Enhancing Cattle Disease Detection Accuracy: A Fusion of VGG16 and InceptionV3 for Simultaneous Diagnosis of LSD and FMD

By

Md. Akhlaq Hossain,	ID:19202103293
Zillur Rahaman,	ID:19202103296
Tamima Nisat,	ID:19202103309
Al Rifat Hasan,	ID:19202103311
Nasir Uddin,	ID:19202103316

Submitted in partial fulfillment of the requirements of the degree of **Bachelor of Science** in

Computer Science and Engineering

Department of Computer Science and Engineering

Bangladesh University of Business and Technology

February 2024

Declaration

We do hereby declare that the research works presented in this thesis,entitled "Enhancing Cattle Disease Detection Accuracy: A Fusion of VGG16 and InceptionV3 for Simultaneous Diagnosis of LSD and FMD" is the result of our work. We further declare that the thesis has been compiled and written by us. No part of this thesis has been submitted elsewhere for the requirements of any degree, award, or diploma, or any other purposes except for publications. The materials that are obtained from other sources are duly acknowledged in this thesis

Signature of Authors

Akhlaq

Md. Akhlaq Hossain

ID: 19202103293

Zillur Rahaman

Md. Zillur Rahaman

ID: 19202103296

Tamima Nisat

ID: 19202103309

Rifat

Al Rifat Hasan

ID: 19202103311

Nasir

Nasir Uddin

ID: 19202103316

Approval

We do hereby acknowledge that the research works presented in this thesis, entitled "Enhancing Cattle Disease Detection Accuracy: A Fusion of VGG16 and InceptionV3 for Simultaneous Diagnosis of LSD and FMD," result from the original works carried out by Md. Saifur Rahman, Assistant Professor and Chairman, Department of Computer Science and Engineering, Bangladesh University of Business and Technology. We further declare that no part of this thesis has been submitted elsewhere for the requirements of any degree, award, diploma, or any other purposes except for publications.

Supervisor: Ashiq

Mr. Md. Ashiqur Rahman

Assistant Professor

Department of CSE

Bangladesh University of Business and Technology

Chairman: Saifur Rahman

Md. Saifur Rahman

Assistant Professor and Chairman

Department of CSE

Bangladesh University of Business and Technology

Acknowledgement

We would like to express our heartfelt gratitude to the almighty Allah, who offered our family and us kind care throughout this journey until the fulfillment of this research. Also, we express our sincere respect and gratitude to our supervisor, Mr. Md. Ashiqur Rahman, Assistant Professor, Department of Computer Science and Engineering, Bangladesh University of Business and Technology (BUBT). Without his guidance, this research work would not exist. We are grateful to him for his excellent supervision and for putting his utmost effort into developing this project. We owe him a lot for his assistance, encouragement, and guidance, which have shaped our mentality as researchers. Finally, we are grateful to all our faculty members of the CSE department, BUBT, for making us compatible to complete this research work with the proper guidance and support throughout the last four years

Abstract

Cattle diseases pose a persistent challenge to global agriculture, impacting both livestock welfare and economic stability. The study proposes a model ensemble VGG16 and Inception V3 for detecting Foot-and-mouth (FMD) disease and lumpy skin (LSD) disease in cattle using images. The model demonstrated proficiency in accurately classifying cattle diseases like Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) with a test accuracy of 90%.

Well-known pre-trained models like VGG16, Resnet50, and Inception are tested on the same dataset to create a comparable baseline. Resnet50 displays an accuracy of 79%, VGG16 83%, and Inception 90%; nevertheless, the combination of VGG16 and InceptionV3 surpasses all of these models in every way.

Our suggested approach analyzes various datasets, such as photographs, using sophisticated deep neural networks, namely convolutional and recurrent networks. High levels of accuracy, sensitivity, and specificity are demonstrated in the experiments, which makes it a useful technique for disease surveillance and the cornerstone of scalable livestock health management in agriculture.

List of Tables

2.1 Previous research works in terms of objectives, used tools, and possible research gaps 16
4.1 Results of different Models 38
4.2 Comparison between Our work and other's work. 40

List of Figures

1.1 Flow of the work 6
3.1 Research Methodology 24
3.2 Research Methodology 24
3.3 Charts of images 25
3.4 Some Images of our data-set 25
3.5 Architecture of VGG16 29
3.6 Architecture of the Inception V3 30
4.1 A Typical Confusion Matrix 35
4.2 Result of Different Classes 38
5.1 Gantt chart of work execution 45

List of Abbreviations

ANN Artificial Neural Network. 11, 13

CNN Convolutional Neural Network. 11, 13–15

DNN Deep Neural Network. 29

ReLU Rectified Linear Unit. 32, 33

ROC Receiver Operating Characteristic Curve. 14

SVM Support vector machine. 11, 12

Contents

Approval iii

Acknowledgement iv

Abstract v

List of Tables vi

List of Figures vii

List of Abbreviations viii

1 Introduction 1

1.1 Introduction . . . 1
1.2 Problem Statement . . . 2
1.3 Problem Background . . . 3
1.4 Research Objectives . . . 4
1.5 Motivations . . . 5
1.6 Flow of the Research . . . 5
1.7 Significance of the Research . . . 7
1.8 Research Contribution . . . 7
1.9 Thesis Organization . . . 8
1.10 Summary . . . 9

2 Background 10

2.1 Introduction . . . 10
2.2 Literature Review . . . 10
2.3 Problem Analysis . . . 21
2.4 Summary . . . 21

3 Methodology 22

3.1 Introduction . . . 22

3.2 Feasibility Analysis 22
3.3 Requirement Analysis 23
3.4 Research Methodology 24
3.4.1 Dataset Visualization 25
3.4.2 Data Pre-processing 27
3.4.2.1 Data noise removal: 27
3.4.2.2 Data Augmentation 27
3.4.3 Deep learning Models 28
3.4.3.1 VGG16 28
3.4.3.2 Inception V3 28
3.4.3.3 ResNet50 30
3.4.3.4 Architecture: 31
3.4.3.5 Training details: 31
3.4.3.6 Performance: 32
4 Implementation, Testing, and Result Analysis **34**
4.1 Introduction 34
4.2 Dataset 34
4.3 System Setup 35
4.4 Evaluation Matrices 35
4.5 Results and Discussion 37
4.6 Summary 40
5 Standards, Constraints, Milestones **41**
5.1 Standards (Sustainability) 41
5.2 Impacts (on Society) 42
5.3 Ethics 42
5.4 Challenges 43
5.5 Constraints 43
5.6 Timeline and Gantt Chart 44
5.7 Summary 46
6 Conclusion **47**
6.1 Introduction 47

6.2 Future Works and Limitations 48
Bibliography **53**

Chapter 1

Introduction

1.1 Introduction

Foot-and-mouth disease (FMD) and lumpy skin disease (LSD) are two diseases caused by highly contagious viruses. FMD is caused by a Picornaviridae family virus, which spreads through direct contact with infected animals, contaminated equipment, and even through the air. Symptoms include fever, lameness, ulcers, and decreased milk production in dairy cattle. Prevention involves vaccination, quarantine, strict biosecurity measures, and the culling of infected animals. LSD is caused by a Capripoxvirus virus and spreads through biting insects and direct contact with infected animals or their products. Prevention involves vaccination, vector control, quarantine measures, and culling of infected or suspected animals. Both diseases can have significant economic impacts on the livestock industry, necessitating early detection, prompt veterinary intervention, and strict biosecurity measures.

D. Wu et al. proposed a method for detecting diseases in cattle lameness using deep learning algorithms like YOLOv3, SVM, KNN, and DTC. The method achieved an accuracy of 98.57 %, outperforming other algorithms, but with limited datasets.[1] A 4-balance system was developed to detect lameness in dairy cows during milking. Data was collected from 73 cows, and a probabilistic neural network model was trained to detect lameness.[2]

Y. Qiao et al. developed a deep learning system for cattle identification using Inception-V3 and Long Short-Term Memory models. The system used two stereo ZED cameras and a GPU-equipped embedded PC for data processing. The CNN-based method achieved 57% identification accuracy but had lower accuracy in cattle with little movement due to limited visual information or challenges in capturing depth information.[3]

- Deep learning-based cattle disease detection utilizes deep convolutional neural networks (CNNs) to analyze images of cattle and identify diseases.
- Automated system detects and classifies cattle diseases using animal images.
- Our research focuses on efficient cattle disease detection for sustainable agriculture.

Cattle diseases pose a global threat to the agricultural sector, food security, and economies, affecting animal health and productivity globally. Cattle diseases pose a global challenge, impacting farmers, regions, and countries. They cause economic losses and trade restrictions. International collaboration is needed to monitor and control disease spread, requiring tailored management strategies like vaccination, biosecurity, and hygiene practices.

1.2 Problem Statement

Cattle farming faces significant challenges in effectively detecting and diagnosing diseases that affect the health and productivity of the animals. This lack of timely and accurate disease diagnosis can result in prolonged suffering for the cattle, increased economic losses for farmers, and the potential for the spread of contagious diseases to other livestock. With the proliferation of smartphones and the advancements in deep learning techniques, there is an opportunity to develop a deep learning-based cattle disease detection system that can empower cattle farmers and field veterinarians to detect diseases accurately and efficiently, even in resource-constrained environments. Therefore, the problem this paper aims to address is the lack of an accessible and user-friendly tool for cattle disease detection that can leverage the power of deep learning and smartphone technology. By addressing this problem, the proposed deep learning-based cattle disease detection has the potential to revolutionize cattle disease detection by providing timely and accurate diagnoses, empowering cattle farmers and field veterinarians, reducing economic losses, improving animal welfare, and preventing the spread of diseases to other livestock. In the following sections of this paper, we will present the methodology, implementation details, evaluation results, and potential impact of the developed model in addressing this critical problem in cattle farming.

1.3 Problem Background

The detection of livestock diseases is very important for livestock production due to potential economic losses. Detection methods include visual inspection, diagnostic testing, and methods such as machine learning, deep learning, and computer vision. Visual inspection is commonly used to detect disease in cattle, but it is time-consuming and may miss infections early. Deep learning and computer vision offer promising solutions. This method uses algorithms to analyze disease and abnormal patterns in cattle images and videos. We are excited to start working on our dataset and image classification model.

1.4 Research Objectives

Our research objectives are as follows:

- Preprocess large image sets of cattle infected with common diseases.
- Evaluation of a deep learning model for image disease classification in cattle.
- Optimize the demonstration by tuning hyperparameters, applying exchange learning, and enriching information.
- Reduce the economic impact of cattle diseases on producers.
- Protect public health from zoonotic diseases.
- Ensure a safe and sustainable food supply.

1.5 Motivations

Developing cattle disease detection technologies aims to improve animal health and welfare by accurately detecting diseases early on. This allows farmers and veterinarians to intervene and provide appropriate treatment, preventing further harm. Early detection also prevents economic losses, such as decreased milk production and increased mortality rates. Researchers can analyze disease outbreak patterns to develop more effective prevention and control strategies. In this work, we have built datasets of Cattle, diseases, and treatments. Also, we have used an image classification model for detecting cattle and diseases with disease suggestions

1.6 Flow of the Research

Detecting cattle diseases early is crucial for the well-being of the animals and the profitability of farmers. Previous studies have explored both traditional diagnostic methods and AI techniques, such as machine learning and computer vision, for disease detection. To collect data for analysis, medical records, lab results, images, and videos from various sources are utilized. The data is preprocessed to remove inconsistencies and extract relevant features. Appropriate machine learning models are selected, trained, and evaluated using appropriate metrics like accuracy and F1-score. Experiments and analysis are conducted to compare model performance and draw conclusions. Future areas of research and improvements are also discussed.

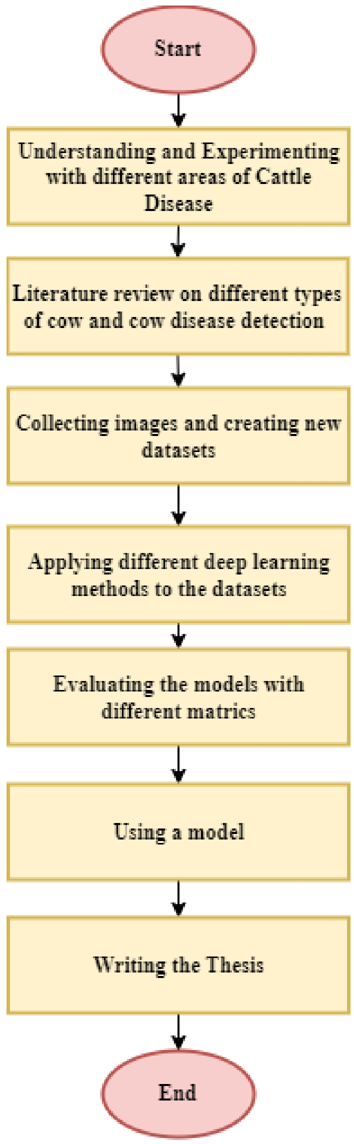


Figure 1.1. The figure illustrates the flow of the thesis work.

1.7 Significance of the Research

Accurate and timely detection of diseases in cattle is crucial for ensuring their welfare and minimizing the spread of infectious diseases within herds. By developing improved methods for disease detection, our research has the potential to improve the overall health and well-being of cattle populations.

There are also economic benefits to this research. The agricultural industry relies heavily on the health and productivity of cattle, and disease outbreaks can have significant financial impacts. Improved disease detection methods can help prevent outbreaks, reducing losses for farmers and producers.

Our research may also contribute to broader efforts to improve food safety and security. By developing more effective disease detection methods, we can help ensure that meat and dairy products from infected animals do not enter the food supply, protecting both human health and the integrity of the food system.

Our research on cattle disease detection is significant because it has the potential to improve animal welfare, reduce economic losses for farmers and producers, and contribute to broader efforts to improve food safety and security.

1.8 Research Contribution

Here is the overall contribution of our research:

- It develops and evaluates new, non-invasive methods for detecting diseases in cattle, which may offer improved accuracy and faster results compared to existing methods.

- We apply deep learning algorithms to analyze data from multiple sources, including images, to develop more robust and accurate disease detection models.

- It contributes to the growing field of precision livestock farming, which seeks to use technology and data analysis to improve animal health and productivity while minimizing environmental impact.

- By collaborating with veterinarians, farmers, and other stakeholders in the agricultural industry, we ensure that our research is relevant and applicable to real-world challenges.

- Our research has the potential to improve the health and welfare of cattle populations, reduce economic losses due to disease outbreaks, and contribute to a more sustainable and efficient food system.

1.9 Thesis Organization

To organize the work for the thesis, follow these steps. The thesis work is organized as follows. This chapter highlights the background and literature review in the field of cattle disease detection with different types of cattle breeds. Chapter 3 contains the human abnormality classification system's proposed architecture and a detailed walk-through of the overall procedures. Chapter 4 includes the details of the tests and evaluations performed to evaluate our proposed architecture. Chapter 5 explains the standards, impacts, ethics, challenges, constraints, timeline, and Gantt chart. Finally, Chapter 6 contains the overall conclusion of our thesis work.

1.10 Summary

In this chapter, we look at the overall issue as well as the context and goals of our study. This chapter not only describes how research is done but also provides an example of how we carried out our study. It aims to address the problem of detecting and diagnosing diseases in cattle by developing a deep learning-based image classification model. The proposed model uses deep convolutional neural networks to analyze images of cattle and identify diseases, offering scalability and adaptability to detect a wide variety of conditions. The lack of an accessible and user-friendly tool for cattle disease detection is a significant problem facing the agricultural industry worldwide. The research has the potential to enhance the livelihoods of cattle farmers worldwide, improve food safety and security, and contribute to a more sustainable and efficient food system.

Chapter 2

Background

2.1 Introduction

Cattle farming is vital for global food production and livelihoods, but disease detection is time-consuming and costly. Deep learning adoption enables real-time analysis of cattle images, eliminating data transfers and cloud-based processing. This paper introduces deep learning-based cattle disease detection, utilizing deep convolutional neural networks to analyze images and identify disease signs. This innovative approach improves animal health management, reduces economic losses, and enhances livestock welfare.

2.2 Literature Review

Y. Li et al.[4] proposed a method for the classification and analysis of multiple cattle unitary behaviors. They used their datasets. In their dataset, they applied support machine learning algorithms (K-nearest neighbors), random forest , and extreme boosting algorithm method, and they achieved a high level of accuracy of F1 score of 94% for the six unitary behavior classes. The F1 score of movements is 78% (feed tossing), 87% (rolling biting), and 87%. The accuracy of unitary behaviors and movements was not as high due to the lack of enough temporal information.

Y. Qiao et al. [5]Proposed a method for mask R-CNN-based multi-cattle segmentation. Desirable cattle segmentation performance with 92% Mean Pixel Accuracy (MPA) and contour extraction with an Average Distance Error (ADE) of 33.56% pixel, which is better than that of the state-of-the-art SharpMask and DeepMask instance segmentation methods.

K. Liakos et al.[6] presented trained and the prediction Artificial Neural NetworksANN, Random Forest , Library for Support Vector Machine , SVMarchitecture. Their primary goal was to detect real-time cattle lameness. In their experiment, LP1 and LP2 are presented for the sets of training and prediction. Which machine learning method could be used to predict with the highest accuracy the lameness in cattle and improve automated lameness detection systems' accuracy, reliability, and practicality.

G. Li et al. [7] proposed computer vision as an approach for developing muzzle images and a deep learning model for identification purposes. They used K-nearest neighbor, convolutional neural networkCNN, and 59 deep learning models in identifying. Accuracy was 98.7%, and the fastest processing speed was 28.3 ms/image. A dataset containing 268 US feedlot cattle and 4923 muzzle images. Dataset limitations, Sometimes not able to recognize with muzzle images.

D. Wu et al. [1] presented a method to detect diseases in cattle lameness. Proposes a method using the YOLOv3 deep learning algorithm ,support vector machine SVM, K-Nearest Neighbour and decision tree classifier algorithms.accuracy of lameness detection based on LSTM was 98.57%, which was 2.93%, 3.88%, and 9.25% higher than SVM, KNN, and DTC, respectively. The datasets are limited.

S. Grampurohit et al. [8] proposed a method for cattle disease prediction using Machine Learning algorithms, decision tree classifier, random forest classifier, and Naive Bayes. Performance on a medical record yields an accuracy of up to 95% percent. Lack of generalizability and performance evaluation in disease prediction systems.

N. V. Kishan et al. [9] proposed a disease prediction using data mining techniques and cattle health monitoring systems. use classification methods like k-nearest neighbor , Naive Bayes , and support vector machine SVM, while others use AI models like GLM, RF, BRT, ANN, CTA, and Neural Networks. Some work uses IoT-based systems to monitor health, while others use massages and fans to ensure cattle fitness, focusing on rare diseases and veterinary practices.

R. Dulal et al. [10] paper explores object detection models for cattle identification, focusing on the YOLOv5 model. They used deep learning algorithms in the Yolov5 model to detect cattle in yards, overcoming RFID limitations. Cost and feasibility analysis for automatic cattle identification system.

M. E. Pastell et al. [11] proposed a method PNN model for lameness detection. Using the PNN model for lameness detection uses 4-balance system data and a probabilistic neural network model. Models were trained on 5,074 measurements from 37 cows, accurately classifying 96.2% of measurements as sound or lame and identifying 100% of lameness cases. This expert system has the potential for on-farm decision aid and real-time lameness monitoring. 73 cows reveal the 4-balance system may not be suitable for all farms.

E. Arazo et al. [12] proposed a technique for segmenting Enhanced Lameness Detection. Using deep learning methods (PyTorch), Softmax normalization layer, HUE, RGB, binary classifier,pre-trained neural networks, computer vision models, and SlowFast network training on the segmentation masks under "Mask," we showed an improvement from 61.76% to 84.56% when compared to training with the side-view RGB videos. The quality of the RGB and depth video data may be low, making it difficult to extract.

E. A. Safavi et al. [13] proposed a technique for forecasting lumpy skin disease occurrence based on meteorological and geospatial features. They used machine learning classification techniques, Artificial Neural Network ANN, Geospatial and meteorological parameters. Accuracy in predicting the occurrence of LSDV in test data (up to 97%) is challenging to collect comprehensive and reliable data on the occurrence of lumpy skin disease as well as pertinent meteorological and geospatial parameters.

G. Rai et al.[14] proposed utilizing Convolutional Neural NetworkCNN to predict Lumpy skin. They used Artificial Neural NetworkANN, VGG-16, VGG-19, Inception-v3, and machine learning techniques. The dataset obtained a result of 92.5% accuracy. There is no standard dataset available.

A. Poursaberi et al.[15] proposed utilizing image analysis techniques for early lameness detection in dairy cattle. They used Classic algorithms, statistical filtering algorithms, Locomotion scoring methods, Image processing, and scoring methods. The results of automatic lameness detection on 184 dairy cattle showed more than 96% correct rate of classification, which reveals the high potential of the developed technique. Body color since the use of classic algorithms for segmentation purposes does not work.

S.Shahinfar et al.[16] proposed utilizing a min predicting pregnant versus non-pregnant cows at the time of insemination. They used machine learning algorithms such as Bayesian network , Naïve Bayes,Decision trees ,Receiver Operating CharacteristicROC methods.RF was significantly better in terms of classification accuracy (72.3 and 73.6% for primiparous and multiparous cows, respectively) and area under the ROC curve (75.6 and 73.6% respectively). The considerable number of misclassified instances remained.

M. L. Williams et al.[17] proposed utilizing a model of the pasture-based dairy cow from GPS data using data mining and machine learning techniques. They used the data mining suite WEKA, Naïve Bayes, Receiver Operating Characteristic ROC, and Mobility Scoring. Ability to classify the main behaviors exhibited by pasture-based dairy cows in a way that is transparent to human scrutiny.

Y. Qiao et al. [3] developed a system for a Deep Learning framework using cattle identification. They used CNN model Inception-V3, LSTM, (Recurrent Neural Network), two stereo ZED cameras, and a GPU-equipped embedded PC.A CNN-based method whose identification accuracy is 57%.Cattle's little movement identification accuracy was not as high.

R.M.D.S.M. Chandrarathna et al. [18] proposed identifying the diseases and breeds and suggested the prevention methods and medicine for the identified disease. They used machine learning algorithms CNN(Convolutional Neural Network), Diseases Identification.h5, (Gate Recurrent Unit). This can identify the cattle's breed, identify cattle diseases, and identify the cattle's age and weight. The image or video identification process can proceed.

V. R. Allugunti.[19] proposed Convolutional Neural NetworksCNN cattle skin disease. They can implement skin disease classification. To prevent ourselves from overfitting the data, they made use of a data augmentation method. Focused on good data accuracy.

N. Krešic et al. [20] proposed an Evaluation of Serological Tests for the Detection of Antibodies against the Lumpy Skin Disease Virus. They used the Virus Neutralisation Test (VNT), MDBK cell test, and Enzyme-Linked Immunosorbent Assay ELISA test. They didn't accurately detect lumpy disease; they described a modified comparison virus available or not.

B. Jiang, et al. [21] suggested deep learning for key parts of dairy cow body detection. They used YOLOV3, Multi-scale forecasting, Darknet-19, Resnet, and R-CNN. The accuracy was 99.18%, the recall rate was 97.51%, the average detection rate was 93.73% and he average detection rate was 93.47%. The detection accuracy was low and did not meet the requirements.

B. Lake et al. [2] proposed an image analysis system that utilizes a Convolutional Neural Network (CNN) algorithm. They combined Expert System (ES), Digital Image Processing (DIP) with deep learning, and the Case-Based Reasoning (CBR) algorithm to achieve a model accuracy of 95 % in just 50 epochs. This system can remotely detect diseases, although it does not offer a complete solution for any disease.

Table 2.1. Previous research works in terms of objectives, used tools, and possible research gaps

References	Research Purpose	Used Technologies/ Techniques	Focused Methods	Challenges/Research Gaps
[4]	Evaluation of Serological Tests for Detection of Antibodies against Lumpy Skin Disease Virus	Virus Neutralisation Test (VNT), MDBK cell test, Enzyme-Linked Immunosorbent Assay ELISA test	Focus on VNT/MDBK demonstrated a strong correlation to the VNT/OIE and ELISA. which indicates its suitability for LSDV-neutralizing antibody detection.	They don't predicted accuratly detect lumpy disease, they described a modified comparestion virus available or not for cow skin
[5]	Artificial Intelligence Algorithm in Image Processing for Cattle Disease Diagnosis	Expert system (ES), Digital image processing (DIP) with Deep learning, Case-based reasoning(CBR) algorithm, CNN	Focus on the integration of expert systems and image processing using deep learning gives an efficient and timely diagnosis of cattle diseases.	Remotely disease detection but not fully any disease solution
[6]	Deep learning for key parts of dairy cow body detection	YOLOV3, Multi-scale forecasting, R-CNN	Center of attention an accurate detection of the key parts of dairy cows	The key challenge of this research is cases of missed detection and false detection during the testing. The detection accuracy was low.
[7]	Machine learning-based skin disease classification	Expert System(ES) with deep learning, Convolutional Neural Network(CNN), Case retrieve algorithm	Intelligient management to classification and analyze images	They implemented multi-class categorization but they don't predict any disease
[1]	A Deep Learning Approach to Detect Lumpy Skin Disease in Cows	Convolutional Neural Networks(CNN),ReLU function(Rectifier Linear Unit), Artificial Neural Network(ANN), machine learning technique	Focused on predicting Lumpy Skin Disease in cows, and the process we using deep convolutional Neural Networks and machine learning Technique	There is no standard dataset available, there are many problems that can arise but we used the standard quality of image dataset due to which our model is working properly.

References	Research Purpose	Used Technologies/ Techniques	Focused Methods	Challenges/Research Gaps
[8]	real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques	Classic algorithms, statistical filtering algorithms, Locomotion scoring methods, Image processing, scoring methods	Focused on analyzing animal behavior about early lameness detection by utilizing image processing technique	A common problem in on-farm collected videos is the similarity of the background and the cow's body color since the use of classic algorithms for segmentation purposes does not work.
[9]	Assessing machine learning techniques in forecasting lumpy skin disease occurrence based on meteorological and geospatial features	Area under the curve (AUC), F1 performance metric scores, Artificial Neural Network (ANN), Geospatial and meteorological parameters, machine learning classification techniques	Focused on predicting lumpy Skin Disease (LSDV)by using artificial neural network (ANN) algorithm	Sometimes it may be challenging to collect comprehensive and reliable data on the occurrence of lumpy skin disease as well as pertinent meteorological and geospatial parameters.
[10]	Segmentation Enhanced Lameness Detection in Dairy Cows from RGB and Depth Video	Building Deep learning methods(PyTorch), Softmax normalization layer, HUE, RGB, binary classifier,pre-trained neural networks, Computer vision models, SlowFast network	Focused on the applicability of the computer vision model for cow lameness detection on farm	In some situations, the quality of the RGB and depth video data may be low, making it difficult to extract important information from the images. This can be caused by either poor illumination or camera placement.
[11]	Prediction of insemination outcomes in Holstein dairy cattle using alternative machine learning algorithms	Progeny Testing Program, Bayesian network (BN), Naïve Bayes (NB), Decision trees (DT), Bootstrap aggregation (BG), Random forest (RF), Receiver Operating Characteristics (ROC)	Focus on Production, reproduction, and health event data obtained from backup files.	Here RF showed the best performance among the methods considered in this study, but a considerable number of misclassified instances remained. So it has some lack of accuracy.

References	Research Purpose	Used Technologies/ Techniques	Focused Methods	Challenges/Research Gaps
[12]	Cattle Breeds and Diseases Identification Mobile Application using Machine Learning	CNN(Convolutional Neural Network), Diseases Identification.h5, GRU (Gate Recurrent Unit)	Focused on dentition according to age, identifying cow's breed and genetic diseases, diseases identification using Images, age and weight Identification	Sometimes not able to recognize and identify the genetic disease lack of dataset and environment issue
[13]	Individual Cattle Identification Using a Deep Learning-Based Framework	CNN model Inception-V3, LSTM, RNN (Recurrent Neural Network), Two stereo ZED cameras, GPU-equipped embedded PC, Image ROI	Focused on CNN-based Feature Extraction, Cattle Identification using LSTM, Proposed Network Training,	For Cattle, little movement identification accuracy was not as high due to the lack of enough temporal information.
[14]	A novel behavioral model of the pasture-based dairy cow from GPS data using data mining and machine learning techniques	Data mining suite WEKA, Naïve Bayes, and JRip rule-based classifier, Greedy hill-climbing, Receiver Operating Characteristic (ROC), Mobility scoring	Focused on Grazing Management and GPS, the popular data mining suite WEKA was used for the analysis of the data in this study.	A behavioral recording system needs to be robust to the cow's environment and as accurate as possible but sometimes it may not be accurate
[15]	Classification and Analysis of Multiple Cattle Unitary Behaviors and Movements Based on Machine Learning Methods	Micro-Electro-Mechanical Systems, 4G transmission module, GPS, KNN (K-nearest neighbors), RF (random forest), and XGBoost: Extreme Boosting Algorithm.	Focused on predicting Multiple Cattle Unitary Behaviors and Movements Based on Machine Learning Methods	For Multiple Cattle Unitary Behaviors and Movements accuracy was not as high due to the lack of enough temporal information.

References	Research Purpose	Used Technologies/ Techniques	Focused Methods	Challenges/Research Gaps
[16]	Cattle segmentation and contour extraction based on Mask R-CNN for precision livestock farming	GPU-equipped small PC, data storage disk, 2D gamma function-based image adaptive correction algorithm, Mask R-CNN network, Feature Pyramid Network (FPN), ResNet101, RPN network	Focused on predict Beef Cattle Identification Using Muzzle Images and Deep Learning Techniques	Obtaining real-time individual cattle information, and extraction problems in a real-life feedlot environment.
[17]	Machine Learning Based Computational Analysis Method for Cattle Lameness Prediction	Artificial Neural Networks(ANN),Random Forest(RF), Library for Support Vector Machine (LIBSVM), SVM, Models (LP1) and (LP2)	Focused on lameness prediction on machine learning methods.	Cattle lameness is a significant issue for dairy farmers Improve automated lameness detection systems' accuracy, reliability, and practicality.
[3]	Beef Cattle Identification Using Muzzle Images and Deep Learning Techniques	Mirrorless digital Cameras, Deep Learning Image Classification Models, K-nearest neighbor, convolutional neural network, deep belief neural network, Data collection	Focused on using deep learning techniques to identify individual cattle using muzzle images and to support precision beef cattle management.	Dataset limitations, Sometimes not able to recognize with muzzle images
[18]	Lameness detection of dairy cows based on the YOLOv3 deep learning algorithm and a relative step size characteristic vector	Deep learning algorithms detect lameness in cows using characteristic vectors.	Focused on the YOLOv3 deep learning algorithm and a relative step size characteristic vector	Dataset limitations, validation, robustness, and ethical considerations.

References	Research Purpose	Used Technologies/ Techniques	Focused Methods	Challenges/Research Gaps
[19]	Disease Prediction using Machine Learning	Machine learning, data mining, and classifiers improve disease prediction.	Focused on the machine learning system, it optimizes 95 symptoms in a 4920-patient dataset.	Lack of generalizability, performance evaluation, interpretability, and feature selection in disease prediction systems.
[20]	Cattle disease identification using Prediction Techniques	IoT, data mining, and sensor technologies monitor cattle health for early disease detection.	Focused on forecasting models using Decision Trees, Random Forests, and Naïve Bayes algorithms for accurate healthcare solutions.	Research gaps in IoT and data mining in dairy farming, focusing on rare diseases and veterinary practices.
[21]	Automatic Cattle Identification using YOLOv5 and Mosaic Augmentation: A Comparative Analysis	Deep Learning and YOLOv5 model detect cattle in yards, overcoming RFID limitations.	They focused on comparing object detection models, YOLOv5 architecture, and mosaic augmentation for automatic cattle identification.	Lack of cost and feasibility analysis for automatic cattle identification system.
[2]	A Probabilistic Neural Network Model for Lameness Detection	PNN model for lameness detection uses 4-balance system data,Probabilistic neural network model.	The focus is on the 4-balance system, which collects data, trains neural network, and evaluates lameness detection.	Study on 73 cows reveals 4-balance system may not suitable for all farms,PNN model effectiveness not evaluated.

2.3 Problem Analysis

In recent years, computer vision has gained a huge amount of attention from researchers regarding cattle disease, identification using prediction, and cattle breed proposals. There is a low number of works that have introduced multiple external cattle diseases. Additionally, most of the research is based on individuals, such as foot & mouth disease and lumpy skin disease. Apart from that, those multiple cattle diseases cannot be utilized through existing mobile apps. We now have a deep-learning algorithm that we can use to overcome this challenge.

2.4 Summary

This chapter contained an analysis and discussion of the most recent methods and recommendations for the various illness detections in cattle, as well as the classification and prediction of diseases. Here we introduce a deep learning-based image classification model for cattle disease detection, using deep convolutional neural networks to analyze images and identify disease signs. The literature review highlights various studies on cattle disease detection using machine learning algorithms, including lameness detection, skin disease classification, and cattle identification. However, there is a need for a comprehensive approach that can detect multiple external cattle diseases and be utilized through existing image classification models. The proposed solution aims to address this challenge by implementing a deep-learning algorithm for cattle disease detection.

Chapter 3

Methodology

3.1 Introduction

In this part, we support the feasibility study of cattle disease identification with anti-inflammatory drugs and antibiotics for secondary infections, if necessary. Vaccines are also used to control disease transmission by evaluating cows. Finally, this chapter depicts the image classification model's general architecture, which is explained in depth.

3.2 Feasibility Analysis

This study project needed one researcher and one supervisor, and it took nine months to complete. The thesis study necessitated technological assistance, including hardware and software. The study activity also necessitated a dataset development and assessment procedure, which the researchers also carried out. The work's massive data collection is carried out while keeping the dataset's legal feasibility in mind. Furthermore, the thesis study did not need any financial assistance from the university or supervisor.

3.3 Requirement Analysis

The following procedures must be followed to carry out the recommended architecture of the overall needs:

- High-performance computer device.
- Images are fed into this gadget.
- Open-source software libraries for scientific computing.
- Open-source software libraries are utilized to implement the deep learning approach.
- Open-source software libraries are utilized to create the image classification model.

3.4 Research Methodology

The purpose of this research is to develop cattle disease detection using deep learning techniques, specifically Convolutional Neural Networks (CNN), and transfer learning. The application aims to assist farmers and veterinarians in the early detection and diagnosis of cattle diseases, thus improving the overall health and productivity of cattle.

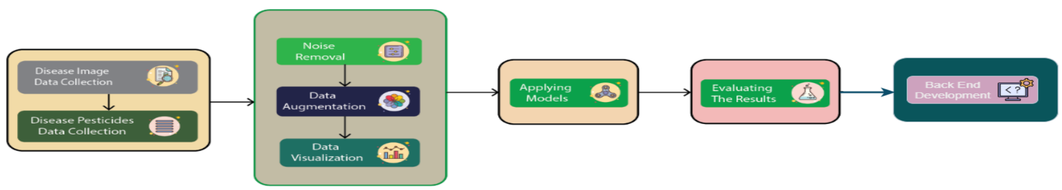


Figure 3.1. The figure illustrates the workflow of the proposed system (from left to right).

name	test	train	val	total
fmd_foot	82	656	82	820
fmd_mouth	88	704	88	880
healthy_foot	84	672	84	840
healthy_mouth	80	644	80	804
healthy_skin	88	704	88	880
lsd_skin	88	704	88	880
total	**510**	**4084**	**510**	**5104**

Figure 3.2. Number of Images in different classes.

3.4.1 Dataset Visualization

In our research, we have managed about 455 different sorts of diseased and healthy photos of Cows.

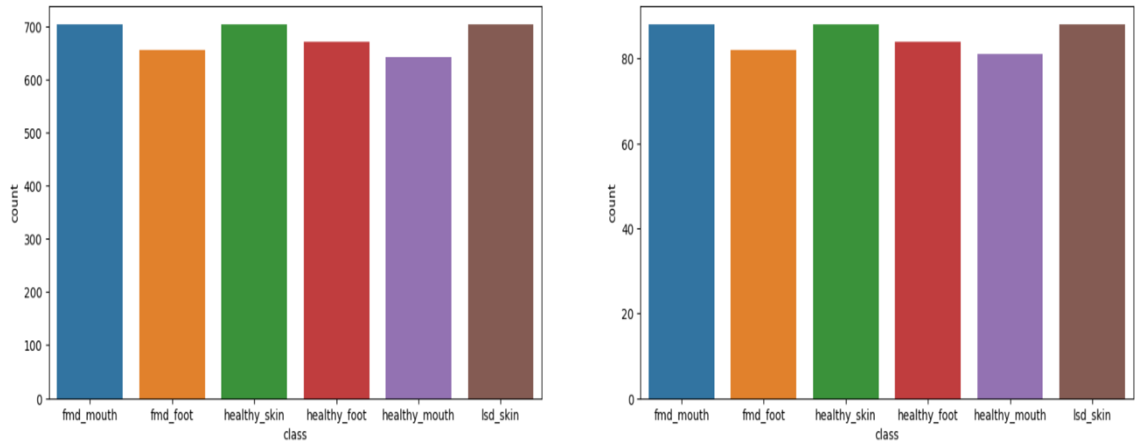


Figure 3.3. The figure illustrates the number of images in different Diseases.

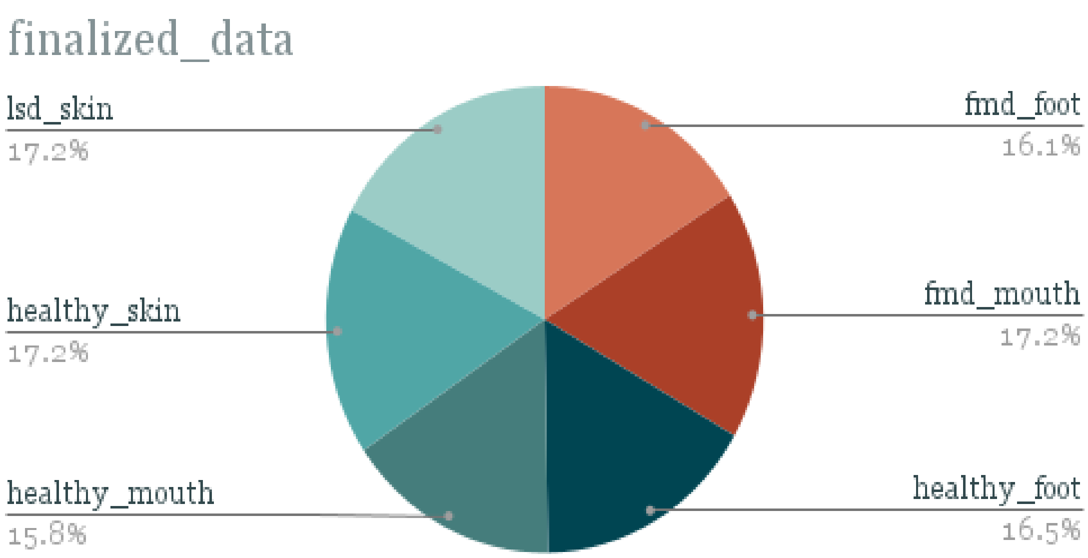
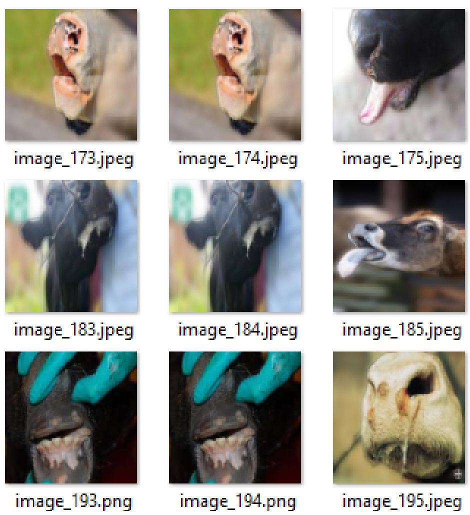


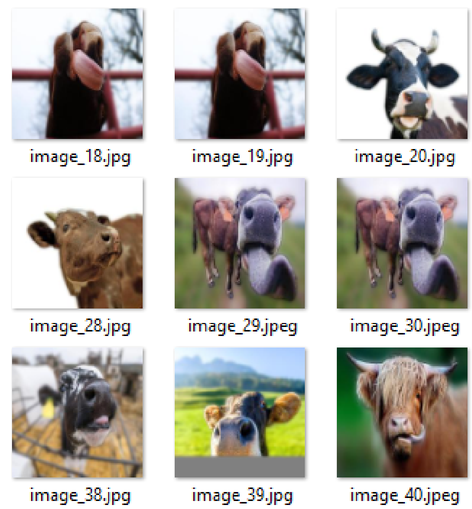
Figure 3.4. The pie chart illustrates some of the images of our data-set.

fmd foot

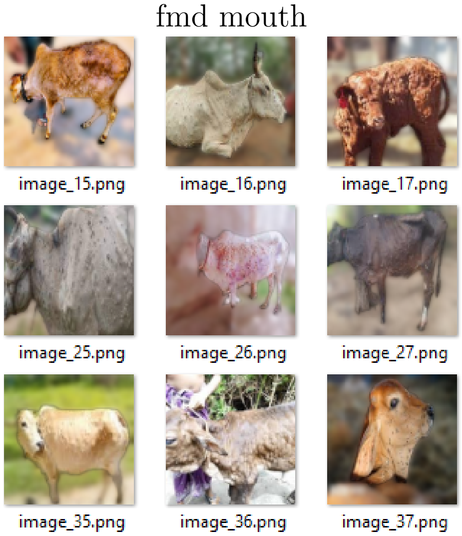
healthy foot



fmd mouth



healthy mouth



lsd skin

healthy skin

3.4.2 Data Pre-processing

The data pre-processing has occurred in two stages, data noise removal and data augmentation. These two techniques are described below.

3.4.2.1 Data noise removal:

Using noise reduction as a tool for visualizing and preprocessing multidimensional images has proven indispensable in the bioimaging field and with electron tomography in particular. Reduced noise levels are especially significant for cryptograms that suffer from low contrast and high noise levels. This includes stuck pixels in the camera or unspecific stains. Our work was helped by the [**?**] sites that blurred the background and removed other objects so that we could focus on the main subject. Noise is removed by focusing on the main or needed object, which results in high accuracy in detection and output.

3.4.2.2 Data Augmentation

By generating new and varied instances to train datasets, data augmentation can help to enhance the performance and results of deep learning models. This would be accomplished by using domain-specific strategies to build new and unique training examples from the training data. The model performs better and is more accurate if the dataset in the deep learning model is rich and sufficient. The most well-known sort of data augmentation is image data augmentation, which entails transforming images in the training dataset into altered copies that belong to the same class as the original image. Shifts flips, zooms, and other picture alteration operations fall under the category of transforms.

Traditional data augmentation methods include geometric transformation, color transformation, rotation reflection transformation, noise injection, and so on. In model training, several strategies are commonly employed. Many articles also point out that classic data augmentation approaches along with other technologies can increase the model's performance, but the simplest geometric transformation stands across the most important among them .

We used the TensorFlow-based data augmentation approach to extend our dataset using horizontal flip, vertical flip, rotation, brightness enhancement, and hybrid augmentation, which combines brightness enhancement, flip, and rotation

3.4.3 Deep learning Models

In this subsection, we have described the different deep-learning methods that we have used in our work.

3.4.3.1 VGG16

VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pre-trained version of the network trained on more than a million images from the ImageNet database [1]. The pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. For more pre-trained networks, see Pretrained Deep Neural Networks.

3.4.3.2 Inception V3

The Inception V3 is a deep learning model for image categorization that is based on Convolutional Neural Networks. The Inception V3 is an improved version of the

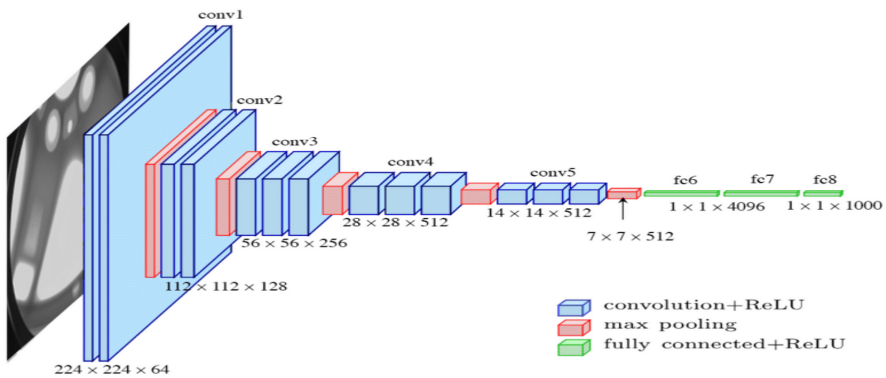


Figure 3.5. The figure illustrates the Architecture VGG16.

fundamental model Inception V1, which was launched in 2014 as GoogLeNet. [**?**]. The Inception v3 model, which was launched in 2015, features 42 layers and a reduced error rate than its predecessors. Several strategies were employed by the Inception V3 model to optimize the network for improved model adaptability. This architecture has the advantage of increasing the network's processing capabilities rather than its depth and nonlinearity. The Inception model is a deep CNN architecture that was proposed by Szegedy et al. The goal of the Large-Scale ImageNet Visual Identification Challenge 2014 was to reduce the impact of low parameters and computing efficiency in application circumstances.[16]

In Inception-v3, a batch normalization (BN) layer is inserted as a regularizer between the auxiliary classifier and the fully connected (FC) layer. In the BN model, the batch gradient descent method can be employed to accelerate the training speed and model convergence of the Deep neural network (DNN). where x is the minimum activation value of batch B, m is the number of activation values, γ and β are learnable parameters (γ is responsible for adjusting the variance in the value distribution and β is responsible for adjusting the position of the average value), μB represents the average value in one dimension, σB 2 is the standard deviation in each dimension of the feature map, and ϵ is a constant.

$$B = X_{1....m}, \gamma, \beta \tag{3.1}$$

$$\{y_i = BN_{\gamma,\beta}(X_i)\} \tag{3.2}$$

$$\gamma_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} X_i \tag{3.3}$$

$$\sigma_B^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(X_i - \gamma_B)^2 \tag{3.4}$$

$$\hat{X}_i \leftarrow \frac{X_i - \gamma_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{3.5}$$

$$y_i \leftarrow \gamma\hat{X}_i + \beta = BN_{\beta,\gamma}(X_i) \tag{3.6}$$

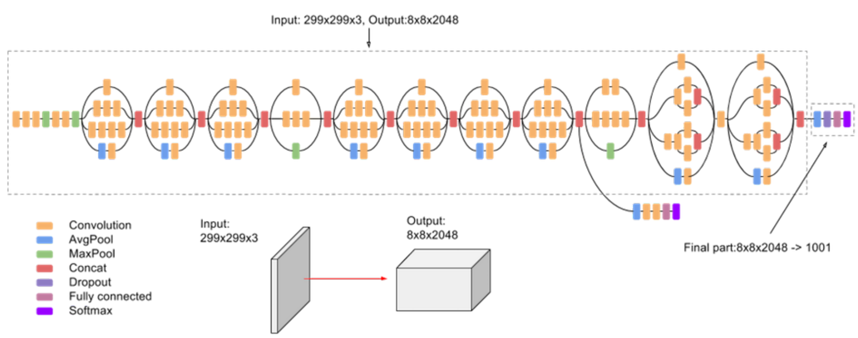


Figure 3.6. The figure illustrates the Architecture of the Inception V3

3.4.3.3 ResNet50

The ResNet50 model is a deep convolutional neural network (CNN) architecture designed for image classification tasks. It was introduced in the paper "Deep Residual Learning for Image Recognition" by He et al. in 2015 and has achieved impressive results on various benchmark datasets, including ImageNet. This report provides a detailed description of the ResNet50 model, focusing on its architecture, training details, and key performance metrics.

3.4.3.4 Architecture:

- Residual connections: The core characteristic of ResNet50 is the use of residual connections, which skip some convolutional layers and directly add the input to the output of a later layer. This helps mitigate the vanishing gradient problem, allowing for deeper networks that perform better than traditional CNNs.
- Bottleneck layers: To make the network more efficient and reduce the number of parameters, ResNet50 utilizes bottleneck layers. These layers consist of two 1x1 convolutional layers sandwiching a 3x3 convolutional layer, reducing the dimensionality of features before and after the expansion layer.
- Stages: The network is organized into four stages, each with decreasing spatial resolution and increasing feature representation complexity. Each stage contains several residual blocks with identical internal structures but different filter sizes and stride values.
- Output layers: Finally, the network has a global average pooling layer, a fully connected layer with 1000 output neurons (corresponding to the 1000 ImageNet classes), and a softmax activation function for predicting the class probabilities.

3.4.3.5 Training details:

- Dataset: ResNet50 was trained on the ImageNet dataset, which contains over 14 million images from 1000 different categories.
- Optimizer: The Adam optimizer was used for training, with a learning rate that starts high and gradually decreases over time.

- Data augmentation: To improve generalization and prevent overfitting, various data augmentation techniques such as random cropping, flipping, and scaling were applied during training.

3.4.3.6 Performance:

- Accuracy: On VGG16, ResNet50, and InceptionV3, it surpasses the performance of previous state-of-the-art models.
- Computational cost: While highly accurate, ResNet50 has a significant computational cost due to its depth and numerous parameters. For real-time applications on resource-constrained devices, alternatives like InceptionV3 might be more suitable.

Any value less than 0 is ignored by the ReLU activation algorithm. This non-linear transformation is said to cause information loss, especially on inputs with fewer channels. Because the lost information in one activation may still be retained by other channels, ReLU may have less impact on input with several channels. To address this problem, MobileNetV2's inverted residual block employs a narrow wide narrow strategy. The low-dimensional input is initially enlarged with a pointwise 11 convolution to create a higher-dimensional space that can accommodate the information loss caused by ReLU activation. The higher-dimensional feature map was then subjected to spatial filtering utilizing depthwise convolution with ReLU activation. Finally, a pointwise convolution was used to project the resultant feature map to a lower-dimensional output feature map. To conserve more information while encoding to a lower-dimensional output map, linear activation was employed instead of ReLU in the last phase. The authors dubbed this concept a "linear bottleneck." The non-linear change took place exclusively within the block's extended, higher-dimensional space. When it came to the output in lower dimensions, a linear transformation was applied.

In addition, to allow gradient flow during backpropagation, a skip connection identical to that of the residual block is added between the input and output of the inverted residual block. To establish a deep network, this strategy is required. The usage of ReLU in this inverted residual block, which limits the maximum output at 6 as defined by, is one final small tweak.

$$f(x) = min(max(0, x), 6) \tag{3.7}$$

Chapter 4

Implementation, Testing, and Result Analysis

4.1 Introduction

This section outlines the architecture of the proposed system for detecting cattle diseases using a classification system. The entire method is divided into phases, each implementing a different deep-learning technique on our constructed dataset.

4.2 Dataset

We observed that the majority of cattle disease detection methods only operate on the foot, mouth lumpy skin, etc. We also noticed that the majority of them work with two or three classes. In this study, we gathered images of cattle and cow illnesses from various internet sources, which were then classified into distinct foot, mouth, and lumpy skin classifications. For these diseases, we also gathered a pesticide dataset.

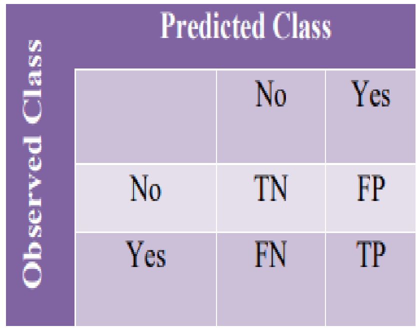


Figure 4.1. A Typical Confusion Matrix

4.3 System Setup

The Python programming language is used for data pre-processing, experimentation, and model evaluation. TensorFlow and Keras are used to implement the described architectures. Furthermore, NumPy is utilized to do mathematical operations on the architecture.

4.4 Evaluation Matrices

To evaluate the algorithms, they used the confusion matrix, which is useful for quickly measuring precision and recall given predicted and real labels from a model. A binary classification confusion matrix depicts the four possible outcomes: true positive, false positive, true negative, and false negative. The columns are the actual values, and the rows are the anticipated values. One of the four outcomes is represented by the intersection of the rows and columns. A typical confusion matrix looks like this:

True Positive (TP) signifies a positive item that is projected to be in the positive class, whereas True Negative (TN) implies a negative item that is predicted to be in the negative class. False Positive (FP) refers to an item in the negative class that is anticipated to be in the positive class, whereas False Negative (FN) refers to an entity in the positive class that is projected to be in the negative class. [1]

Accuracy [2] is defined as the ratio of successfully predicted objects to a total number of objects. We can calculate it from the confusion matrix as follows:

$$Accuracy = \frac{numberofcorrectlypredicatedobject}{totalnumberofobject} \tag{4.1}$$

$$Accuracy = \frac{TN + TP}{TP + FP + FN + TP} \tag{4.2}$$

Precision [2] refers to how many of the picked things are relevant. Precision may be calculated using the confusion matrix as follows:

$$Precision = \frac{TP}{TP + FP} \tag{4.3}$$

Recall [**?**] [**?**] refers to how many relevant items are chosen. As a result of the confusion matrix, it may be expressed as follows:

$$Recall = \frac{TP}{TP + FN} \tag{4.4}$$

4.5 Results and Discussion

On our build dataset, we have applied different algorithms such as InceptionV3, MobileNetV2, and DenseNet169. Using these algorithms produces training accuracy, validation accuracy, precision, recall, and the F1-score, which is given below in the table. For inceptionV3 training accuracy 97.60%, validating accuracy 97.98%, precision 95%, Recall 94%, and F1-Score 93%. DenseNet169 training accuracy 97.81%, validating accuracy 99.37%, precision 97%, Recall 96%, and F1-Score 96%. For inceptionV3 training accuracy 97.50%, validating accuracy 97.12%, precision 95%, Recall 93%, and F1-Score 93%.

Table 4.1. Results of different Models

MODEL	Training Accuracy	Validation Accuracy	Precision	Recall	F1-Score
INCEPTION V3	0.995	0.976	0.90	0.90	0.90
VGG-16	0.947	0.914	0.97	0.96	0.96
RESNET-50	0.994	0.971	0.73	0.69	0.69
COMBINE	0.896	0.901	0.90	0.90	0.90

In Figure shows the confusion metrics of InceptionV3, shows the confusion metrics of Densenet169, Figure shows the confusion metrics of MobilenetV2,

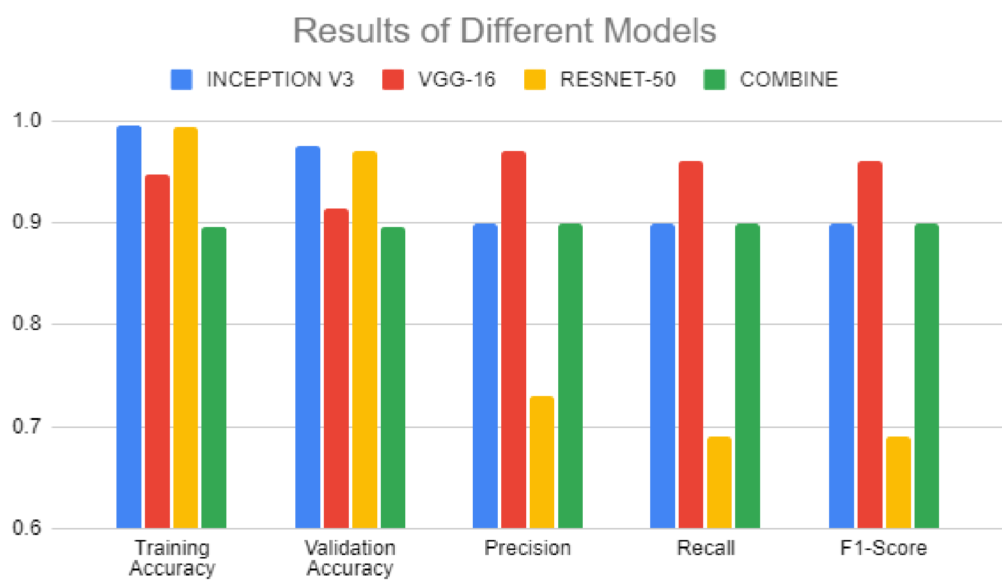
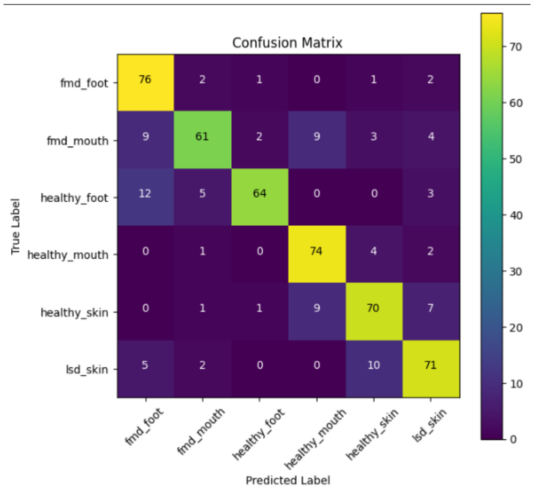
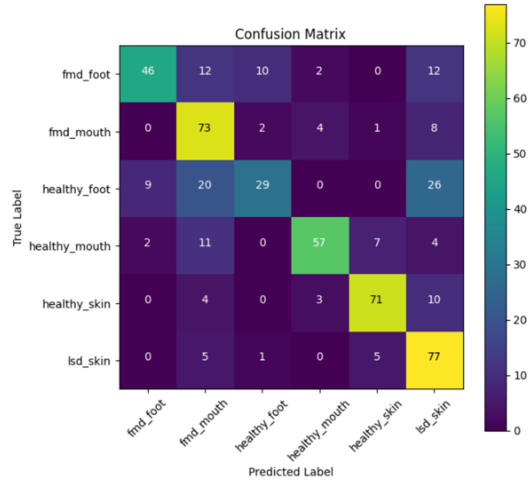


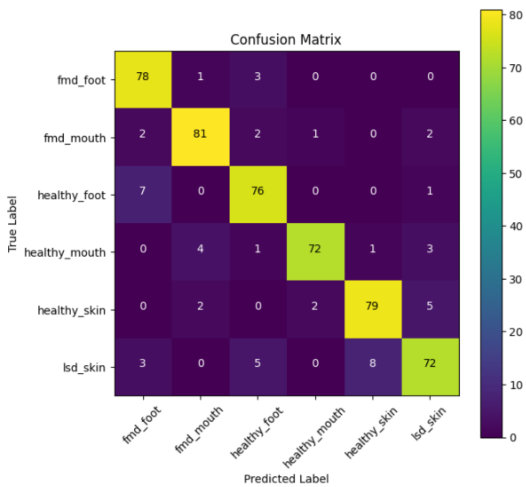
Figure 4.2. Result of Different Classes.



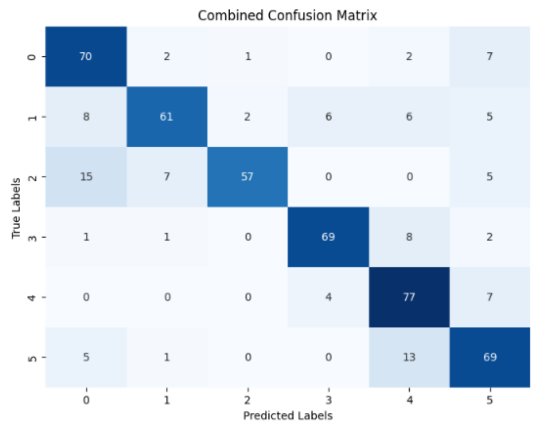
Confusion Metrics - VGG-16



Confusion Metrics - RESNET-50 confusion matrix



Confusion Metrics - Inception V3



Ensemble Confusion Metrics - VGG-16,InceptionV3

Figure 4.3. Confusion Metrics

Table 4.2. Comparison between Our work and other's work.

Paper no	**Own Dataset (Yes/No)**	**Methodology**	**Accuracy**	**Classes**
[4]	Yes	ML Techniques	73.73%	2
[5]	No	CNN	95%	3
[6]	Yes	R-CNN, YoloV3	90.60%	1
[7]	Yes	FCRN,CNN with K-Fold	94.93%	3
[1]	Yes	InceptionV3,VGG16,VGG19	92.5%	2
[8]	Yes	CNN	94%	2
[9]	Yes	ANN	97%	2
[10]	Yes	YoloV3,LSTM	85%	3
[11]	Yes	Random Forest	85%	6
[12]	Yes	InceptionV3, MobileNetV2	90%	3
[13]	Yes	ML Techniques	93%	4
[15]	Yes	CNN	98%	3
[15]	Yes	CNN	90.16%	4
[16]	Yes	R-CNN with ResNet	92%	2
[17]	Yes		83%	3
Proposed method	**Yes**	**VGG16, IncepsionV3**	**90.1%**	**6**

In Table 4.2 we presented a comparison of different parameters between our work and other's work we have reviewed.

4.6 Summary

From the evaluation analysis, it is proved that DenseNet169 architecture has performed better. The mobile application performs well in terms of detecting disease and suggesting pesticides.

Chapter 5

Standards, Constraints, Milestones

This part highlights the thesis work's Standards, Impacts, Ethics, and Challenges. The Constraints and Alternatives are then shown. Finally, the planned work Schedules, Tasks, and Milestones are displayed.

5.1 Standards (Sustainability)

Our solution allows users to quickly detect problems and take action to improve output. There are several existing projects on the same theme, but they are not accessible to all people. The majority of the data in the classes is not acceptable. Furthermore, some systems identify disease ineffectively and with low precision, making it difficult to utilize the system. When compared to other systems, ours is more efficient. The identification and categorization of cattle diseases, as well as their treatment, are two difficult challenges to solve. We utilized inceptionV3, VGG-16, and ResNetV50 in this project. The unique aspect of our job is that we can identify cattle diseases and primarily solve them almost instantly.

5.2 Impacts (on Society)

Agriculture is the country's backbone of economic growth, as it is primarily agricultural. A profitable, sustainable, and ecologically acceptable agricultural system is required to provide long-term food security for humanity. This industry's market is profitable, and many individuals are involved in it presently. Different breeds of cattle are grown all over the world. Cattle breeders are raising different breeds of cattle on their farms as well as producing cattle. Farm cattle are attacked by a variety of illnesses and diseases, and Cattle breeders sometimes have insufficient awareness of these issues and address the wrong problems without thorough diagnosis. People who lack knowledge on this topic, on the other hand, suffer greatly as a result of their lack of grasp of the subject. Due to the shortage of data on the internet, a lack of data made the work much more difficult. So, in this work, we'll look at how deep learning may be used to classify cattle diseases into distinct groups. This makes it simple to detect and remedy problems.

5.3 Ethics

The cattle disease diagnosis and Providing solutions about diseases, based on the dataset used to train the model, offers a wide range of applications. The systems must be installed in a way that addresses people's concerns and should not be used for any purpose that increases a social, national, or global security danger. The dataset collected must be completed in accordance with the code of moral principles and ethics.

5.4 Challenges

Even though cattle disease detection exploration designs are quickly expanding, the companies that produce them still face information security concerns. This method is mostly used to categorize illnesses based on user-supplied disease photos. Farmers can increase their agricultural production by having access to contemporary agricultural practices and financial services. Farmers who do not have access to cell phones or social media are unable to increase the production of their crops. So, in this work, we'll look at how deep learning may be used to classify diseases into distinct groups. This makes it simple to detect and remedy problems.

5.5 Constraints

This section discusses various restrictions such as design constraints, component constraints, and budget constraints. Based on the picture dataset, an overarching structure is presented. To handle a huge number of photos, we'll need a powerful processor to get our modal to work properly. However, no graphics processing unit (GPU) is required. Our model is trained using this component:

- Minimum processor: Intel Core i3 (8th gen)
- Minimum memory: 4GB (DDR4, 2400bus)
- DSLR model: Canon EOS R10

However, because the price of the product component varies, budgets might fluctuate in the market.

5.6 Timeline and Gantt Chart

Our thesis work is separated into two sections since we have two semesters to finish it. Our task was completed according to our supervisor's instructions. We submitted a proposal and assessed the relevant work of the thesis work in the first semester. We also created a prototype of the planned systems by analyzing and planning with existing systems. We produced a dataset and partially developed the model in the first semester. Finally, in the second semester, we developed the entire design and tested it using the provided dataset, as well as reporting on the overall workflow.

The work execution procedure for completing this thesis work is depicted in the Gantt-Chart (Figure 5.1). The thesis work is performed in two semesters, with each semester lasting four months, for a total of eight months.

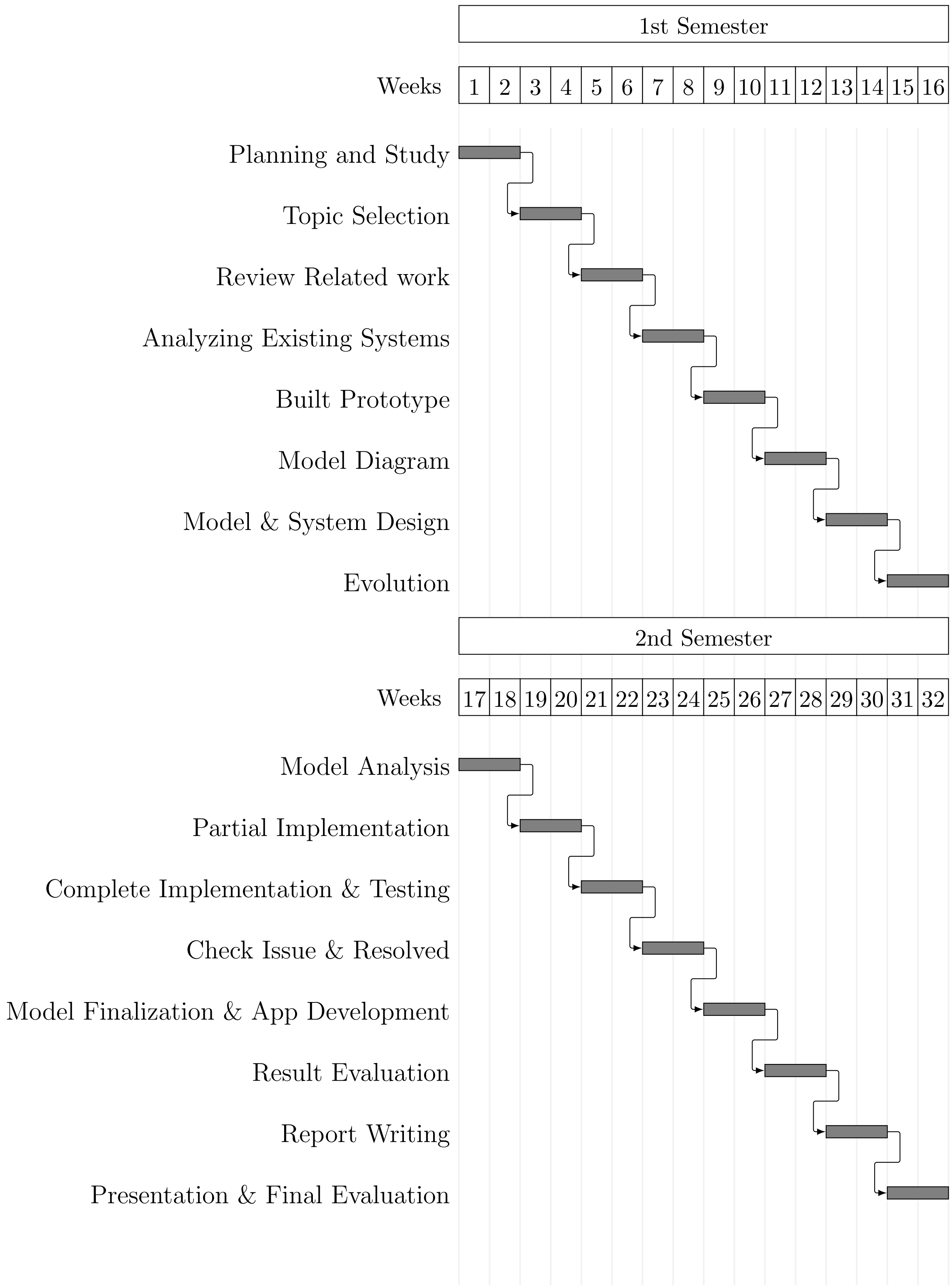


Figure 5.1. Gantt chart of the work execution process.

5.7 Summary

This chapter, on the other hand, briefly outlines the thesis work's standards, effects, ethics, and challenges. The proposed work's restrictions, alternatives, timelines, tasks, and milestones are also shown.

Chapter 6

Conclusion

6.1 Introduction

Foots Mouths, Lumpy(skin) diseases are a big threat to cattle. These diseases are responsible for the fatal destruction of cattle. These diseases are caused by viruses. If these diseases occur in one herd on a farm or area, all the cattle in that area or farm may be affected by the disease. These disease predictions for cattle using Deep Learning Approaches have become a very promising area in terms of deep learning and big data analysis. Most importantly, ensuring disease-free cattle is a very challenging task. Early detection of diseases with solutions can be the key to avoiding the demolition of cattle. This thesis paper introduced new datasets of cattle diseases and solutions. It includes a sufficient number of cattle disease datasets with cattle suggestions. This paper also proposes a new deep-learning method to classify cattle diseases and their solutions.

6.2 Future Works and Limitations

Cattle now constitute a significant part of the national GDP. Cattle disease is a severe restriction to cows of genealogy. For this research, we collected a cattle disease dataset from several online sources. This dataset covers three different cattle disease classifications. We used the InceptionV3, ResNet50, and VGG-16 models in our research. VGG-16 and InceptionV3 ensemble seems to have the best accuracy of 83.00% among them. In the future, we will develop a mobile application that saves a lot of time and money and makes use of technology that would be advantageous to consumers. By uploading images to the application, we will evaluate different machine learning methods to automatically detect the symptoms of cattle diseases and also check easily confidence.

Though we have built a dataset that includes quality images, the number of images can be increased. In the future, we want to expand our dataset. We will also add live camera-based disease detection to our application.

References

[1] G. Rai, Naveen, A. Hussain, A. Kumar, A. Ansari, and N. Khanduja, "A deep learning approach to detect lumpy skin disease in cows," in *Computer Networks, Big Data and IoT: Proceedings of ICCBI 2020*. Springer, 2021, pp. 369–377.

[2] M. Pastell and M. Kujala, "A probabilistic neural network model for lameness detection," *Journal of dairy science*, vol. 90, no. 5, pp. 2283–2292, 2007.

[3] G. Li, G. E. Erickson, and Y. Xiong, "Individual beef cattle identification using muzzle images and deep learning techniques," *Animals*, vol. 12, no. 11, p. 1453, 2022.

[4] N. Krešić, I. Šimić, T. Bedeković, Ž. Acinger-Rogić, and I. Lojkić, "Evaluation of serological tests for detection of antibodies against lumpy skin disease virus," *Journal of Clinical Microbiology*, vol. 58, no. 9, pp. 10–1128, 2020.

[5] B. Lake, F. Getahun, and F. T. Teshome, "Application of artificial intelligence algorithm in image processing for cattle disease diagnosis," *Journal of Intelligent Learning Systems and Applications*, vol. 14, no. 04, pp. 71–88, 2022.

[6] B. Jiang, Q. Wu, X. Yin, D. Wu, H. Song, and D. He, "Flyolov3 deep learning for key parts of dairy cow body detection," *Computers and Electronics in Agriculture*, vol. 166, p. 104982, 2019.

[7] V. R. Allugunti, "A machine learning model for skin disease classification using convolution neural network," *International Journal of Computing, Programming and Database Management*, vol. 3, no. 1, pp. 141–147, 2022.

[8] A. Poursaberi, C. Bahr, A. Pluk, A. Van Nuffel, and D. Berckmans, "Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques," *Computers and electronics in agriculture*, vol. 74, no. 1, pp. 110–119, 2010.

[9] E. Afshari Safavi, "Assessing machine learning techniques in forecasting lumpy skin disease occurrence based on meteorological and geospatial features," *Tropical Animal Health and Production*, vol. 54, no. 1, p. 55, 2022.

[10] E. Arazo, R. Aly, and K. McGuinness, "Segmentation enhanced lameness detection in dairy cows from rgb and depth video," *arXiv preprint arXiv:2206.04449*, 2022.

[11] S. Shahinfar, D. Page, J. Guenther, V. Cabrera, P. Fricke, and K. Weigel, "Prediction of insemination outcomes in holstein dairy cattle using alternative machine learning algorithms," *Journal of dairy science*, vol. 97, no. 2, pp. 731–742, 2014.

[12] R. Chandrarathna, T. Weerasinghe, N. Madhuranga, T. Thennakoon, A. Gamage, and E. Lakmali, "'the taurus': Cattle breeds & diseases identification mobile application using machine learning," *arXiv preprint arXiv:2302.10920*, 2023.

[13] Y. Qiao, D. Su, H. Kong, S. Sukkarieh, S. Lomax, and C. Clark, "Individual cattle identification using a deep learning based framework," *IFAC-PapersOnLine*, vol. 52, no. 30, pp. 318–323, 2019.

[14] M. Williams, N. Mac Parthaláin, P. Brewer, W. James, and M. Rose, "A novel behavioral model of the pasture-based dairy cow from gps data using data mining and machine learning techniques," *Journal of dairy science*, vol. 99, no. 3, pp. 2063–2075, 2016.

[15] Y. Li, H. Shu, J. Bindelle, B. Xu, W. Zhang, Z. Jin, L. Guo, and W. Wang, "Classification and analysis of multiple cattle unitary behaviors and movements based on machine learning methods," *Animals*, vol. 12, no. 9, p. 1060, 2022.

[16] Y. Qiao, M. Truman, and S. Sukkarieh, "Cattle segmentation and contour extraction based on mask r-cnn for precision livestock farming," *Computers and Electronics in Agriculture*, vol. 165, p. 104958, 2019.

[17] K. Liakos, S. P. Moustakidis, G. Tsiotra, T. Bartzanas, D. Bochtis, and C. Parisses, "Machine learning based computational analysis method for cattle lameness prediction." *HAICTA*, vol. 128, p. 139, 2017.

[18] D. Wu, Q. Wu, X. Yin, B. Jiang, H. Wang, D. He, and H. Song, "Lameness detection of dairy cows based on the yolov3 deep learning algorithm and a relative step size characteristic vector," *Biosystems Engineering*, vol. 189, pp. 150–163, 2020.

[19] S. Grampurohit and C. Sagarnal, "Disease prediction using machine learning algorithms," in *2020 International Conference for Emerging Technology (INCET)*. IEEE, 2020, pp. 1–7.

[20] N. V. Kishan, Y. S. Trinath, S. Kavalur, V. Sangamesha, and S. Reddy, "Cattle disease identification using prediction techniques," *IJARIIE-ISSN (O)*, pp. 2395–4396, 2021.

[21] R. Dulal, L. Zheng, M. A. Kabir, S. McGrath, J. Medway, D. Swain, and W. Swain, "Automatic cattle identification using yolov5 and mosaic augmentation: A comparative analysis," in *2022 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*. IEEE, 2022, pp. 1–8.

[22] N. Abdul Ghafoor and B. Sitkowska, "A machine learning application to predict risk of mastitis in cattle from ams sensor data," *AgriEngineering*, vol. 3, no. 3, pp. 575–583, 2021.

[23] I. Ramirez-Morales, L. Aguilar, E. Fernandez-Blanco, D. Rivero, J. Perez, and

A. Pazos, "Detection of bovine mastitis in raw milk, using a low-cost nir spectrometer and k-nn algorithm," *Applied Sciences*, vol. 11, no. 22, p. 10751, 2021.

[24] D. M. Amin, G. Shehab, R. Emran, R. T. Hassanien, G. N. Alagmy, N. M. Hagag, M. I. Abd-El-Moniem, A. R. Habashi, E. M. Ibraheem, and M. A. Shahein, "Diagnosis of naturally occurring lumpy skin disease virus infection in cattle using virological, molecular, and immunohistopathological assays," *Veterinary World*, vol. 14, no. 8, p. 2230, 2021.

[25] G. Limon, A. A. Gamawa, A. I. Ahmed, N. A. Lyons, and P. M. Beard, "Epidemiological characteristics and economic impact of lumpy skin disease, sheeppox and goatpox among subsistence farmers in northeast nigeria," *Frontiers in veterinary science*, vol. 7, p. 8, 2020.

[26] L. Aerts, A. Haegeman, I. De Leeuw, W. Philips, W. Van Campe, I. Behaeghel, L. Mostin, and K. De Clercq, "Detection of clinical and subclinical lumpy skin disease using ear notch testing and skin biopsies," *Microorganisms*, vol. 9, no. 10, p. 2171, 2021.

[27] V. Punyapornwithaya, O. Arjkumpa, N. Buamithup, C. Jainonthee, R. Salvador, and K. Jampachaisri, "The impact of mass vaccination policy and control measures on lumpy skin disease cases in thailand: insights from a bayesian structural time series analysis," *Frontiers in Veterinary Science*, vol. 10, p. 1301546, 2024.

[28] N. Murti, E. Safitri, P. Srianto, S. Madyawati, and A. Rofikoh, "Prevalence and progression of lumpy skin disease cases in cattle over the six months leading up to eid al-adha in 2023 in the cirebon district of west java province, indonesia," in *IOP Conference Series: Earth and Environmental Science*, vol. 1292, no. 1. IOP Publishing, 2024, p. 012037.

[29] G. Mackereth, K. Rayner, A. Larkins, D. Morrell, E. Pierce, and P. Letchford,

"Surveillance for lumpy skin disease and foot and mouth disease in the kimberley, western australia," *Australian Veterinary Journal*, 2024.

[30] A. Elsonbaty, M. Alharbi, A. El-Mesady, and W. Adel, "Dynamical analysis of a novel discrete fractional lumpy skin disease model," *Partial Differential Equations in Applied Mathematics*, vol. 9, p. 100604, 2024.

[22] [23] [24] [25] [26] [27] [28] [29] [30]