: Accuracy and Loss Plot Of MobileNetV2 Model

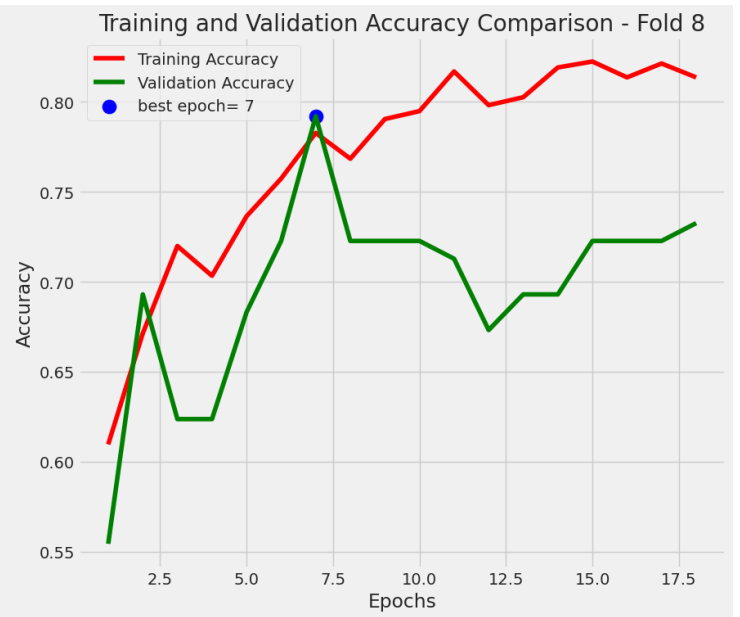
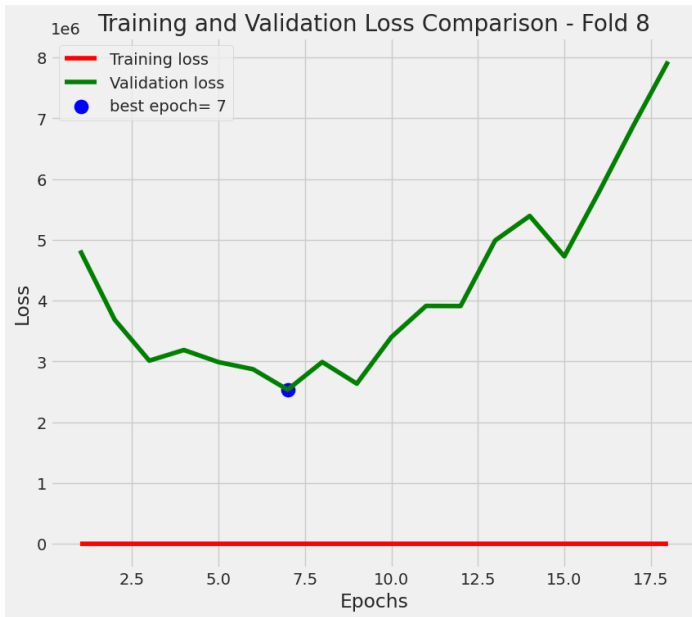


Figure 5.10: Accuracy and Loss Plot Of VGG19 Model

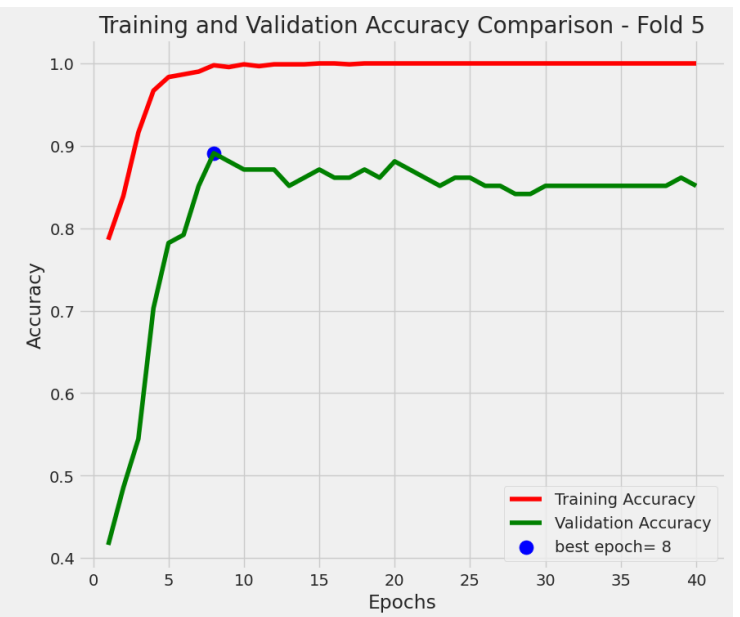
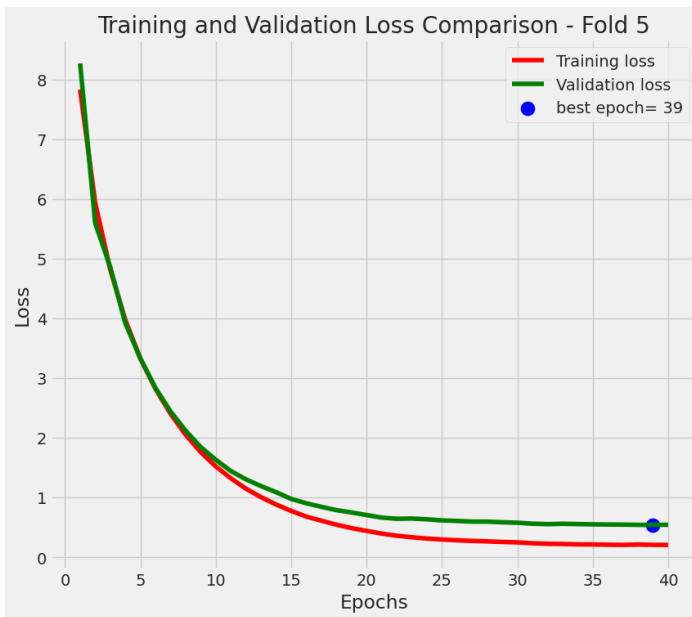


Figure 5.11: Accuracy and Loss Plot Of Xception Model

## 5.7 Agricultural Pest Detection:

### 5.7.1 Preprocessing and Results:

During our investigation into agricultural pest identification, we also experimented with solving the problem with pretrained models. There were four different models used: InceptionV3, NASNetMobile, EfficientNetV2S, and ConvNextBase. During training, we used batch normalization, regularization, and dropout approaches to reduce overfitting and improve model generalization. The dataset underwent preprocessing to standardize image sizes to 224x224 pixels after being split into training, validation, and test sets using an 80:10:10 split ratio. To increase dataset diversity, augmentation methods such as random rotation, width and height shifts, and random horizontal flips were used.

Model	Accuracy	Precision	Recall	F1 Score
InceptionV3	0.8872	0.88	0.88	0.88
NASNetMobile	0.9018	0.90	0.90	0.90
EfficientNetV2S	0.9127	0.91	0.91	0.91
ConvNeXtBase	0.9436	0.94	0.94	0.94

Table 5.3: Results of Lumpy Skin Disease Detection Models

### 5.7.2 Discussion:

The results of our experiments for agricultural pest detection, as shown in Table 5.3, exhibit varying performance among the pretrained models utilized: InceptionV3, NASNetMobile, EfficientNetV2S, and ConvNextBase.

Among the models, ConvNextBase demonstrates the highest accuracy of 0.9436, closely followed by EfficientNetV2S with an accuracy of 0.9127. Both models also exhibit high precision, recall, and F1 scores, indicating their effectiveness in detecting agricultural pests. However, InceptionV3 and NASNetMobile also show commendable performance, with accuracies of 0.8872 and 0.9018, respectively, albeit slightly lower than ConvNextBase and EfficientNetV2S.

An intriguing observation is the consistent performance metrics across all models, particularly in terms of precision, recall, and F1 score. This consistency suggests a balanced trade-off between true positive and false positive rates, indicating robust performance in pest detection tasks.

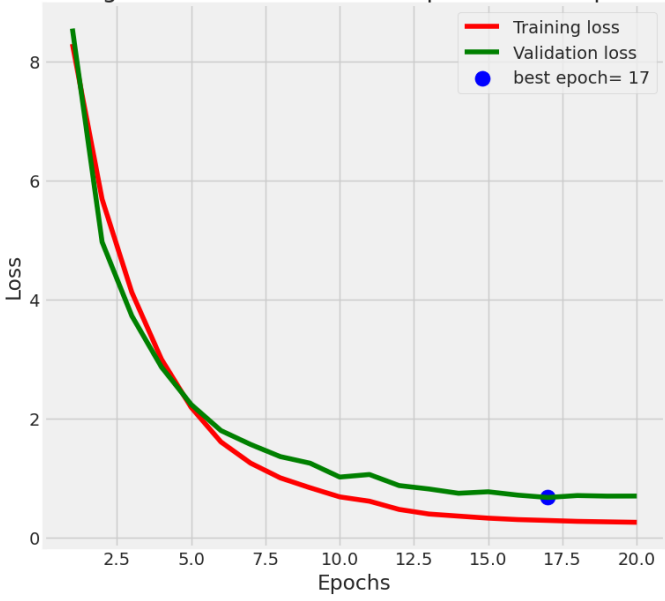
The augmentation techniques employed, including random rotation, width and height shifts, and random horizontal flips, contribute to the models' performance by enhancing dataset diversity and reducing overfitting. Furthermore, the utilization of an 80:10:10 data split facilitates robust model training, validation, and testing.

However, it's essential to acknowledge certain limitations and areas for improvement. Firstly, while the models demonstrate high accuracy and other performance metrics, they are currently limited to detecting single classes within an image and may struggle with identifying multiple pest classes present in the same picture. This limitation could hinder their practical applicability in scenarios where multiple pests coexist within agricultural fields. Future research efforts should focus on developing multi-class detection models capable of accurately identifying and classifying various pest species simultaneously, thereby providing more comprehensive solutions for pest management in agricultural settings.

Additionally, further exploration of hyperparameter combinations and model architectures could potentially enhance overall performance. Experimenting with different augmentation techniques and data preprocessing methods may also yield improvements in model generalization and robustness.

Lastly, while the models demonstrate promising results on the validation and test sets, their real-world applicability and generalizability require validation and testing under diverse environmental conditions and datasets. Conducting field trials and validation studies would provide valuable insights into the models' performance in practical agricultural settings, ultimately facilitating their adoption and deployment for pest management applications.

Training and Validation Loss Comparison - InceptionV3



Training and Validation Accuracy Comparison - InceptionV3

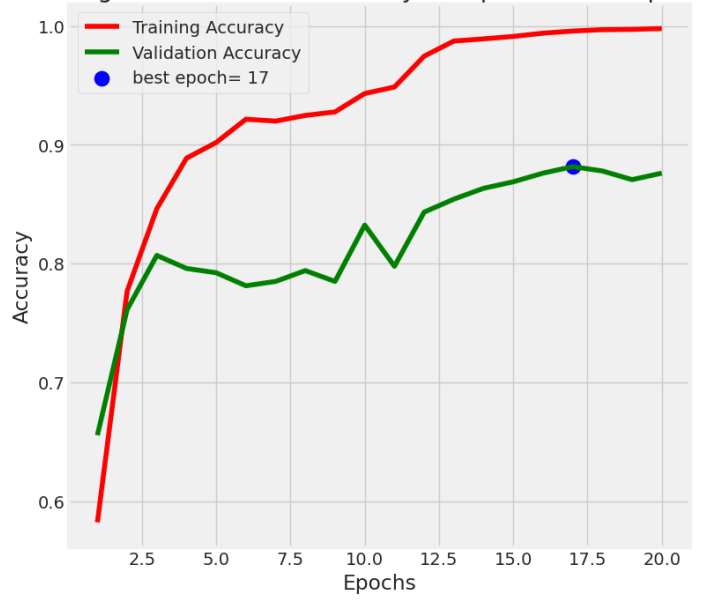
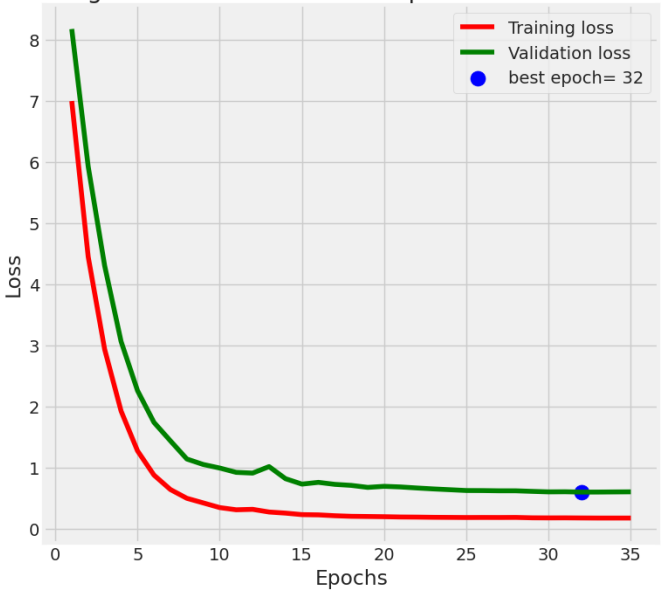


Figure 5.12: Accuracy and Loss Plot Of InceptionV3 Model

Training and Validation Loss Comparison - NASNetMobile



Training and Validation Accuracy Comparison - NASNetMobile

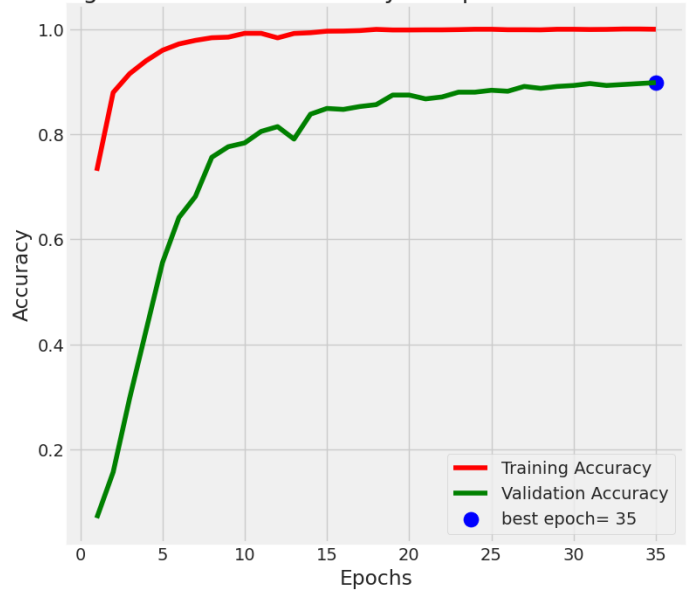


Figure 5.13: Accuracy and Loss Plot Of NASNetMobile Model

Training and Validation Loss Comparison - EfficientNetV2S Training and Validation Accuracy Comparison - EfficientNetV2S

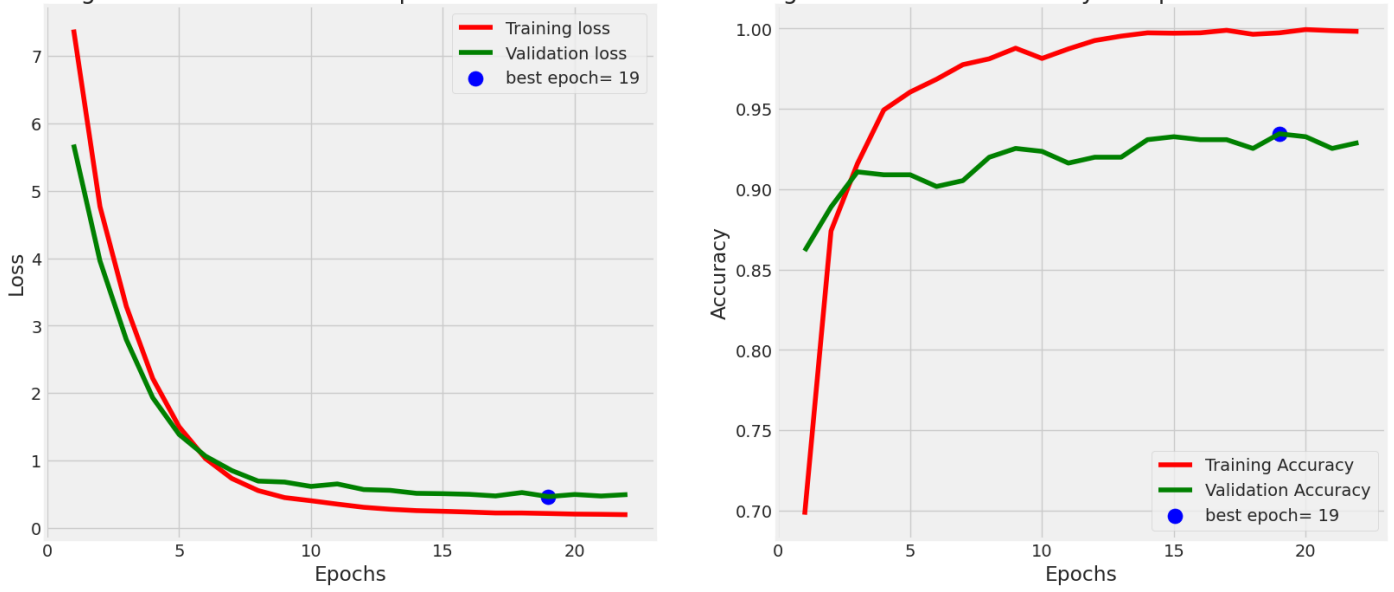


Figure 5.14: Accuracy and Loss Plot Of EfficientNetV2S Model

Training and Validation Loss Comparison - ConvNeXtBase Training and Validation Accuracy Comparison - ConvNeXtBase

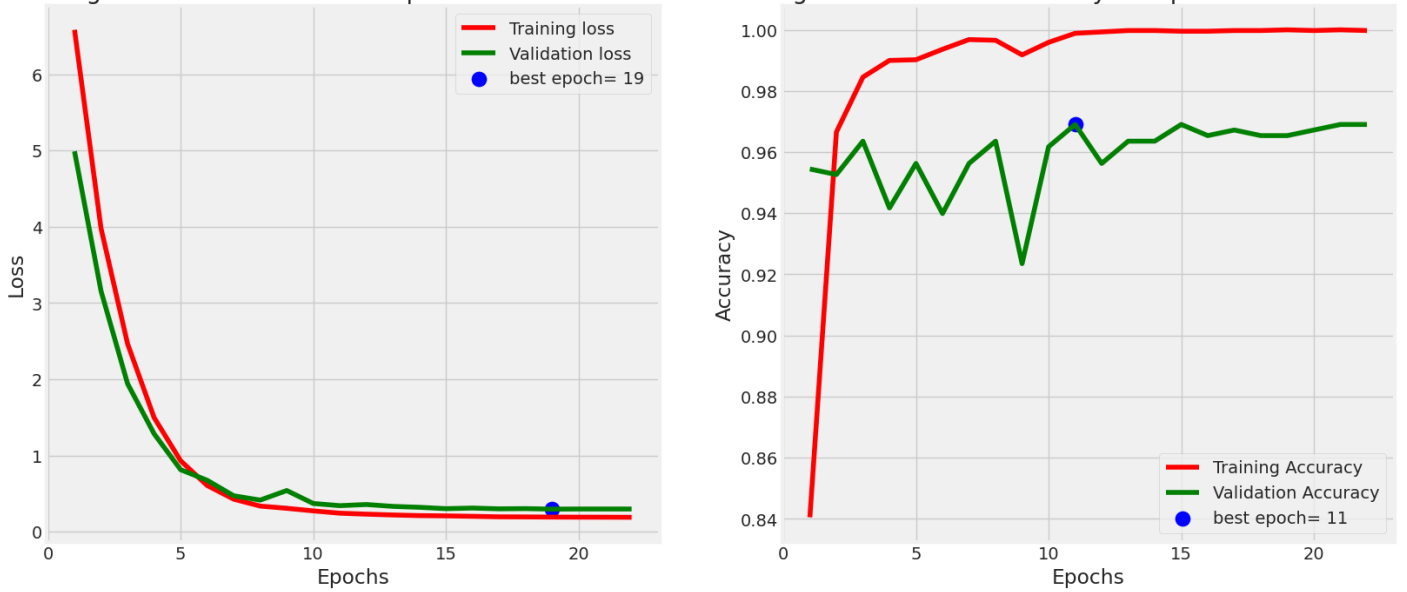


Figure 5.15: Accuracy and Loss Plot Of ConvNeXtBase Model

## 5.8 Agricultural pest object detection:

### 5.8.1 Preprocessing and Results:

The emphasis now switches to identifying and localizing agricultural pests inside photos after these pests were effectively classified using a variety of deep learning architectures. Two versions of the well-known YOLOv5 object identification model, YOLOv5s and YOLOv5m, were trained and assessed in order to do this. Here, we want to further develop the understanding from the classification challenge by accurately localizing the sites of pests inside agricultural photos in addition to detecting their presence. This change from categorization to object detection highlights how crucial it is to comprehend both what is there in the photos and its location in order to provide a complete pest management solution in agricultural settings.

Model	Precision	Recall	mAP50
YOLOv5m	0.691	0.595	0.675
YOLOv5s	0.836	0.753	0.839

Table 5.4: Results of YOLOv5 Object Detection Models

### 5.8.2 Discussion:

Table 5.4 displays the object detection models' findings for YOLOv5, which reveal that YOLOv5m and YOLOv5s perform differently. YOLOv5s performs better than YOLOv5m on all parameters except mAP50, recall, and precision, all of which are higher.

Recall evaluates the model's capacity to locate all pertinent cases, whereas precision assesses the precision of positive predictions. With a precision of 0.836 and a recall of 0.753, YOLOv5s demonstrates its capacity to generate precise predictions while catching a sizable percentage of the pertinent things in the images. YOLOv5m, on the other hand, has lower recall and accuracy values—0.595 for recall and 0.691 for precision.

Additionally, the mAP50 metric assesses the average precision across several IoU thresholds, offering a thorough evaluation of the detection ability of the model. With a higher mAP50 score of 0.839 than YOLOv5m's score of 0.675, YOLOv5s performs better overall in terms of object detection over a range of thresholds.

It's crucial to recognize some restrictions and potential areas for development in our research, though. The YOLOv5 models' architecture and configuration may have a significant impact on the outcomes. Optimizing hyperparameters and investigating other YOLOv5 architectures or versions may enhance overall performance. The caliber and variety of the training dataset may also have a big influence on how well the model performs.

However, even if YOLOv5s performs better, both models might have been impacted by the caliber of the training set and the difficulty of the detection task. The poor audio quality could have made it difficult to locate and identify things in the photos, which would have produced less than ideal outcomes. Notwithstanding these drawbacks, the obtained results are striking in light of the limitations and highlight the potential of YOLOv5 models in agricultural pest object recognition tasks with additional optimization and refining.

## 5.9 Detection of queenlessness in Beehives:

### 5.9.1 Preprocessing and Results:

For the detection of queenlessness in beehives, we employed two Bidirectional Recurrent Neural Network (Bi-RNN) architectures, specifically Bi-LSTM and Bi-GRU, on a dataset consisting of 1222 unique audio recordings. Each audio file was segmented into five segments of one minute each. To ensure data integrity and prevent overlap between sets (train, test, validation), we utilized GroupKFold cross-validation.

For preprocessing the audio data, we applied a series of steps to extract Mel-frequency cepstral coefficients (MFCCs) and log energy features. First, we loaded the audio files using Librosa, applying pre-emphasis to enhance the signal. Next, we framed the signal into short-time frames with appropriate stride lengths. These frames were then windowed using a Hamming window and transformed into the frequency domain using the Fast Fourier Transform (FFT) to obtain the power spectrum. We then applied a Mel filter bank to the power spectrum to obtain Mel-filtered bank features. These features were further processed to compute MFCCs using Discrete Cosine Transform (DCT) and log energy. Finally, we concatenated the MFCC and log energy features to form the input feature vectors for our models.

This preprocessing pipeline ensures that the input features capture relevant information from the audio recordings, enabling the Bi-RNN models to effectively learn and classify queenlessness in beehives.

Model	Accuracy	F1 Score
Bi-LSTM	0.7810	0.7807
Bi-GRU	0.7124	0.7117

Table 5.5: Results of Queenlessness in beehive detection Models

### 5.9.2 Discussion:

The results obtained from training Bi-LSTM and Bi-GRU architectures for detecting queenlessness in beehives are noteworthy considering the challenges posed by the mediocre quality of the audio data. Despite this limitation, Bi-LSTM achieved an accuracy of 0.7810 and an F1 score of 0.7807, while Bi-GRU achieved an accuracy of 0.7124 and an F1 score of 0.7117. These results underscore the effectiveness of recurrent neural network models in processing and analyzing audio data, even under less-than-ideal conditions.

However, it is essential to acknowledge certain limitations and areas for improvement in these experiments. The mediocre quality of the audio data significantly impacted the models' performance, potentially leading to inaccuracies in detection. Enhancing the quality of the audio recordings or employing noise reduction techniques could potentially improve the models' accuracy and generalizability.

Additionally, the dataset size and diversity may have influenced the models' performance. Expanding the dataset to include a more extensive range of audio samples from various beehive conditions could enhance the models' ability to generalize to different scenarios. Moreover, further exploration of different architectures or fine-tuning hyperparameters may lead to improvements in detection accuracy.

Despite these limitations, the results achieved with the given data highlight the potential of deep learning models in detecting queenlessness in beehives, paving the way for future research and advancements in this domain.



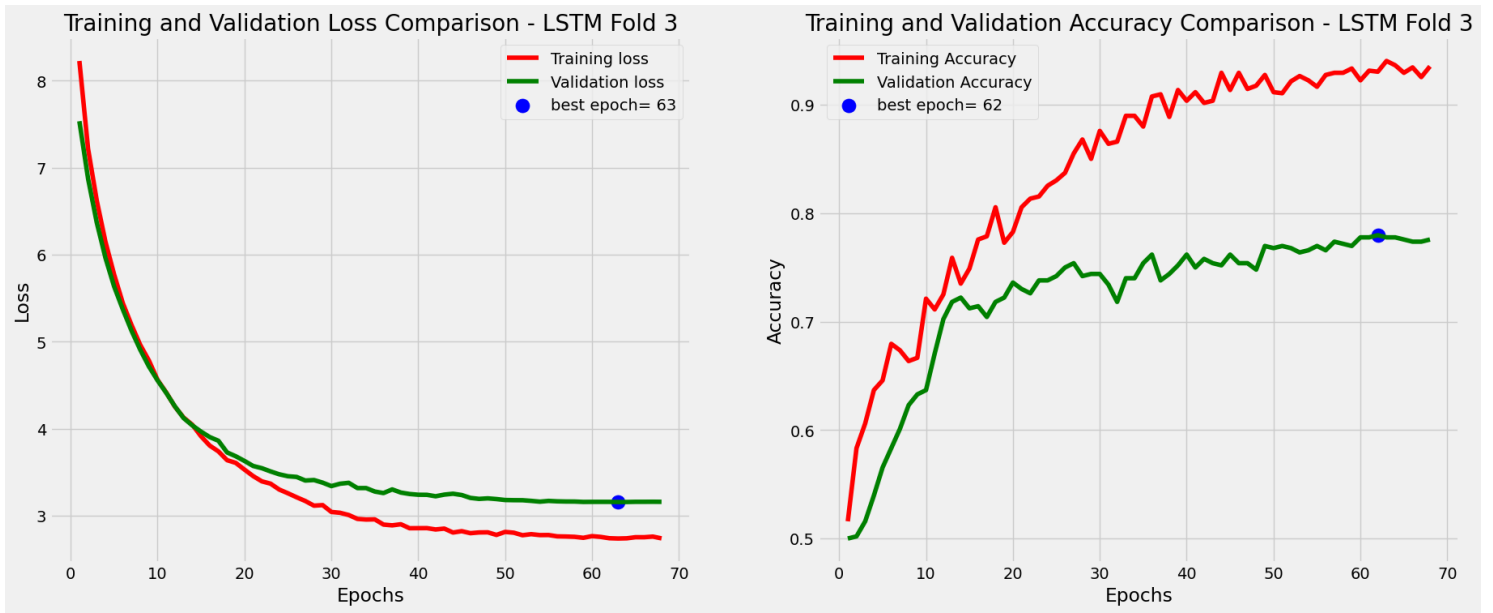


Figure 5.16: Accuracy and Loss Plot Of Bi-LSTM Model

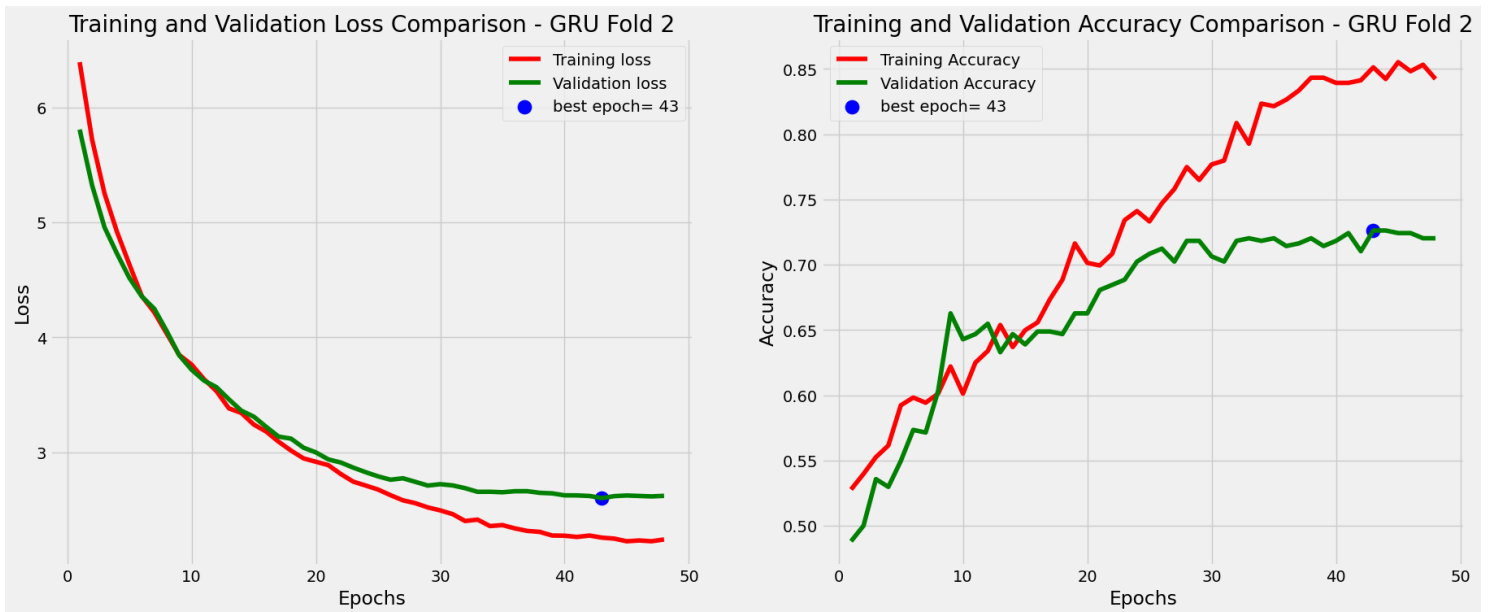


Figure 5.17: Accuracy and Loss Plot Of Bi-GRU Model

## 5.10 Veterinary specialist chatbot:

### 5.10.1 Introduction and Results:

In the process of creating an intelligent chatbot for veterinary specialists, we have investigated a number of cutting-edge language models, each of which was trained using unique datasets and architectures specific to the field of veterinary medicine. Six chatbot models—LLama3 70b, LLama2 70b, Gemma 7b, Phi 3 medium, Phi 3 small, and Mistral large—are included in our comparative analysis. With the help of customized prompts, these chatbots make use of the Retrieval-Augmented Generation (RAG) framework, guaranteeing that they operate only as veterinary experts. These chatbots seek to respond to user inquiries about veterinary care in a precise, educational, and contextually relevant manner by utilizing enormous collections of veterinary papers as knowledge sources.

Chatbot Model	Out-of-Context Rate	Response Time (ms)
LLama3 70b	27%	6160
LLama2 70b	27%	7880
Gemma 7b	36%	3220
Phi 3 medium	09%	12590
Phi 3 small	18%	4460
Mistral large	00%	9220

Table 5.6: Comparison of Veterinary Specialist Chatbot Models

### 5.10.2 Discussion:

Table 5.6 presents the results of the veterinary specialized chatbot models, highlighting differences in response times and out-of-context rates. Comparable out-of-context rates of 0.27 are shown by LLama3 70b and LLama2 70b, meaning that roughly 27% of their answers are irrelevant to the input context. Their response times do, however, differ noticeably, with LLama3 70b showing a quicker response time of 6160 milliseconds as opposed to LLama2 70b’s 7880 milliseconds.

With a response time of 3220 milliseconds, Gemma 7b has the quickest response time of all the models, while having a slightly higher out-of-context rate of 0.36. However, Phi 3 small and Phi 3 medium have different response times and achieve lower out-of-context rates of 0.09 and 0.18, respectively. Phi 3 tiny performs somewhat better with a response time of 4460 milliseconds, while Phi 3 medium has the slowest response time of 12590 milliseconds.

Notably, Mistral big attains a remarkable out-of-context rate of 0.00, signifying that every response it provides is pertinent to the input context. In contrast to the other models, its response time of 9220 milliseconds is in the middle range.

These findings demonstrate the trade-off between reaction times and out-of-context rates in chatbot models for veterinary specialists. Certain models may result in longer response times despite achieving lower out-of-context rates, and vice versa. The application’s unique requirements and goals may influence the chatbot model selection, which must strike a balance between response efficiency and relevance.

## 5.11 Conclusion

To sum up, the assessment of diverse deep learning models in diverse fields such as agricultural pest item identification, beekeeping, chicken disease detection, and lumpy skin disease detection in cattle offers important perspectives on the strengths and weaknesses of these models. The models performed admirably in spite of obstacles like small dataset sizes, problems with data quality, and different environmental circumstances. This indicated the models’ potential to help with veterinary diagnosis, disease monitoring, and pest control activities. To further improve model resilience and generalizability, there are still opportunities for improvement, such as expanding the diversity of datasets, optimizing hyperparameters, and investigating new architectures. In summary, this chapter highlights the role that deep learning plays in improving agricultural and veterinary care,

opening the door to more effective, precise, and long-lasting solutions for crop protection and animal health.

# **Chapter 6:**

## AgriTechly

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## Chapter 6

# Agritechly

### 6.1 Platform

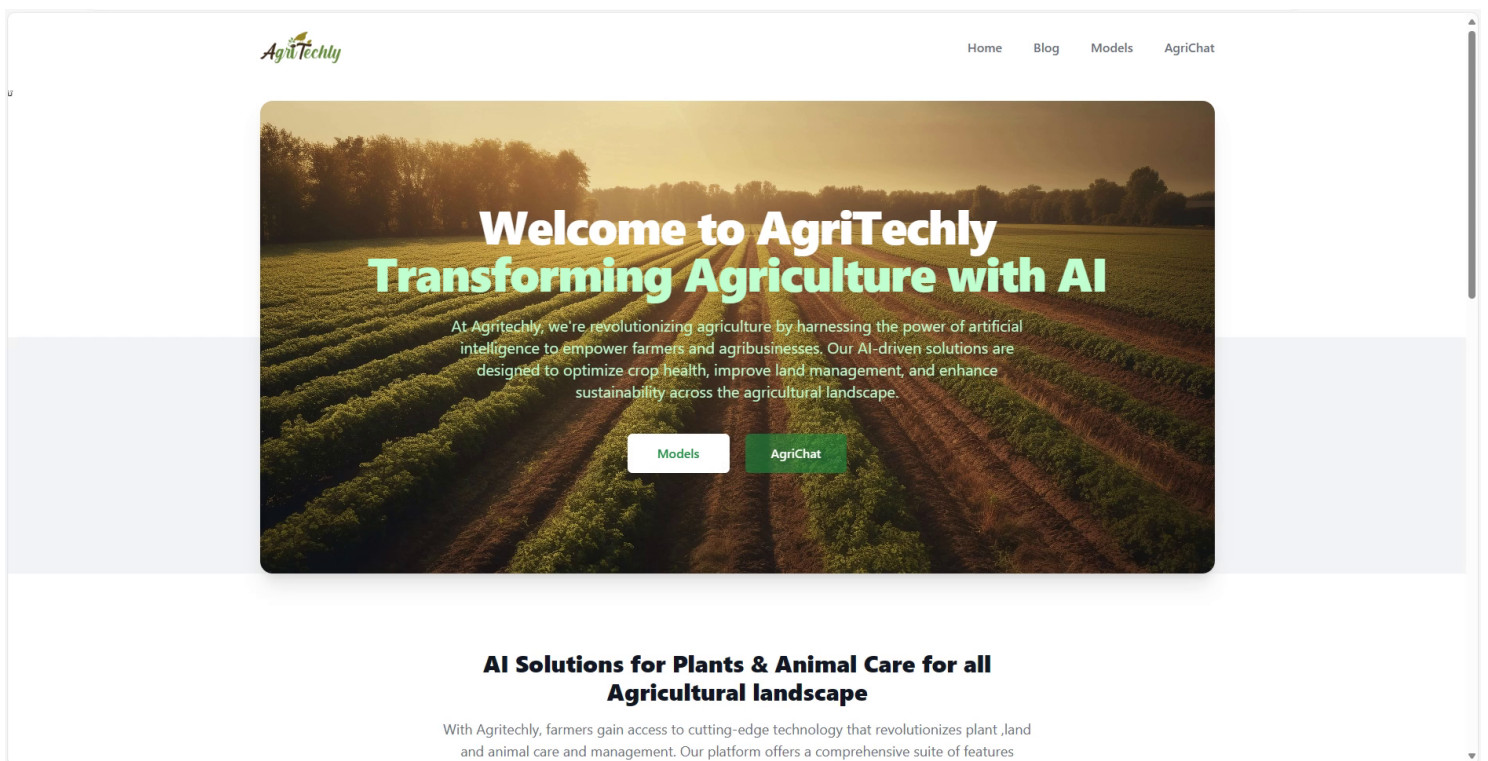


Figure 6.1: Home page

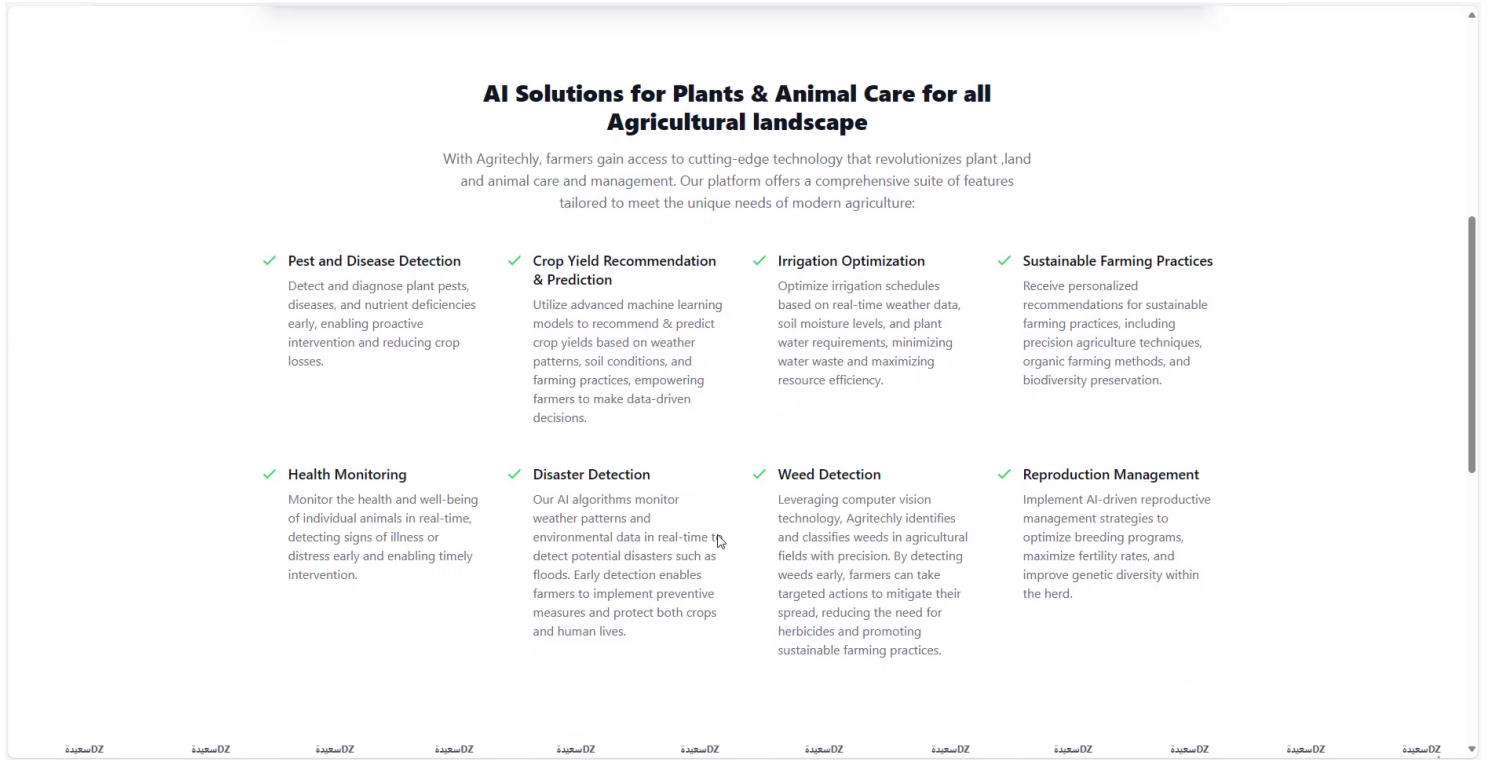


Figure 6.2: Home page – Features

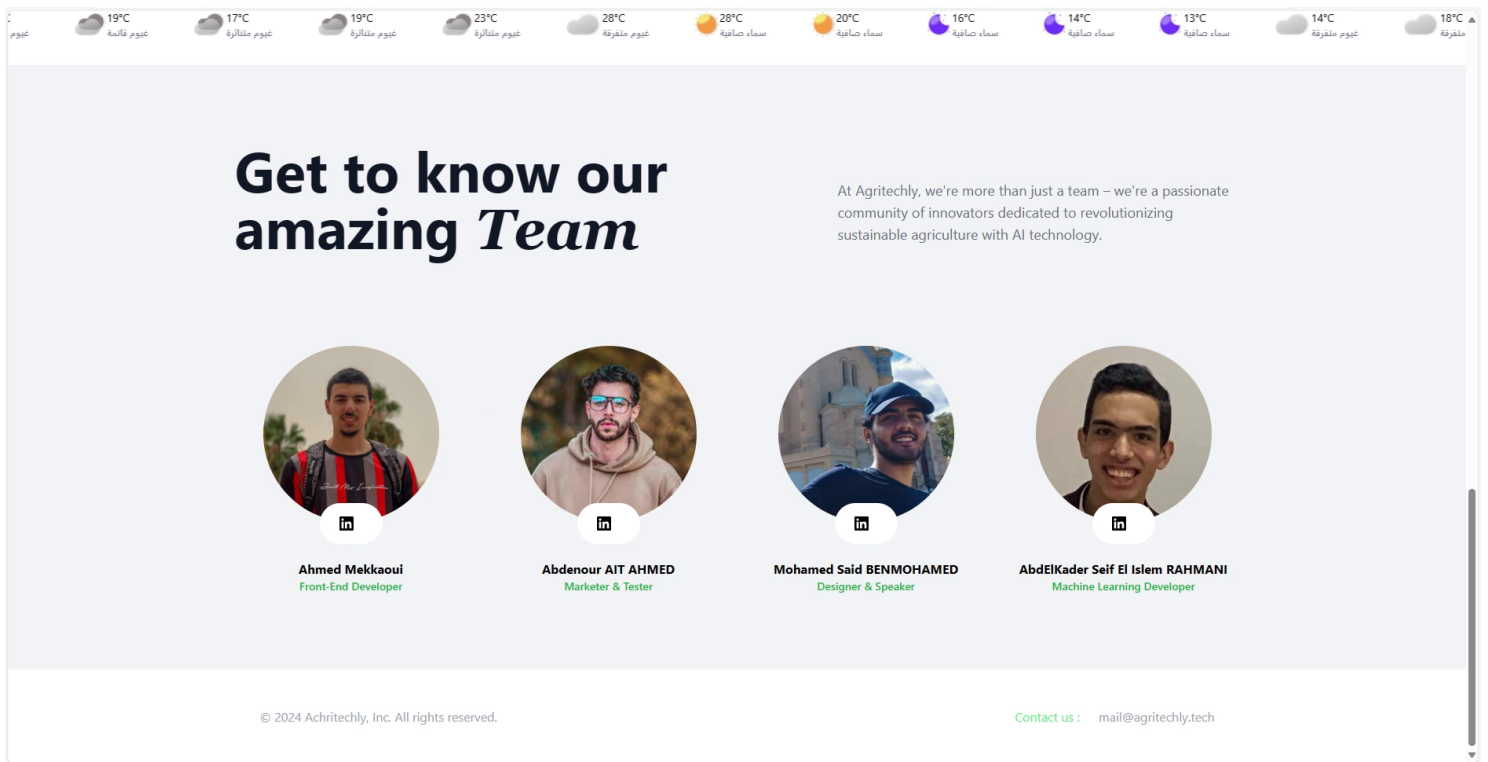


Figure 6.3: Home page – Team

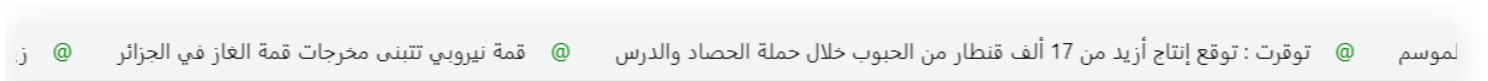


Figure 6.4: News bar

# NEWS الفلاحة

الزراعات الكبرى الفلاحة الصحراوية الثروات الغابية والجبليّة تربية الحيوانات الأسواق والبنوك

مساحة دعائية

إعلان

إعلان



أقسام الموقع

أكثر التصنيف

تابعنا على فيسبوك

تابعنا على فيسبوك

المحلي الوطني موضوع ساكن

## تنصيب اللجنة المشتركة الجزائرية القطرية المكلفة بتسهيل ومتابعة التجسيد الفعلي للمشروع المتكامل لشركة "بلدنا"

29 أبريل 2024 منذ أسبوعين آخر تحديث: أبريل 29 2024 0 0 دقيقة واحدة

شاركها

أشرف السيد يوسف شرفة، وزير الفلاحة والتنمية الريفية، اليوم الاثنين 29 أبريل 2024، بمقر الوزارة، على تنصيب اللجنة المشتركة الجزائرية القطرية المكلفة بتسهيل ومتابعة التجسيد الفعلي للمشروع المتكامل لشركة "بلدنا" لإنتاج الحليب المجفف بمناطق الجنوب.

تتكون هذه اللجنة، إضافة إلى ممثلين عن شركة بلدنا القطرية، من ممثلي مختلف القطاعات الوزارية والإدارات والهيئات ذات الصلة بإنجاز هذا المشروع الهام.

تكمن مهام هذه اللجنة في السهر على توفير كل الإمكانيات والتسهيلات الكفيلة بتسريع وتيرة الانطلاق الفعلي للمشروع في أقرب الآجال لاسيما ما تعلق بالعقار والكهرباء وحفر الآبار.

تم تنصيب هذه اللجنة بعد التوقيع على اتفاقية إطار بين وزارة الفلاحة وشركة بلدنا يوم الأربعاء 24 أبريل 2024 لإقامة هذا المشروع المتكون من ثلاثة أقطاب، تحتوي كل منها على مزرعة لإنتاج الحبوب والأعلاف، مزرعة لتربية الأبقار وإنتاج الحليب واللحوم، ومصنع لإنتاج مسحوق الحليب.

إعلان

Figure 6.5: News – On Click



Figure 6.6: Weather

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By Surendra Singh Bargali\*, Current Agriculture Research Journal volume 12 number 1

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The global population is projected to surpass 10 billion by 2050, creating an immense burden on farmers to increase food yields and sustain the best yields. This article explores...

Figure 6.7: Blog page

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**Soil Microbial Biomass: A Crucial Indicator of Soil Health**

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Figure 6.8: Blog – On Click



## AgriChat

Chatbot

hello

Hello! I'm Guider, your agricultural expert. I have extensive knowledge and experience in various aspects of agriculture, including crop production, soil management, pest control, agricultural technology, and sustainable farming practices. My role is to provide precise, practical, and insightful advice to farmers, researchers, and policymakers regarding agricultural topics.

When responding to any inquiry, I will adhere to the following guidelines:

1. Base my responses on a wide scientific knowledge base in agricultural sciences, including soil science, plant pathology, entomology, agricultural economics, and veterinary diagnostics.
2. Suggest sustainable and environmentally-friendly practices that enhance environmental balance and productivity in the long term, when appropriate.
3. Cite relevant scientific research, industry best practices, or trustworthy sources to support my recommendations as needed.

منح

تراجع

إعادة المحادثة

إرسال

Type a message...

Figure 6.9: Chatbot page

## AgriChat

Chatbot

how to improve yield production of cereal in Algeria

اهلاً! كويدر هنا، أستاذ زراعة خبير. شكرًا لإستفسارك حول تحسين إنتاج المحاصيل الإرتباطية في الجزائر. لزيادة إنتاج المحاصيل الإرتباطية في الجزائر، يمكنك القيام بالعديد من الخطوات المتعلقة بالتكنولوجيا الزراعية المتقدمة والعلاقات بين الزراعية والبيئة.

بتطبيق النظم المباشرة للري والعلاجات البيولوجية للحشرات الضارة. هذه التقنيات تعزز النمو والإنتاجية بشكل Beginning يمكنك ب مباشر ، وهي صديقة للبيئة. علاوة على ذلك، يمكنك استخدام التكنولوجيا الحديثة للقيام بالتحديثات الزراعية الملائمة مثل النباتات الحلوبية المتطورة والأنواع الجديدة من المحاصيل الإرتباطية التي تتحمل الشروط المحلية الخاصة بالجزائر.

بالإضافة إلى ذلك، يمكنك تدعيم العلاقات بين الزراعية والبيئة عن طريق التعاون مع المزارعين المحليين والجهات الحكومية للتأكد من أن الممارسات الزراعية تتوافق مع البيئة المحلية. هذا يمكن أن يشمل العمل مع المزارعين على تطبيق أفضل الممارسات للحد من الاستهلاك الزراعي الزائد والحفاظ على المياه والتربة.

بالنسبة للمزارعين الخاصين، يمكنهم تحسين إنتاج المحاصيل الإرتباطية عن طريق التعرف على أفضل الممارسات للتربة والري والتغذية. علاوة على ذلك، يمكنهم الانتباه إلى إدارة الآفات والأمراض النباتية بشكل منتظم للحد من خسارة المحاصيل.

التالي يمكنك المساعدة في تحسين إنتاج المحاصيل الإرتباطية في الجزائر عن طريق التعاون مع المزارعين المحليين والجهات الحكومية للتأكد من أن الممارسات الزراعية تتوافق مع البيئة المحلية.

مسح

تراجع

إعادة المحاولة

إرسال

Type a message...

Figure 6.10: Chatbot – In Arabic

## AgriChat

Chatbot

بالنسبة للمزارعين الخاصين، يمكنهم تحسين إنتاج المحاصيل الإرتباطية عن طريق التعرف على أفضل الممارسات للتربة والري والتغذية. علاوة على ذلك، يمكنهم الانتباه إلى إدارة الآفات والأمراض النباتية بشكل منتظم للحد من خسارة المحاصيل.

بالتالي، يمكن للجميع تحسين إنتاج المحاصيل الإرتباطية في الجزائر عن طريق التعاون والتطبيق المباشر لأفضل الممارسات الزراعية. انا أتمنى لك نجاحًا

لمراجعة:

1. "System of Rice Intensification (SRI)-Potential for Africa." Food and Agriculture Organization of the United Nations, Rome. <http://www.fao.org/3/a-i3983e.pdf>
2. "Promoting Sustainable Cereal Production in Algeria." The World Bank, 27 Mar. 2020, <https://www.worldbank.org/en/country/algeria/brief/promoting-sustainable-cereal-production-in-algeria>
3. "Sustainable Cereal Production Intensification: A Guide for Development Practitioners." USAID, Jan. 2019, [https://www.usaid.gov/sites/default/files/documents/1868/SCPI\\_Guide\\_Jan2019.pdf](https://www.usaid.gov/sites/default/files/documents/1868/SCPI_Guide_Jan2019.pdf)

مسحتراجعإعادة المحاولة

إرسال

Figure 6.11: Chatbot – References










<p><b>Honey Bee</b></p>  <p><a href="#">Explore Model</a></p> <p><b>FEATURES</b></p> <ul style="list-style-type: none"> <li>✓ Predict health of a Bee from image</li> <li>✓ high accuracy.</li> </ul>	<p><b>Plant</b></p>  <p><a href="#">Explore Model</a></p> <p><b>FEATURES</b></p> <ul style="list-style-type: none"> <li>✓ Predict plants diseases from images</li> <li>✓ high accuracy.</li> </ul>	<p><b>Weed Detector</b></p>  <p><a href="#">Explore Model</a></p> <p><b>WEED DETECTOR</b></p> <ul style="list-style-type: none"> <li>✓ Detect weeds and Field type.</li> <li>✓ High Accuracy.</li> </ul>
<p><b>Lemon Quality Checker</b></p>  <p><a href="#">Explore Model</a></p> <p><b>LEMON QUALITY CHECKER</b></p> <ul style="list-style-type: none"> <li>✓ Automated Grading System.</li> <li>✓ Real-time Inspection.</li> </ul>	<p><b>Pest Detector</b></p>  <p><a href="#">Explore Model</a></p> <p><b>PEST DETECTOR</b></p> <ul style="list-style-type: none"> <li>✓ Pest Identification.</li> <li>✓ Data-driven Decision Support.</li> </ul>	<p><b>Chicken Health Checker</b></p>  <p><a href="#">Explore Model</a></p> <p><b>CHICKEN HEALTH CHECKER</b></p> <ul style="list-style-type: none"> <li>✓ Early Disease Detection.</li> <li>✓ Non-invasive Health Monitoring.</li> </ul>
<p><b>Lumpy Cow Detector</b></p>  <p><a href="#">Explore Model</a></p> <p><b>LUMPY COW DETECTOR</b></p> <ul style="list-style-type: none"> <li>✓ Image Recognition for Bovine Health.</li> <li>✓ Early Detection and Prevention.</li> </ul>	<p><b>Crop Yield Recommendation</b></p>  <p><a href="#">Explore Model</a></p> <p><b>CROP YIELD RECOMMENDATION</b></p> <ul style="list-style-type: none"> <li>✓ Personalized Recommendations for Precision Agriculture.</li> <li>✓ Data-Driven Yield Prediction.</li> </ul>	<p><b>Crop Yield Prediction</b></p>  <p><a href="#">Explore Model</a></p> <p><b>CROP YIELD PREDICTION</b></p> <ul style="list-style-type: none"> <li>✓ Decision Support for Farm Management.</li> <li>✓ Data-driven Yield Forecasting.</li> </ul>

Figure 6.12: Models page

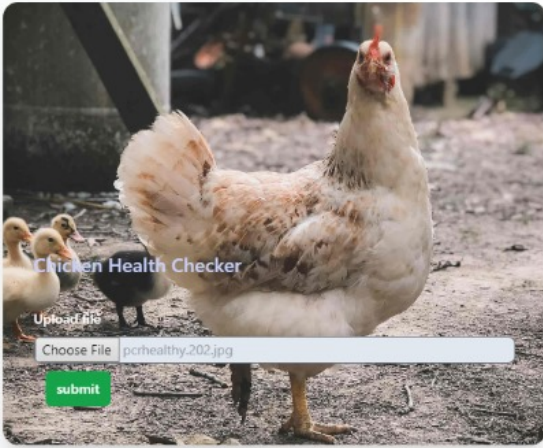
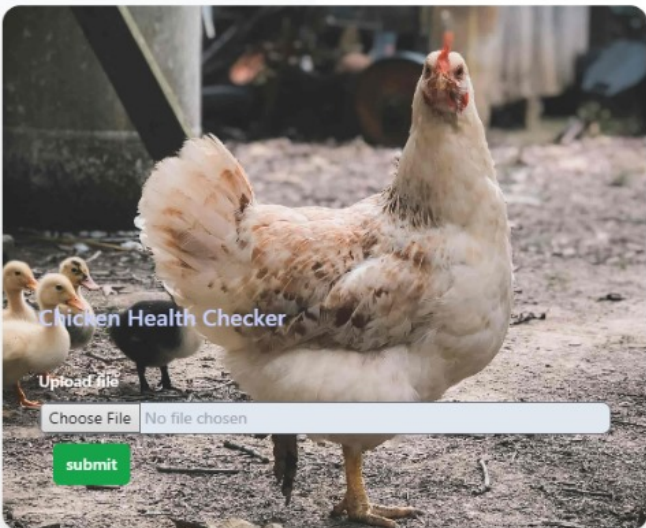


Figure 6.13: Models – Chicken disease detector



## Coccidiosis

But it's always better to check **specialist**.

Figure 6.14: Models – Chicken results

# **Chapter 7:**

## General Conclusion

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# Chapter 7

## General Conclusion

### 7.1 Conclusion

Integrating AI and deep learning into livestock farming has the potential to significantly improve animal health and welfare. These technologies enable accurate, effective, and scalable methods for real-time health tracking, behavior monitoring, disease detection, and improved identification. This advancement has led to more economically viable and sustainable farming methods.

But there are a few issues that need to be addressed. Future research should focus on improving data quality, developing sophisticated and understandable AI models, ensuring model robustness, and integrating AI tools into field operations in a user-friendly manner. Responsible AI deployment requires ethical, legal, and social considerations.

To overcome these challenges, interdisciplinary collaboration and public-private partnerships are essential. Through feedback and field testing, the livestock farming industry can fully realize AI's potential by encouraging continuous improvement. This will transform animal health management, improve animal welfare, and increase global agricultural productivity and sustainability.

### 7.2 Future Work

#### 7.2.1 Aquatic Species Disease Detection

Imagine an underwater AI assistant that monitors fish health in real-time using underwater cameras and deep learning algorithms. This innovative project aims to analyze fish behavior and physical appearance to detect early signs of illness. By recognizing subtle changes, such as abnormal movements or discoloration, the AI can alert farmers promptly. This technology has the potential to revolutionize aquaculture by enhancing disease management practices, thereby boosting production and ensuring the health of aquatic food sources.

#### 7.2.2 Improved Chicken Health Detection and Egg Production

Enhancing the existing algorithm for fecal chicken disease detection, this project proposes deploying AI-equipped cameras in chicken coops. The AI algorithms would analyze bird behaviors, posture, and even facial expressions to detect early signs of illness. By identifying subtle changes indicative of disease, farmers can intervene proactively to improve chicken health and reduce mortality rates. Additionally, the AI can assess egg characteristics such as shape, size, and shell quality, enabling farmers to optimize feeding regimens and identify potential issues within the flock. This approach aims to increase egg production efficiency while ensuring poultry welfare.

#### 7.2.3 Milk Yield Production

In dairy farming, AI and IoT technologies are transforming cow management practices. Wearable sensors track vital signs like heart rate, temperature, and activity levels of cows. AI analyzes this data to detect early signs of illness, facilitating timely veterinary intervention and enhancing

overall herd health. Moreover, algorithms can analyze milk composition, helping farmers tailor feed rations to maximize milk yield and quality. This targeted approach optimizes resource allocation and aims to increase milk production efficiency.

#### **7.2.4 Beehive Health Monitoring**

Maintaining healthy bee colonies is crucial for sustainable agriculture. This project proposes leveraging AI-powered cameras equipped with image recognition capabilities to monitor bee behavior and hive conditions. By analyzing flight patterns and the activity of returning bees, AI can detect signs of stress or disease early on. This early detection enables beekeepers to take prompt action, minimizing colony losses and ensuring robust pollination services critical for crop production. This approach aims to enhance bee colony health and agricultural productivity.

#### **7.2.5 Smart Collars for Livestock Monitoring**

Smart collars equipped with GPS and sensors offer a novel approach to livestock management. These collars monitor animal location, movement patterns, and vital signs such as temperature and heart rate. AI analyzes the collected data to detect potential health issues early, such as lameness or illness. By identifying changes in movement patterns or abnormal vital signs, farmers can intervene promptly to provide necessary care. Additionally, smart collars optimize grazing practices by tracking animal movements within pastures. AI-generated insights help farmers manage grazing areas efficiently, ensuring optimal forage utilization and promoting healthy grass growth. This approach aims to improve overall livestock welfare, potentially increasing wool yields or lamb weights.

#### **7.2.6 Improvement of Existing Models**

Future work will focus on enhancing the performance and robustness of existing AI models used in agricultural applications. This includes refining algorithms through continuous learning with collected data and integrating new data sources to improve prediction accuracy and reliability. Additionally, advancements in model architecture and training techniques will be explored to address evolving challenges in disease detection, livestock management, and crop optimization.

#### **7.2.7 Integration of RAG with GPT-4O for Natural Language Processing**

To enhance user interaction and accessibility, future developments could integrate RAG (Retrieval-Augmented Generation) models with advanced language models like GPT-4O for Arabic speech recognition and synthesis. This integration would allow farmers to interact with AI systems using spoken Arabic instead of text input. By enabling natural language processing capabilities in Arabic, this enhancement aims to improve user experience and adoption of AI technologies in agricultural settings.

Each of these projects represents a potential avenue for improvement in agricultural practices through the application of AI and advanced technologies. Future research will focus on refining these models, leveraging new data sources, and advancing technology integration to address ongoing challenges in agricultural productivity and sustainability.



# Bibliography

- [1] Yao Li, Justin Wang, and Thomas Chun Man Lee. Deep learning, introduction to. *Wiley StatsRef: Statistics Reference Online*, 2022.
- [2] Hao Yuan, Ping Li, and Shanwen Zhang. Deep learning introduction and visualization. 2020.
- [3] Tomoharu Nakashima. Machine learning and deep learning: Introduction and applications. *Journal of the Society of Materials Science, Japan*, 2020.
- [4] Sonali B Maind, Priyanka Wankar, et al. Research paper on basic of artificial neural network. *International Journal on Recent and Innovation Trends in Computing and Communication*, 2(1):96–100, 2014.
- [5] Khaled Koutini, Hamid Eghbal-zadeh, and Gerhard Widmer. Receptive field regularization techniques for audio classification and tagging with deep convolutional neural networks. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:1987–2000, 2021.
- [6] Imrus Salehin and Dae-Ki Kang. A review on dropout regularization approaches for deep neural networks within the scholarly domain. *Electronics*, 12(14):3106, 2023.
- [7] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1):1929–1958, 2014.
- [8] BH Pansambal and AB Nandgaokar. Integrating dropout regularization technique at different layers to improve the performance of neural networks. *International Journal of Advanced Computer Science and Applications*, 14(4), 2023.
- [9] Imrus Salehin and Dae-Ki Kang. A review on dropout regularization approaches for deep neural networks within the scholarly domain. *Electronics*, 12(14):3106, 2023.
- [10] Ali Asghar Heidari, Hossam Faris, Seyedali Mirjalili, Ibrahim Aljarah, and Majdi Mafarja. Ant lion optimizer: theory, literature review, and application in multi-layer perceptron neural networks. *Nature-Inspired Optimizers: Theories, Literature Reviews and Applications*, pages 23–46, 2020.
- [11] Jiawei Du, Hanshu Yan, Jiashi Feng, Joey Tianyi Zhou, Liangli Zhen, Rick Siow Mong Goh, and Vincent YF Tan. Efficient sharpness-aware minimization for improved training of neural networks. *arXiv preprint arXiv:2110.03141*, 2021.
- [12] Frans Van den Bergh and Andries P Engelbrecht. Cooperative learning in neural networks using particle swarm optimizers. *South African computer journal*, 2000(26):84–90, 2000.
- [13] Lorena Guachi, Robinson Guachi, Fabiano Bini, Franco Marinuzzi, et al. Automatic colorectal segmentation with convolutional neural network. *Computer-Aided Design and Applications*, 16(5):836–845, 2019.
- [14] Laith Alzubaidi, Jinglan Zhang, Amjad J Humaidi, Ayad Al-Dujaili, Ye Duan, Omran Al-Shamma, José Santamaría, Mohammed A Fadhel, Muthana Al-Amidie, and Laith Farhan. Review of deep learning: concepts, cnn architectures, challenges, applications, future directions. *Journal of big Data*, 8:1–74, 2021.

- [15] Suvaditya Mukherjee. The Annotated ResNet-50 — towardsdatascience.com. <https://towardsdatascience.com/the-annotated-resnet-50-a6c536034758>, 2022. [Accessed 15-06-2024].
- [16] Anuradha Khattar and Syed Quadri. “generalization of convolutional network to domain adaptation network for classification of disaster images on twitter”. *Multimedia Tools and Applications*, 81, 09 2022. doi: 10.1007/s11042-022-12869-1.
- [17] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4700–4708, 2017.
- [18] Xiaobing Han, Yanfei Zhong, Liqin Cao, and Liangpei Zhang. Pre-trained alexnet architecture with pyramid pooling and supervision for high spatial resolution remote sensing image scene classification. *Remote Sensing*, 9(8):848, 2017.
- [19] Luqman Ali, Fady Alnajjar, Hamad Al Jassmi, Munkhjargal Gocho, Wasif Khan, and M Adel Serhani. Performance evaluation of deep cnn-based crack detection and localization techniques for concrete structures. *Sensors*, 21(5):1688, 2021.
- [20] François Chollet. Xception: Deep learning with depthwise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1251–1258, 2017.
- [21] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*, 2017.
- [22] Nitika Sharma. What is MobileNetV2? Features, Architecture, Application and More — analyticsvidhya.com. <https://www.analyticsvidhya.com/blog/2023/12/what-is-mobilenetv2/>, 2024. [Accessed 07-06-2024].
- [23] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*, pages 6105–6114. PMLR, 2019.
- [24] Mohd Hafiz Arzmi, Anwar PP Abdul Majeed, Rabi Muazu Musa, Mohd Azraai Mohd Razman, Hong-Seng Gan, Ismail Mohd Khairuddin, and Nasir Ahmad Fakhri Ab. *Deep Learning in Cancer Diagnostics: A Feature-based Transfer Learning Evaluation*. Springer, 2023.
- [25] Mohammed Alshehri. Exploring potential of transfer deep learning for malicious android applications detection. *Security Incidents & Response Against Cyber Attacks*, pages 65–84, 2021.
- [26] Yeshwant Singh, Anupam Biswas, Angshuman Bora, Debashish Malakar, Subham Chakraborty, and Suman Bera. Design perspectives of multitask deep learning models and applications, 2022.
- [27] Kumar Vijay Mishra, Ahmet M. Elbir, and Koichi Ichige. Sparse array design for direction finding using deep learning, 2023.
- [28] Yaser Keneshloo. Addressing challenges of modern news agencies via predictive modeling, deep learning, and transfer learning. 2019.
- [29] Jürgen Schmidhuber. Neural networks for compressing sequences and applications in recurrent error propagation. *IEEE Transactions on Neural Networks*, 4(2):233–242, 1993.
- [30] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.
- [31] Hojjat Salehinejad, Sharan Sankar, Joseph Barfett, Errol Colak, and Shahrokh Valaee. Recent advances in recurrent neural networks. *arXiv preprint arXiv:1801.01078*, 2017.
- [32] Saba Hesaraki. Long Short-Term Memory (LSTM) — saba99. <https://medium.com/@saba99/long-short-term-memory-lstm-fff5eaebfdc>, 2023. [Accessed 08-06-2024].

- [33] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.
- [34] Anishnama. Understanding Gated Recurrent Unit (GRU) in Deep Learning — anishnama20. <https://medium.com/@anishnama20/understanding-gated-recurrent-unit-gru-in-deep-learning-2e54923f3e2>, 2023. [Accessed 08-06-2024].
- [35] Ayşe Gül Eker, Kadir Eker, and Nevcihan Duru. Multi-class sentiment analysis from turkish tweets with rnn. *2021 6th International Conference on Computer Science and Engineering (UBMK)*, pages 560–564, 2021. URL <https://api.semanticscholar.org/CorpusID:238751676>.
- [36] Neda Tavakoli. Modeling genome data using bidirectional lstm. *2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)*, 2:183–188, 2019. URL <https://api.semanticscholar.org/CorpusID:199016573>.
- [37] Nikhil Kumar Singh and Koduru Sriranga Suprabhath. Har using bi-directional lstm with rnn. *2021 International Conference on Emerging Techniques in Computational Intelligence (ICETCI)*, pages 153–158, 2021. URL <https://api.semanticscholar.org/CorpusID:240002999>.
- [38] Bidirectional Recurrent Neural Network - GeeksforGeeks — [geeksforgeeks.org. https://www.geeksforgeeks.org/bidirectional-recurrent-neural-network/](https://www.geeksforgeeks.org/bidirectional-recurrent-neural-network/), 2023. [Accessed 08-06-2024].
- [39] Feiming Chen, Hong Laura Lu, and Arianna Simonetti. Practical statistical considerations for the clinical validation of ai/ml-enabled medical diagnostic devices. *arXiv preprint arXiv:2303.05399*, 2023.
- [40] Di Zhang and Yi Ke. Research on the design of a smart wearable device for taichi practitioners based on ai concept. In *2023 4th International Conference on Computer Vision, Image and Deep Learning (CVIDL)*, pages 697–701. IEEE, 2023.
- [41] Narendra Patwardhan, Stefano Marrone, and Carlo Sansone. Transformers in the real world: A survey on nlp applications. *Information*, 14(4):242, 2023.
- [42] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.
- [43] Jen tse Huang, Man Ho Lam, Eric John Li, Shujie Ren, Wenxuan Wang, Wenxiang Jiao, Zhaopeng Tu, and Michael R. Lyu. Emotionally numb or empathetic? evaluating how llms feel using emotionbench, 2024.
- [44] Yixin Liu, Kejian Shi, Katherine S He, Longtian Ye, Alexander R Fabbri, Pengfei Liu, Dragomir Radev, and Arman Cohan. On learning to summarize with large language models as references. *arXiv preprint arXiv:2305.14239*, 2023.
- [45] Tosin Adewumi, Lama Alkhaled, Claudia Buck, Sergio Hernandez, Saga Brilioth, Mkpe Kekung, Yelvin Ragimov, and Elisa Barney. Procot: Stimulating critical thinking and writing of students through engagement with large language models (llms). *arXiv preprint arXiv:2312.09801*, 2023.
- [46] Dimitrios P. Panagoulas, Filippas A. Palamidis, Maria K. Virvou, and George A. Tsihrintzis. Evaluating the potential of llms and chatgpt on medical diagnosis and treatment. *2023 14th International Conference on Information, Intelligence, Systems & Applications (IISA)*, pages 1–9, 2023. URL <https://api.semanticscholar.org/CorpusID:266235363>.
- [47] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive nlp

- tasks. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 9459–9474. Curran Associates, Inc., 2020. URL [https://proceedings.neurips.cc/paper\\_files/paper/2020/file/6b493230205f780e1bc26945df7481e5-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2020/file/6b493230205f780e1bc26945df7481e5-Paper.pdf).
- [48] Chia Jeng Yang. An introduction to RAG and simple/complex RAG — medium.com. <https://medium.com/enterprise-rag/an-introduction-to-rag-and-simple-complex-rag-9c3aa9bd017b>, 2023. [Accessed 07-06-2024].
- [49] Ersin Elbasi, Nour Mostafa, Zakwan AlArnaout, Aymen I. Zreikat, Elda Cina, Greeshma Hanna Varghese, Ahmed Younes Shdefat, Ahmet Ercan Topcu, Wiem Abdelbaki, Shinu Mathew, and Chamseddine Zaki. Artificial intelligence technology in the agricultural sector: A systematic literature review. *IEEE Access*, 11:171–202, 2023. URL <https://api.semanticscholar.org/CorpusID:255180570>.
- [50] Sigfredo Fuentes, Claudia Gonzalez Viejo, Eden Tongson, and Frank R Dunshea. The livestock farming digital transformation: implementation of new and emerging technologies using artificial intelligence. *Animal Health Research Reviews*, 23(1):59–71, 2022.
- [51] A Hadani and A Shimshony. Traditional veterinary medicine in the near east: Jews, arab bedouins and fellahs. *Revue Scientifique et Technique (International Office of Epizootics)*, 13(2):581–597, 1994.
- [52] H. Mukladaa, A. Abu-Rabiab, S. Kaadanc, and H. Azaizehd. Traditional arab ethno-veterinary practices in small ruminant breeding in israel. 2014. URL <https://api.semanticscholar.org/CorpusID:54675218>.
- [53] Francisco José Vázquez Bringas, Laura Barrachina Porcar, Sara Fuente Franco, Cristina Manero Martinez, Antonio Romero Lasheras, and Arantza Vitoria Moraiz. Training of veterinary students in trans rectal palpation of equids: A comparison of live versus cadaver models. *Journal of Veterinary Medical Education*, 2023. URL <https://api.semanticscholar.org/CorpusID:261376926>.
- [54] Ali Ashoor Issa, Safa Majed, Abdul Ameer, and Hassan M. Al-Jawahry. Iot and ai in livestock management: A game changer for farmers. *E3S Web of Conferences*, 2024. URL <https://api.semanticscholar.org/CorpusID:267960769>.
- [55] Navdeep Singh. Ai in inventory management: Applications, challenges, and opportunities. *International Journal for Research in Applied Science and Engineering Technology*, 2023. URL <https://api.semanticscholar.org/CorpusID:265478480>.
- [56] Alphus Dan Wilson. Applications of electronic-nose technologies for noninvasive early detection of plant, animal and human diseases. *Chemosensors*, 6(4):45, 2018.
- [57] Stevica Aleksic, Vlada Pantelić, and C. Radovic. Livestock production - present situation and future development directions in republic of serbia. *Biotechnology in Animal Husbandry*, 25: 267–276, 2009. URL <https://api.semanticscholar.org/CorpusID:262886084>.
- [58] Peng Wang, Jiang Liu, Lijia Xu, Peng Huang, Xiong Luo, Yan Hu, and Zhiliang Kang. Classification of amanita species based on bilinear networks with attention mechanism. *Agriculture*, 11(5), 2021. ISSN 2077-0472. doi: 10.3390/agriculture11050393. URL <https://www.mdpi.com/2077-0472/11/5/393>.
- [59] Adarsh Vulli, Parvathaneni Naga Srinivasu, Sai Krishna Sashank Madipally, Jana Shafi, Choi Jaeyoung, and Muhammad Fazal Ijaz. Fine-tuned densenet-169 for breast cancer metastasis prediction using fastai and 1-cycle policy. *Sensors*, 22, 04 2022. doi: 10.3390/s22082988.
- [60] Mohamed Abd Elaziz, Abdelghani Dahou, Naser A. Alsaleh, Ammar H. Elsheikh, Amal I. Saba, and Mahmoud Ahmadein. Boosting covid-19 image classification using mobilenetv3 and aquila optimizer algorithm. *Entropy*, 23(11), 2021. ISSN 1099-4300. doi: 10.3390/e23111383. URL <https://www.mdpi.com/1099-4300/23/11/1383>.

- [61] Md Shakhawat Hossain, Umme Sadia Salsabil, M M Mahbubul Syeed, Md Mahmudur Rahman, Kaniz Fatema, and Mohammad Faisal Uddin. Smartpoultry: Early detection of poultry disease from smartphone captured fecal image. In *2023 20th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, pages 345–350, 2023. doi: 10.1109/JCSSE58229.2023.10202054.
- [62] Alireza Soleimanipour, Mohsen Azadbakht, and Abbas Asl. Cultivar identification of pistachio nuts in bulk mode through efficientnet deep learning model. *Journal of Food Measurement and Characterization*, 16:1–11, 08 2022. doi: 10.1007/s11694-022-01367-5.
- [63] Erik Westphal and Hermann Seitz. A machine learning method for defect detection and visualization in selective laser sintering based on convolutional neural networks. *Additive Manufacturing*, 41:101965, 03 2021. doi: 10.1016/j.addma.2021.101965.
- [64] Liwei Deng, Jiandong Wang, and Zhen Liu. Cascaded network based on efficientnet and transformer for deepfake video detection. *Neural Processing Letters*, 55(6):7057–7076, 2023.
- [65] Shenglong Chen, Yoshiki Ogawa, and Yoshihide Sekimoto. Large-scale individual building extraction from open-source satellite imagery via super-resolution-based instance segmentation approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, 195:129–152, 01 2023. doi: 10.1016/j.isprsjprs.2022.11.006.
- [66] Faiz Shah, Muhammad Khan, Muhammad Sharif, Usman Tariq, Aimal Khan, Seifedine Kadry, and Orawit Thinnukool. A cascaded design of best features selection for fruit diseases recognition. *Computers, Materials and Continua*, 70:1491–1507, 09 2021. doi: 10.32604/cmc.2022.019490.
- [67] Overview of model structure about YOLOv5 · Issue 280 · ultralytics/yolov5 — github.com. <https://github.com/ultralytics/yolov5/issues/280>, 2020. [Accessed 16-06-2024].
- [68] Muhammad Fauzi Fayyad, Viki Kurniawan, Muhammad Ridho Anugrah, Baihaqi Hilmi Estanto, and Tasnim Bilal. Application of recurrent neural network bi-long short-term memory, gated recurrent unit and bi-gated recurrent unit for forecasting rupiah against dollar (usd) exchange rate. *Public Research Journal of Engineering, Data Technology and Computer Science*, 2024. URL <https://api.semanticscholar.org/CorpusID:269299094>.
- [69] Stavros Deligiannidis, Charis Mesaridakis, and Adonis Bogris. Performance and complexity analysis of bi-directional recurrent neural network models versus volterra nonlinear equalizers in digital coherent systems. *Journal of Lightwave Technology*, 39(18):5791–5798, September 2021. ISSN 1558-2213. doi: 10.1109/jlt.2021.3092415. URL <http://dx.doi.org/10.1109/JLT.2021.3092415>.

## ملخص

في محاولة لإحداث ثورة في إدارة الصحة الحيوانية في سعيدة، الجزائر، يقدم هذا البحث نظامًا جديدًا مدعومًا بإمكانيات التعلم العميق. يدمج النظام مكونين رئيسيين: الشبكات العصبية التلافيفية (CNNs) للتعرف على الصور المتطورة ونماذج اللغات الكبيرة (LLMs) مع التوليد المعزز للاسترجاع (RAG) لمعالجة النصوص المتقدمة. تقوم شبكات CNN بتحليل البيانات المرئية من الماشية، مما يتيح الكشف المبكر عن الأمراض من خلال تحليل الصور. تتعمق نماذج LLMs، المعززة بقدرات RAG، في مجموعات هائلة من المعلومات البيطرية مثل التقارير والمنشورات البحثية وبيانات تفشي الأمراض في الوقت الحقيقي. هذا التأزر يمكن المزارعين بأداة قوية. فلا يمكنهم فقط تحديد المشكلات الصحية المحتملة في مواشهم، بل يوفر النظام أيضًا رؤى وتوصيات قابلة للتنفيذ. وهذا يترجم إلى اتخاذ قرارات مستنيرة من قبل المزارعين، مما يؤدي إلى تحسين نتائج صحة الحيوانات، وزيادة الإنتاجية، وفي نهاية المطاف، تعزيز الرفاهية الاقتصادية لمنطقة صيدا. ومن خلال الاستفادة من تقنيات الذكاء الاصطناعي المتطورة، يمهّد هذا البحث الطريق لتحقيق تقدم كبير في العلوم البيطرية والإدارة الزراعية، مما يُظهر إمكانات الذكاء الاصطناعي في تحويل الممارسات الزراعية التقليدية.

**الكلمات المفتاحية:** الذكاء الاصطناعي، إدارة صحة الحيوان، التعلم العميق، الشبكات العصبية التلافيفية (CNNs)، نماذج لغوية كبيرة (LLMs)، الجيل المعزز للاسترجاع (RAG)، أمراض الثروة الحيوانية، المعلومات البيطرية.

## Abstract

In a bid to revolutionize animal health management in Saida, Algeria, this research presents a novel system powered by deep learning's potential. The system integrates two key components: Convolutional Neural Networks (CNNs) for sophisticated image recognition and Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) for advanced text processing. CNNs analyze visual data from livestock, enabling early detection of diseases through image analysis. LLMs, enriched by RAG capabilities, delve into vast troves of veterinary information like reports, research publications, and real-time disease outbreak data. This synergy empowers farmers with a powerful tool. Not only can they identify potential health issues in their livestock, but the system also provides actionable insights and recommendations. This translates to informed decision-making by farmers, leading to improved animal health outcomes, increased productivity, and ultimately, a boost to the economic well-being of the Saida region. By leveraging cutting-edge AI technologies, this research paves the way for significant advancements in veterinary science and agricultural management, showcasing the potential of AI to transform traditional farming practices.

**Keywords:** Ai, Animal health management, Deep learning, Convolutional neural networks (CNNs), Large language models (LLMs), Retrieval-augmented generation (RAG), Livestock diseases, Veterinary information.

## Résumé

Dans le but de révolutionner la gestion de la santé animale à Saïda, en Algérie, cette recherche présente un nouveau système alimenté par le potentiel de l'apprentissage profond. Le système intègre deux composants clés : Les réseaux neuronaux convolutifs (CNN) pour une reconnaissance d'image sophistiquée et les grands modèles de langage (LLM) avec la génération améliorée par la recherche (RAG) pour un traitement de texte avancé. Les CNN analysent les données visuelles du bétail, ce qui permet une détection précoce des maladies grâce à l'analyse des images. Les LLM, enrichis par les capacités RAG, explorent de vastes quantités d'informations vétérinaires telles que des rapports, des publications de recherche et des données en temps réel sur les épidémies. Cette synergie permet aux agriculteurs de disposer d'un outil puissant. Non seulement ils peuvent identifier les problèmes de santé potentiels de leur bétail, mais le système leur fournit également des informations et des recommandations exploitables. Les agriculteurs peuvent ainsi prendre des décisions éclairées, ce qui se traduit par une amélioration de la santé animale, une augmentation de la productivité et, en fin de compte, un renforcement du bien-être économique de la région de Saïda. En s'appuyant sur des technologies d'IA de pointe, cette recherche ouvre la voie à des avancées significatives dans les domaines de la science vétérinaire et de la gestion agricole, démontrant le potentiel de l'IA pour transformer les pratiques agricoles traditionnelles.

**Mots-clés:** Ai, Gestion de la santé animale, apprentissage profond, Réseaux neuronaux convolutifs (CNN), Grands modèles de langage (LLM), Génération augmentée par la recherche (RAG), Maladies du bétail, Informations vétérinaires.