

FACULTY OF ENGINEERING

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FINAL YEAR PROJECT REPORT

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**DIAGNOSING FOOT AND MOUTH DISEASE AND LUMPY SKIN DISEASE IN CATTLE
USING COMPUTER VISION**

BY

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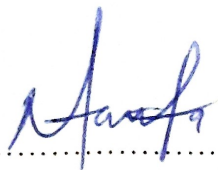
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A final year project report Submitted to the Department of Computer Engineering in Partial Fulfillment of the Requirements for the Award of a Bachelor of Science in Computer Engineering from Busitema University.

DECLARATION.

We **NTANDA NASSAR** and **AINESASI EVELYNE**, Registration Number **BU/UG/2021/0019** and **BU/UG/2021/0021** respectively under the supervision and guidance of the University supervisors, declare that this is our original work and the Information gathered and used has not been utilized in the acquisition if any academic award in any other learning Institution.

Signature



Date.....

22nd/05/2025

Signature



Date.....

22nd/05/2025

APPROVAL

This is to certify that this proposal report has been compiled by NTANDA NASSAR and AINESASI EVELYNE and has been submitted for examination. With my approval as a University Supervisor, it is now ready for submission to the Department of Computer Engineering.

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This project would not have been possible without the contributions of all these individuals, and for that, I am truly thankful

Dedication

This project is dedicated to all the farmers and veterinarians who work tirelessly to ensure the health and well-being of livestock, often under challenging conditions. Your dedication to animal care inspires the development of solutions that aim to make a positive impact in the field of agriculture.

I also dedicate this work to my family, whose constant love, support, and belief in me have been a source of strength throughout this journey. To our supervisors and mentors, thank you for your guidance and encouragement that propelled us forward.

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List of Acronyms

FMD - Foot and Mouth Disease

LSD - Lumpy Skin Disease

AI - Artificial Intelligence

MAAIF - Ministry Of Agriculture, Animal Industry and Fisheries

GDP - Gross Domestic Product

ML - Machine Learning

CNN - Convolutional Neural Network

Abstract

Cattle farming is a major source of income for many people in the Sub-Harran region, and the livestock sector played a vital role in supporting the region's economy and food security [2]. However, the prevalence of infectious cattle diseases, particularly Lumpy Skin Disease (LSD) and Foot and Mouth Disease (FMD), posed serious threats to food security, farmer livelihoods, and animal productivity. Addressing the impacts of these diseases required early and accurate diagnosis [1].

This study presents a computer vision-based diagnostic model that utilizes deep learning techniques to detect and classify FMD and LSD in cattle. The proposed system captured the visible signs of infection using a Convolutional Neural Network (CNN) trained on a dataset of annotated cattle images [3]. The model achieved high levels of accuracy and robustness under diverse environmental conditions and was capable of distinguishing between healthy cattle and those infected with FMD or LSD.

To improve accessibility, the trained model was integrated into a mobile application, enabling rural farmers and veterinary practitioners to perform real-time diagnosis without the need for specialized equipment. The study also addressed challenges related to image data collection in the Sub-Harran region, such as variations in cattle breeds, lighting conditions, and disease presentation. Data augmentation and transfer learning techniques were employed to improve the model's generalization.

The model's performance will be evaluated using standard metrics, including accuracy, precision, recall, and F1-score, with results indicating strong potential for practical deployment [4]. Overall, this study will offer a scalable solution for improving cattle disease management through the application of artificial intelligence, with implications for enhancing disease surveillance, reducing economic losses, and improving animal health in resource-constrained settings.

CHAPTER ONE: INTRODUCTION

1.1 Introduction

Cattle farming is a key economic activity in the Sub-Saharan region, particularly in its lower areas, where the livestock industry provides livelihoods for many rural households [5]. However, diseases such as Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease

(LSD) pose significant challenges to cattle health, leading to reduced productivity, increased mortality, and considerable economic losses. Early detection of these diseases is crucial in preventing their spread and mitigating their impact.

With advancements in artificial intelligence (AI), new opportunities have emerged to integrate technology into agriculture and enhance cattle disease management [6]. This project therefore aimed to develop a mobile application that leveraged computer vision and deep learning techniques to detect early signs of FMD and LSD in cattle. The application was designed to provide farmers in the region with a reliable tool for detecting these diseases at the stage when visible signs first appear, thereby enabling timely response and intervention.

This approach sought to replace traditional manual observation methods often prone to error and mismanagement with a more precise and automated diagnostic system.

1.2 Background

The Sub-Saharan region is one of the major cattle-producing areas in the world, where livestock farming plays a crucial role in ensuring food security, creating employment, and driving rural development. Livestock remains one of the backbones of the region's economy; however, it faces serious challenges from diseases such as FMD and LSD. These diseases take a significant toll on livestock production by reducing milk yield, slowing weight gain, and causing substantial cattle mortality. The economic

consequences are devastating, with farmers reportedly losing more than USD 4.1 billion annually, further deepening poverty in farming communities [7].

FMD, caused by the Aphthovirus, is highly contagious and primarily affects cloven-hoofed animals such as cattle. Infected animals commonly exhibit symptoms such as fever, increased heart rate, and reduced activity within the first two weeks of infection. In contrast, LSD, caused by the Capripoxvirus, presents as skin nodules, fever, and swollen lymph nodes. Despite the existence of vaccination programs and other control measures, both diseases continue to spread, particularly in rural areas where access to veterinary services is limited making early detection extremely difficult for many farmers [8].

This project aimed to bridge that gap by introducing computer vision technology into livestock health management. Specifically, the project sought to develop a mobile application that employed a computer vision model to assist farmers in diagnosing cattle diseases simply by capturing images of affected animals. These models, trained on thousands of annotated images, were capable of detecting early signs of FMD and LSD with high accuracy.

By enabling rapid and accurate diagnoses, the system had the potential to significantly reduce livestock losses and improve animal health. The integration of mobile technology and machine learning made this approach both practical and accessible. Farmers could use the application without requiring advanced technical skills or immediate veterinary support, resulting in quicker diagnosis, fewer cattle deaths, and improved overall productivity on farms.

Previous research had already demonstrated the effectiveness of deep learning in disease detection. Studies had shown that such models were highly capable of identifying common cattle diseases from images. Moreover, early diagnosis was consistently linked to better livestock health outcomes. Building upon this foundation, the project developed a user-friendly mobile application tailored specifically for farmers in the Sub-Saharan region. By focusing on FMD and LSD, the initiative aimed to revolutionize cattle disease management, reduce economic losses, and help sustain farming livelihoods in the region.

1.3 Problem statement

Farmers in the Sub-Saharan region are grappling with frequent outbreaks of Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD). These diseases significantly reduce livestock productivity, resulting in severe economic losses due to high cattle mortality, decreased milk production, and stunted weight gain [8]. The detection of these diseases often requires skilled veterinary personnel; however, **limited access to veterinary services** in rural areas leads to delayed diagnoses and ineffective treatment interventions. Consequently, the diseases spread rapidly across herds, compelling authorities to impose quarantines on affected areas, which further intensifies the financial burden on already struggling farmers.

There is an urgent need for an easily accessible solution that can facilitate early diagnosis of these cattle diseases. Early detection is critical to curbing the spread of infections, enabling timely quarantine measures, and supporting continuous monitoring of affected livestock.

This project therefore proposed a mobile application powered by computer vision algorithms to address this challenge. The application aimed to enable farmers to diagnose diseases such as FMD and LSD at **an early stage** using smartphone cameras offering a practical and scalable solution to mitigate the devastating impact of these diseases on both livestock and livelihoods.

1.4 Objectives of the Study

1.4.1 Main Objective

The main objective of this project was to develop a mobile application that leverages a computer vision model to accurately diagnose Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) in cattle.

1.4.2 Specific Objectives

- To identify functional and non-functional requirements for developing FMD and LSD diagnostic mobile Application.
- To train a computer vision model capable of identifying and detecting FMD and LSD symptoms in cattle images.
- To develop a user-friendly mobile application capable of diagnosing FMD and LSD.
- To validate and test the developed mobile application and computer vision model.

1.5 Justification

Livestock farmers in rural areas of the Sub-Saharan region continue to face serious challenges due to diseases such as Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD). These diseases pose significant threats to cattle health, leading to high mortality rates and reduced productivity. The economic impact remains considerable, as delayed diagnosis often results in major financial losses. The situation is further exacerbated by limited access to veterinary services and ineffective disease management practices in remote areas.

This project was undertaken to provide a timely and accessible solution by leveraging computer vision technologies for the diagnosis of cattle diseases. The system's ability to facilitate early detection enabled farmers to take prompt action, thereby minimizing economic losses and improving the overall health and well-being of their livestock.

1.6 Significance

This project holds substantial potential to improve cattle disease management, specifically for Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD), by providing an accessible early diagnosis tool. Accurate and timely identification of these diseases empowers farmers and veterinarians to quickly control outbreaks, thereby reducing the risk of significant economic losses. It also enhances animal welfare by minimizing suffering and supporting quicker recovery. The mobile app

is especially beneficial for rural and resource-limited areas, offering a low-cost, portable solution for farmers who lack access to regular veterinary services. Early intervention brings economic benefits by preserving cattle health, reducing productivity losses, and lowering containment costs. Furthermore, the app contributes to future research by collecting valuable data on disease symptoms and patterns across regions, thus supporting predictive modeling for outbreaks.

Ultimately, this project not only addressed critical challenges in livestock disease detection but also encouraged the adoption of advanced technological solutions in agriculture. It plays a role in driving progress in AI-driven agricultural tools, contributing to food security and economic stability in livestock-dependent communities.

1.7 Scope of study

1.7.1 Disease Focus

The study focused exclusively on diagnosing Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) in cattle. Other diseases or health conditions were not addressed in this initial model.

1.7.2 Technology and Model Development

The project involved the development of a computer vision model specifically trained to recognize visual symptoms of FMD and LSD in cattle images. The study detailed the model's architecture, training process, and evaluation metrics used to assess its performance.

1.7.3 Data Collection and Preprocessing

The study included the collection of a dataset consisting of labeled images of cattle showing symptoms of FMD, LSD, and healthy conditions. Data preprocessing techniques, including image augmentation and normalization, were employed to prepare the images for model training and enhance the model's accuracy.

1.7.4 Mobile Application Integration

The computer vision model was integrated into a mobile application designed to provide a user-friendly interface. The app enabled users to upload images, run diagnostics, and receive results, along with guidance on the next steps if disease symptoms were detected.

1.7.5 User Scope

The primary users of the app were farmers and veterinarians. The study addressed how the app's design, functionality, and ease of use catered to their specific needs, especially in rural or resource-limited areas. This project was conducted for academic research purposes.

1.7.6 Time Scope

The time scope of this project spanned approximately 3 months, with each phase contributing to the development of a mobile app for diagnosing cattle diseases. Initially, the project focused on data collection and preprocessing, gathering and preparing images of cattle with symptoms of Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) over the first three weeks. This was followed by a model development phase, where different computer vision algorithms were trained, validated, and optimized. The model was then integrated into a mobile app, with a focus on creating a user-friendly interface and ensuring compatibility across devices. The app underwent testing and evaluation to assess diagnostic accuracy and usability in real-world conditions. Finally, the last few weeks involved analyzing results, incorporating feedback, and completing the final report or research paper. This phased approach ensured the project remained organized and met its objectives within the defined timeline.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Cattle farming has long been a critical component of the Sub-Saharan region's agricultural sector, contributing significantly to rural livelihoods, food security, and national economies. The region has hosted an estimated 16% of the world's cattle population. However, cattle diseases such as Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) have posed substantial threats to the productivity and profitability of cattle farming [9].

Cattle diseases have consistently been a major source of economic losses in the Sub-Saharan region, costing the livestock sector billions of dollars each year. These losses have resulted primarily from reduced milk production, slower weight gain, high mortality rates, and significant expenditures on veterinary services and disease control. Livestock farming has played a vital role in the region's economy, contributing substantially to household incomes and national GDP. According to reports from the African Union [10], livestock accounts for 30–40% of agricultural GDP in many Sub-Saharan countries, highlighting its importance for economic growth.

These challenges extend beyond the economy, affecting food security, employment, and trade. The persistent impact of cattle diseases has underscored the need for more effective and accessible strategies to manage and prevent outbreaks in the region [10].

2.2 Foot-and-Mouth Disease

Foot-and-Mouth Disease (FMD) is a highly contagious viral disease that affects cloven-hoofed animals, including cattle, pigs, and sheep. In Uganda, FMD outbreaks have led to significant financial losses for cattle farmers, particularly in regions such as Kiruhura District, where livestock farming serves as a primary economic activity [12]. It has been estimated that FMD outbreaks can reduce milk production by up to 50% and decrease cattle weight gain, further aggravating the financial burden on farmers.

Several studies have emphasized the importance of early diagnosis in mitigating the effects of FMD. Early detection can help prevent the rapid spread of the disease, especially in areas where cattle are raised under communal grazing systems. Although government-led vaccination campaigns have been implemented, the effectiveness of these interventions is often compromised by the lack of timely and accurate diagnosis—particularly in remote or rural areas with limited access to veterinary services.

2.3 Lumpy Skin Disease

Lumpy Skin Disease (LSD) is a viral infection caused by the *Capripoxvirus* and is primarily transmitted by insect vectors such as ticks and mosquitoes. The disease typically presents with symptoms such as skin nodules, fever, and enlarged lymph nodes in infected cattle. A study by Namazi and Khodakaram Tafti (2021) highlighted the increasing frequency of LSD outbreaks in Sub-Saharan Africa, emphasizing that inadequate control measures in rural areas remain a significant barrier to the disease's eradication.

LSD has a considerable impact on cattle productivity, particularly through reduced milk yield and deteriorating overall health. Economic losses stem from the cost of treatment, decreased productivity, and the necessity to cull severely affected animals. Recent research suggests that the use of automated diagnostic tools, including deep learning models and IoT sensor systems, could enhance early detection of LSD, thereby enabling prompt intervention and effective disease management [13].

2.4 Other Related Work Reviewed

Many research papers have been published on disease prediction using data mining techniques and cattle health monitoring systems. Different data mining methods were used for prediction, resulting in varying outcomes across different models.

Fuzzy Logic and Expert Systems

Mahdi Jampour et al. – *“A Fuzzy Expert System to Diagnose Diseases with Neurological Signs in Domestic Animals”*

Developed a Fuzzy Expert System capable of detecting and assessing the presence or absence of neurological diseases in domestic animals. This system utilized fuzzy rules to handle the uncertainty and vagueness associated with medical diagnosis.

Neural Networks and Machine Learning Techniques

Varun Garg and Kritika Garg – *“Early-Stage Disease Detection Platform in Cattles”*

Applied Neural Networks to develop a cost-effective platform for early-stage disease detection in cattle.

U. I. Bajwa et al. – *“Skin Disease Classification Using Neural Network”*

Used Artificial Neural Networks (ANNs) to automatically classify skin diseases, aiding general practitioners in lesion detection and categorization.

IoT and Sensor-Based Monitoring Systems

Kunja Bihari Swain et al. – “*Cattle Health Monitoring System Using Arduino and LabVIEW for Early Detection of Diseases*”

Designed a real-time cattle health monitoring system using Arduino UNO, Arduino NANO, Xbee modules, and sensors to track physiological parameters. Integrated with LabVIEW, this system allowed early disease detection based on sensor readings.

Noone Vijay Kishan et al. – “*Cattle Disease Diagnosis Using Prediction Technique*”

Employed IoT devices and data mining techniques to monitor cattle health. Sensor data (e.g., heartbeat) was collected, transmitted, and analyzed using data mining algorithms for disease prediction.

Epidemiological Analysis and Disease Spread Modeling

Francisco Gomez et al. – “*Identification of Super-Spreaders of Foot-and-Mouth Disease in the Cattle Transportation Network: The 2018 Outbreak Case in Cesar (Colombia)*”

Investigated disease spread using a cattle transportation network model. By analyzing network centrality, the study identified super-spreaders and provided insights into FMD (Foot-and-Mouth Disease) epidemiology and animal movement patterns.

In machine learning, a dataset is essentially a collection of data bits that can be analyzed and predicted by a computer as a single entity. This means that the data collected should be homogeneous and interpretable by machines, which perceive data differently from humans. After data collection, it is crucial to clean, complete, and label the dataset with computer-readable tags. A useful dataset should meet certain quality and quantity standards—it must be relevant and well-balanced to ensure a smooth and efficient training process.

2.5 Comparative study of Research papers reviewed

Methodology	Dataset	Description	Limitations
Fuzzy Expert System [16]	20 test board of animal	The fuzzy logic system method is used to determine and compare the absence of participation of each probable disease with neurological symptoms	Used only to Diagnose Diseases with Neurological signs
Arduino UNO, Arduino NANO, Xbee module [17]	Data from sensors	Designed a system that allows farmers to monitor and compare the current health parameters of their livestock to the conventional healthy reference parameters	Only used to monitor the cattle health conditions
Cattle Transportation Network(ranking nodes) [18]		The Cow transportation network is computed using several centrality measures, each of which may provide useful information about the animal movement	only used to monitor the “foot and mouth disease.”small dataset used
Naive Bayes and Apriori [19]	Disease Symptom Knowledge data set prepared by New YOrk Presbyterian Hospital of patients	The authors compared different machine learning algorithms like naive algorithm, neighbor algorithms, and apriori where the Apriori algorithm performed well and the naive algorithms were	The disease being predicted based on the input symptoms, using multiple algorithms

	admitted during 2004	also good based on the data set they studied	
K Nearest Neighbours for Regression. Decision Tree for Regression MultiLayer Perceptron Long Short Term Memory [20]	Clinical Dataset	Using algorithms they have analyzed the disease behavior characteristics	Less accuracy

2.6 Existing systems

Cattle health monitoring systems are innovative livestock management solutions that assist farmers and veterinarians in monitoring cattle health and productivity through the integration of IoT. These systems utilize wearable tags that track critical health indicators such as temperature, heart rate, and movement, thereby enabling early detection of diseases like Foot-and-Mouth Disease (FMD) and providing traceability to locate animals in the event of theft. This technology enhances livestock management by providing real-time data insights, thereby supporting proactive animal care and improving farm productivity【12】.

Other existing systems include Fuzzy Logic-Based Model systems, which apply fuzzy logic algorithms to diagnose cattle diseases by interpreting clinical symptoms with high accuracy. These models use a rule-based approach to process multiple health metrics, identifying subtle disease patterns even when symptoms overlap with other conditions. By constructing a knowledge base, such systems make real-time diagnostic decisions and recommend treatment options, which are particularly beneficial in resource-scarce environments. However, these systems are often prone to errors, time-consuming, and complex due to rule-based programming challenges【7】.

2.7 Developed Solution

To address the challenges faced by farmers in the Sub-Saharan region due to frequent outbreaks of Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD), this project developed a cost-effective and accessible mobile application powered by computer vision algorithms. The application enables farmers to use their smartphone cameras to detect signs of FMD and LSD at an early stage. By providing a quick and reliable diagnostic tool, the solution facilitates prompt action, thereby helping to reduce the spread of these diseases and improve overall livestock health and productivity.

2.8 Background

2.8.1 Machine learning

Machine learning is classified as a multidisciplinary branch of computer science. The main goal of machine learning is to find undiscovered facts, hidden insights, correlations, patterns, and knowledge in massive data sets that are difficult to find and identify using traditional statistical approaches; the design and development of data- learning systems. The main steps involved in machine learning are preprocessing, modeling, and post-processing of data [3]

Machine learning is classified into three categories:

Supervised Machine learning: -The algorithms that use externally given cases to build a broad hypothesis and make use of it in the future for predictions are called supervised machine learning algorithms. One of the distinguishing features is their capacity to use annotated data. SML algorithms use class labels for the classification process. There is a wide range of supervised algorithms some of them are: Linear Classifiers, Support Vector Machine Logistic Regression, Naïve Bayes Classifier, Perceptron, Quadratic Classifiers, Decision Tree, K-Means Clustering, Boosting, Random Forest (RF); Bayesian Networks, Neural Networks and

so on [3]

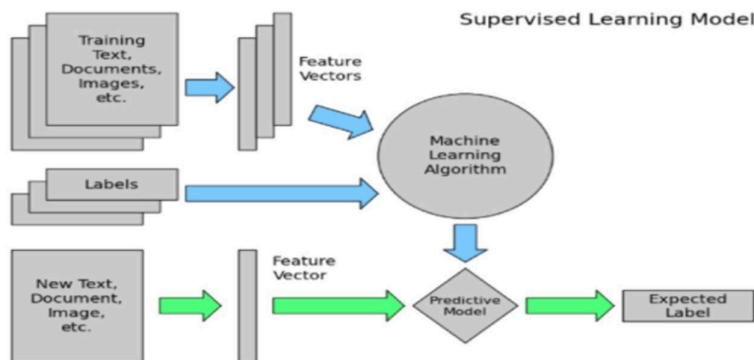


Figure. 2 Supervised machine learning model

Support Vector Machine: SVM being a supervised machine learning algorithm was formulated by Vapnik et al. in 1995. Support Vector Machine (SVM) models are similar to traditional multilayer perceptron neural networks. The concept of “margin” (separates two different classes) is used in SVM. The margin is maximized to produce the biggest possible space between the separating hyperplane and instances and thus reduces the predicted generalization error. SVM first calculates the low dimensional space. Then the kernel function is used to map high dimensional feature space and input space. Finally, in the high dimensional feature space, the best-classified hyperplane is built.

Input: Consider the training dataset T with multiple symptoms, where symptoms of diseases and category of diseases are denoted by x_i and y_i respectively. $f(x)$ is the decision function which produces the optimal classification plane is shown below

Neural Networks: Neural Networks (NN) can execute many classifications and/or regression tasks at the same time, despite the fact that most networks can only do one. In the great majority of situations, there will be a single output variable for the network. However, with respect to many state classification problems, it equates to the number of output units. [4]

$$\int f(x) = \text{sgn}\left(\sum_{i=1}^n a_i^* y_i (x \cdot x_i) + b^*\right)$$

$$b^* = y_i - \sum_{i=1}^l a_i^* y_i (x \cdot x_i)$$

Figure. 3 Neural Network Equation

Fuzzy Neural Networks: A simple fuzzy neural network produces a Gaussian function by narrowing down the set of input vectors, which is then correlated to the target label. Secondly, in order to obtain a fuzzy truth, the previously found gaussian function is used, hence classifying the unknown feature vector. Thirdly, to find the class of input feature vectors, fuzzy truths are maximized [16].

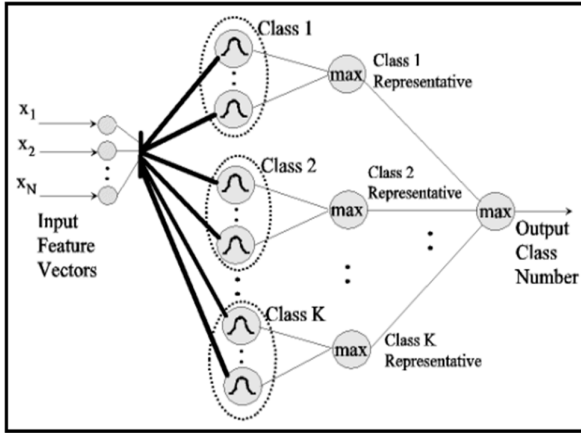
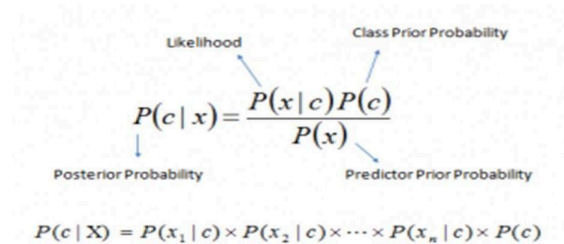


Figure. 4 Simple Fuzzy Neural Network [16]

Naive Bayes Classifier: Naive Bayes Classifier is a classification method based on Bayes' Theorem and the condition of predictor independence. A Naive Bayes classifier, in simple terms, asserts that the existence of one feature in a class is independent of the presence of any other feature. The Naive Bayes model is simple to construct and is exceptionally effective for

huge datasets. Naive Bayes is recognized to outperform even the most advanced classification systems due to its simplicity [15].



The diagram shows the Naive Bayes equation with labels for its components. The equation is:

$$P(c | x) = \frac{P(x | c)P(c)}{P(x)}$$

Labels with arrows pointing to the equation:

- Likelihood** points to $P(x | c)$
- Class Prior Probability** points to $P(c)$
- Posterior Probability** points to $P(c | x)$
- Predictor Prior Probability** points to $P(x)$

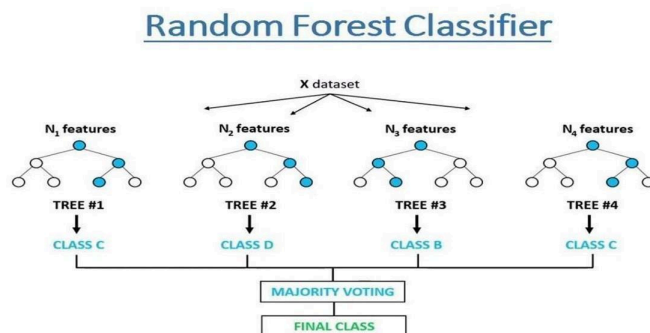
Below the equation, the joint probability formula is given:

$$P(c | X) = P(x_1 | c) \times P(x_2 | c) \times \dots \times P(x_n | c) \times P(c)$$

Figure. 5 Naive Bayes Equation

Random Forest Classifier: A random forest is a meta estimator that uses averaging to increase predicted accuracy and control over-fitting by fitting a number of decision tree classifiers on various sub-samples of the dataset. If bootstrap = True (default), the sub-sample size is regulated by the max samples' argument; otherwise, the entire dataset is utilized to create each tree.

Figure. 6 Random Forest Classifier



Decision Tree Classifier: Decision Tree is a supervised learning technique that may be used to solve both classification and regression problems, however, it is most commonly used to solve classification issues. Internal nodes represent dataset attributes, branches represent decision rules, and each leaf node provides the result in this tree-structured classifier. The Decision Node and the Leaf Node are the two nodes of a Decision tree.

Leaf nodes are the output of those decisions and do not contain any more branches, whereas Decision nodes are used to make any decision and have several branches. The decisions or tests are made based on the characteristics of the given dataset [20].

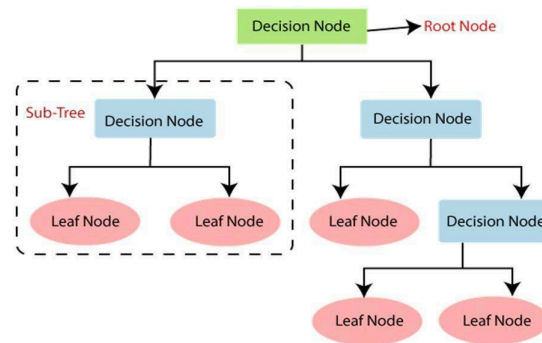


Figure. 7 Decision Tree Classifier

A) Unsupervised learning

This Learning technique will not make use of training datasets to build models, but instead, find the hidden patterns in the given dataset. In this technique, class labels are not present. Unsupervised techniques cannot be applied to classification or regression tasks. It covers the underlying patterns based on similarities to display the dataset in a compact fashion. Different algorithms that come under unsupervised methodologies are “eclat algorithm”, “FP Growth algorithm”, “AIT algorithm” and many more [21].

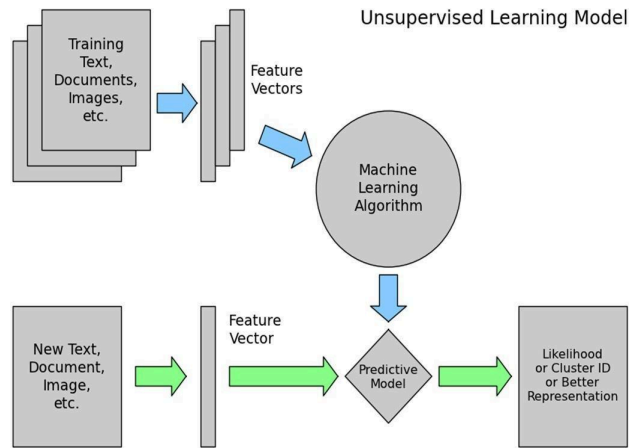
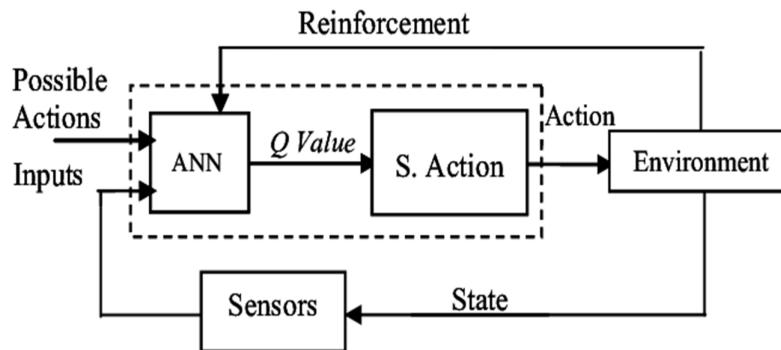


Figure. 8 Unsupervised learning model

B) Reinforcement Learning

Machine Learning includes the field of reinforcement learning. It's all about taking the right steps to maximize your reward in a given situation. It is used by a variety of software and computers to determine the best feasible action or path in a given situation. Reinforcement learning differs from supervised learning in that supervised learning includes the answer key, allowing the model to be trained with the correct answer, whereas reinforcement learning does not include an answer and instead relies on the reinforcement agent to decide what to do to complete the task. It is obligated to learn from its experience in the absence of a training dataset [20].



CHAPTER THREE: METHODOLOGY

3.1 Introduction

This chapter outlined the methodology that will be followed in the development of a mobile application that utilized computer vision to detect Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) in cattle. The project involved training a deep learning model on a dataset of cattle images and converting the trained model into a mobile-compatible format suitable for integration into an Android application.

The system will be designed to allow users primarily farmers and veterinarians to upload or capture images of cattle for real-time disease diagnosis. The methodology included key phases such as data collection and preprocessing, model training and evaluation, model optimization, and Android-based application development. TensorFlow Lite was considered for converting the trained model to run efficiently on mobile devices.

In addition, the application will be tested to evaluate its diagnostic accuracy and usability in field-like conditions. This methodology will be aimed at delivering a reliable, low-cost, and user-friendly tool to support early disease detection and improved cattle disease management, especially in rural and resource-limited settings.

3.2 Methodology for identifying functional and non-functional requirements for developing an FMD and LSD diagnostic mobile app.

To achieve the objective of identifying both functional and non-functional requirements for developing a mobile application for diagnosing Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) in cattle, the study adopted a systematic approach that includes literature review, image dataset obtaining and requirement analysis techniques. The methodology comprised the following phases:

3.2.1 Stakeholders:

Key stakeholders relevant to the diagnosis and management of FMD and LSD were identified. These may include:

- Veterinarians and veterinary officers
- Livestock farmers and cattle herders
- Small hold cattle keepers.

Engagement with these stakeholders were done through:

- One-on-one interviews
- questionnaires.

These interactions provided insights into:

- Common challenges in diagnosing and managing FMD and LSD
- Desired features and expectations from a mobile diagnostic app
- Environmental and contextual considerations for using mobile tools in rural or semi-urban settings

3.2.2 Functional Requirements Elicitation

Functional requirements describe what the system should do. Based on stakeholder input and literature analysis, the following were identified:

- Disease symptom input (e.g., image uploads, symptom checklists)
- Diagnostic suggestion system

- Report generation and sharing
- Offline functionality for remote areas
- Question and answer system.

4. Non-Functional Requirements Identification

Non-functional requirements address how the system should perform. These included;

- **Usability:** Simple interface for farmers and animal health workers
- **Reliability:** Accurate diagnosis suggestions and data integrity
- **Performance:** Fast response time even with low-end devices
- **Scalability:** Ability to expand to include other livestock diseases in the future

5. Requirement Validation

The gathered requirements were validated through stakeholder feedback sessions.

- Confirm if the identified requirements match user needs
- Refine and prioritize features
- Identify any overlooked needs or concerns

3.3 Methodology for Developing and Training a Computer Vision Model

To develop a computer vision model capable of identifying and detecting FMD and LSD symptoms in cattle images and measuring model performance, we followed the steps outlined below:

3.3.1 Image Data Collection and Cleaning

A labelled image dataset was obtained from publicly available sources, including the Lumpy Skin Disease Cow Images dataset on Kaggle(kaggle.com/datasets/warcoder/lumpy-skin-images-dataset) and the FMD Cattle dataset from the Zenodo organization <https://zenodo.org/records/7779246>. The collected data was categorized into three main classes: FMD, LSD, and Healthy.

Once collected, the dataset was cleaned by removing corrupted images that failed to load or were unreadable. Additionally, any missing or duplicate images were identified and dropped to ensure the integrity and quality of the dataset.

3.3.2 Data Visualization

Effective image data visualization was conducted to gain insights into the characteristics of the dataset and identify any anomalies that could affect model training. Visualization also assisted in understanding the distribution of images across classes and verifying the labeling accuracy.

Popular Python libraries such as Matplotlib and Seaborn were used to create visualizations, which included class distribution graphs and sample image previews.

3.3.2.1 Exploratory Data Analysis with Image Visualization

Exploratory Data Analysis (EDA) included randomly displaying images from the dataset to visually inspect their variety, clarity, and relevance. This step helped confirm whether the images were properly labeled and suitable for the

classification task. Visual inspections also guided further preprocessing decisions and model architecture considerations.

3.3.2.2 Class Distribution Visualization

Bar charts were plotted to visualize the number of images per disease class. This helped identify class imbalances that could potentially affect model training and informed the need for augmentation or resampling strategies.

3.3.2.3 Pixel Intensity Distribution

Histograms of pixel intensities were generated to examine brightness and contrast variations across the dataset. This analysis helped determine whether normalization or contrast enhancement techniques were necessary during preprocessing.

3.3.3 Image Resolution

Image resolution, defined by the number of pixels in width and height (e.g., 1920×1080), plays a critical role in deep learning. It affects the model's ability to extract features, computational load, and training efficiency.

3.2.3.1 Image Resizing

All images were resized using libraries such as Pillow and OpenCV to a consistent input size (e.g., 224×224 pixels) suitable for the selected deep learning model.

3.3.3.2 Importance of Image Resolution

- **Detail and Feature Extraction:** Higher resolutions enabled better capture of intricate details essential for identifying disease symptoms.
- **Model Performance:** Optimal resolution balanced model accuracy and resource usage.

- **Computational Cost:** Resolution was adjusted to manage memory and speed trade-offs during training.

3.3.4 Image Color Analysis

Color analysis was conducted to extract meaningful information from images by analyzing color distributions and patterns that may correlate with disease symptoms.

3.3.4.1 Techniques for Color Analysis

- **Color Space Representation:**
 - *RGB*: Standard format for digital images.
 - *HSV*: Useful for segmentation and color-based analysis.
 - *Grayscale*: Simplified format retaining only brightness levels.
- **Color Histograms:**
 - Histograms were plotted to summarize the distribution of colors in each image.
- **Color Feature Extraction:**
 - The mean and standard deviation of each color channel were computed to quantify the image's color properties.
- **Color Segmentation:**
 - Thresholding and masking techniques were applied to isolate specific color regions, which aided in detecting diseased areas.

3.3.5 Additional Data Preprocessing Techniques

3.3.5.1 Image Augmentation

Data augmentation techniques such as rotation, flipping, scaling, cropping, and brightness adjustments were applied to improve model generalization and reduce overfitting.

3.3.5.2 Normalization

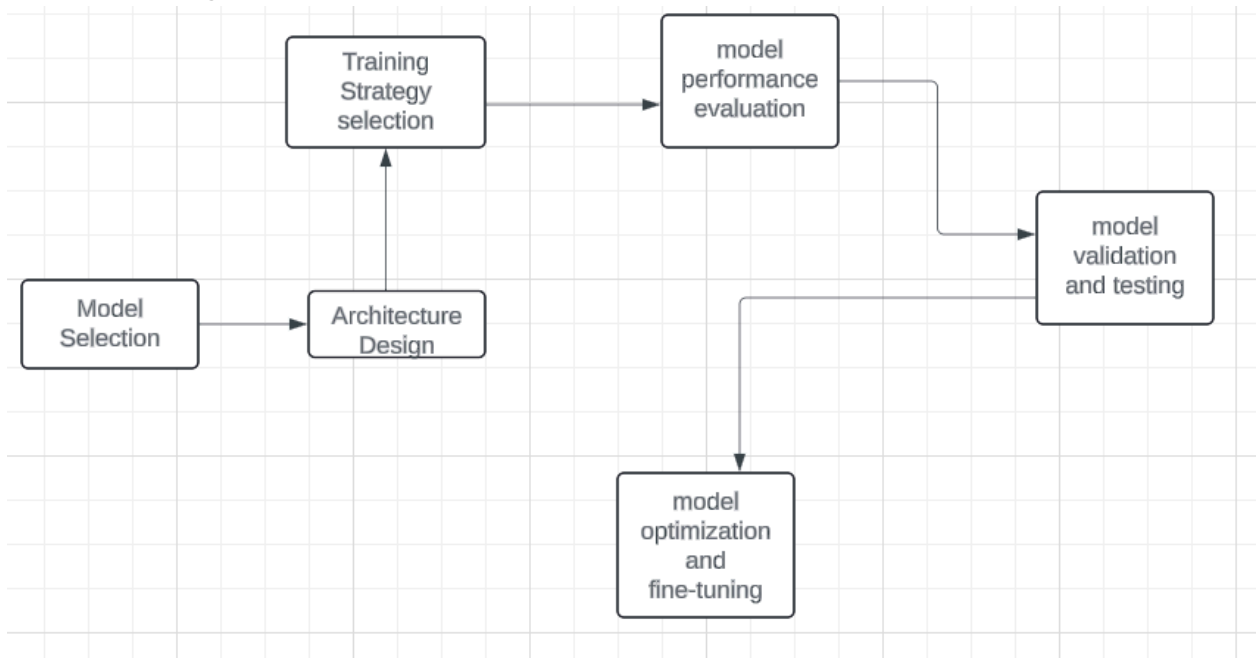
Normalization was performed to enhance model convergence and training stability:

- **Min-Max Scaling:** Pixel values were scaled to a $[0, 1]$ or $[-1, 1]$ range.
- **Mean-Standard Deviation Normalization:** Pixel values were centered by subtracting the dataset mean and dividing by the standard deviation, resulting in a standardized input.

3.3.5.3 Resizing

All images were resized to a consistent dimension compatible with the deep learning model architecture, such as 224×224 pixels, to ensure uniformity

across training batches.



3.3.6 Model Selection and Architecture Design

To develop a robust model for disease detection, we adopted a multi-stage model selection strategy:

- **Baseline Models:**

As an initial step, simple baseline models were developed to provide a reference point for evaluating the performance of more complex models. These included basic Convolutional Neural Network (CNN) architectures built from scratch, allowing for quick experimentation and understanding of the dataset characteristics.

- **Pre-trained Models:**

Following the establishment of baselines, transfer learning techniques were employed using pre-trained CNN architectures such as VGG16,

ResNet50, and InceptionV3. These models, trained on large datasets like ImageNet, offered powerful feature extraction capabilities. By fine-tuning these models on our specific cattle disease dataset, we leveraged their prior learning to enhance model performance while reducing training time.

- **Model Customization:**

Custom modifications were made to the pre-trained models, including the addition of extra dense layers, dropout layers for regularization, and specialized output layers designed for multi-class classification (FMD, LSD, Healthy).

- **Framework Selection:**

TensorFlow, an open-source deep learning framework, was selected for model development due to its robustness, flexibility, and strong community support. TensorFlow facilitated seamless integration of data pipelines, model building, training, and deployment processes.

3.3.7 Training Strategy

- **Training-Validation Split:** We split the dataset into training, validation, and test sets (80% training, 20% testing) to monitor performance during training.
- **Data Augmentation During Training:** We applied real-time data augmentation during the training phase to increase dataset variability and reduce overfitting.

- **Loss Function:** We used cross-entropy loss as the objective function for the classification task.
- **Optimization and Learning Rate Scheduling:** We chose optimizers such as Adam, coupled with a learning rate scheduler (ReduceLROnPlateau) to dynamically adjust the learning rate. Additionally, we tuned hyperparameters such as the learning rate, batch size, and number of epochs using grid search and random search methods.

3.3.8 Model Performance Evaluation Metrics

- We evaluated the model's performance using metrics such as accuracy, precision, recall, and F1-score.
- We plotted a confusion matrix, which provided detailed insights into the types of errors the model made. Metrics derived from the confusion matrix were especially helpful in handling imbalanced data.
- We also plotted Receiver Operating Characteristic (ROC) curves and calculated the Area Under the Curve (AUC) to gain deeper insight into the model's performance, particularly in terms of classification thresholds.

3.3.9 Model Validation and Testing

- **Cross-Validation:** We performed k-fold cross-validation to assess the model's consistency and reduce bias.

- **Test Set Performance:** We evaluated the final model on the reserved test set to ensure an unbiased assessment.
 - **Error Analysis:** We analyzed misclassified images and poorly localized lesions to identify common failure cases and opportunities for model improvement.
-

3.3.10 Model Optimization and Fine-Tuning

- **Hyperparameter Tuning:** We conducted automated hyperparameter searches using tools like Optuna to find optimal configurations.
- **Regularization Techniques:** We applied regularization techniques such as dropout, batch normalization, and weight decay to prevent overfitting.
- **Transfer Learning Adjustments:** We fine-tuned additional layers of the pre-trained models to better adapt them to the specific features and patterns of cattle disease images.

3.4 METHODOLOGY FOR DEVELOPING USER-FRIENDLY MOBILE APPLICATION CAPABLE OF DIAGNOSING FMD AND LSD.

This section presents the methodology used to develop a lightweight and practical mobile application that integrates computer vision functionalities for the diagnosis of Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) in cattle. The application was designed with simplicity and usability in mind, particularly for rural farmers with limited digital literacy.

3.4.1 System Requirements

Hardware Requirements

- Laptop with a high-performance processor
- Sufficient RAM (8 GB or more) for smooth development and testing

Software Requirements

- Android Studio (Integrated Development Environment)
- Android Emulator for virtual device testing
- Java Development Kit (JDK)
- Kotlin and Java dependencies for app development
- TensorFlow Lite or ONNX for model integration

3.4.2 Mobile Application Design and Features

The application was developed with two main screens:

a) Main Diagnosis Screen

This screen served as the central hub for image input and disease diagnosis. It comprised the following modules:

- Camera Capture Module: Enabled users to take live photos of affected cattle directly within the app.
- Gallery Upload Module: Allowed users to upload existing images of cattle from the phone's storage.

- **Diagnosis Button:** Triggered the integrated deep learning model to analyze the image and return a diagnosis (FMD, LSD, or Healthy).
- **Result Display Area:** Presented the model's diagnosis in a simple and interpretable format.

b) Support & Information Screen

This secondary screen offered support and disease-related resources, including:

- **Q&A Module:** Contained frequently asked questions about cattle diseases, symptoms, and preventive measures.

3.4.3 Development Approach

The mobile application was developed using Kotlin as the primary programming language within Android Studio. The trained deep learning model was converted to a mobile-compatible format (TensorFlow Lite) and integrated into the app to allow offline diagnosis. User interface elements were kept minimalistic and accessible to cater to both literate and semi-literate farmers.

3.4.4 Mobile Development Tools

Android Studio and Kotlin: Used as the primary development environment for building the mobile application, providing a robust and flexible platform for designing a user-friendly interface.

TensorFlow Lite: Used to convert and optimize the trained deep learning model, making it lightweight and efficient for on-device predictions.

SQLite: Served as the local database for storing user diagnosis records securely on the device.

3.4.4.1 Implementation Steps

The model integration process was executed in several key steps:

Step 1: Preparing the Trained Model for Deployment

The deep learning model was first converted into the TensorFlow Lite format. This step optimized the model for mobile deployment by reducing its size and improving inference speed on low-resource devices.

Step 2: Configuring the Android Project with TensorFlow Lite

TensorFlow Lite support was integrated into the Android project by adding the required dependency in the build.gradle file. The .tflite model file was placed in the assets directory of the app. Within Kotlin, the model was initialized using TensorFlow Lite's Interpreter class, enabling real-time predictions.

Step 3: Image Preprocessing

Images captured through the camera or selected from the gallery were preprocessed to match the input requirements of the model. This included resizing, normalization, and converting the image into a tensor format. This functionality was implemented using Kotlin-based helper functions.

Step 4: Model Inference and Disease Diagnosis

Once the image was preprocessed, it was passed to the TensorFlow Lite interpreter. The model then generated predictions based on the image data, providing the probability scores for disease categories. The output was interpreted and displayed as results such as "Healthy," "FMD Detected," or "LSD Detected."

Step 5: User Interface Design

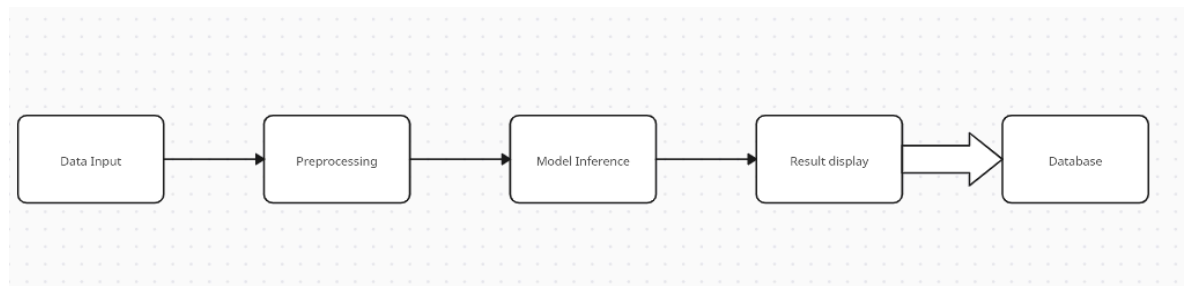
A minimalistic and intuitive interface was developed to facilitate easy navigation. Users could upload or capture images, and a "Diagnose" button was provided to initiate inference. Diagnosis results were displayed clearly, with visual cues and actionable feedback.

Step 6: Displaying Results and Accessing Vet Support

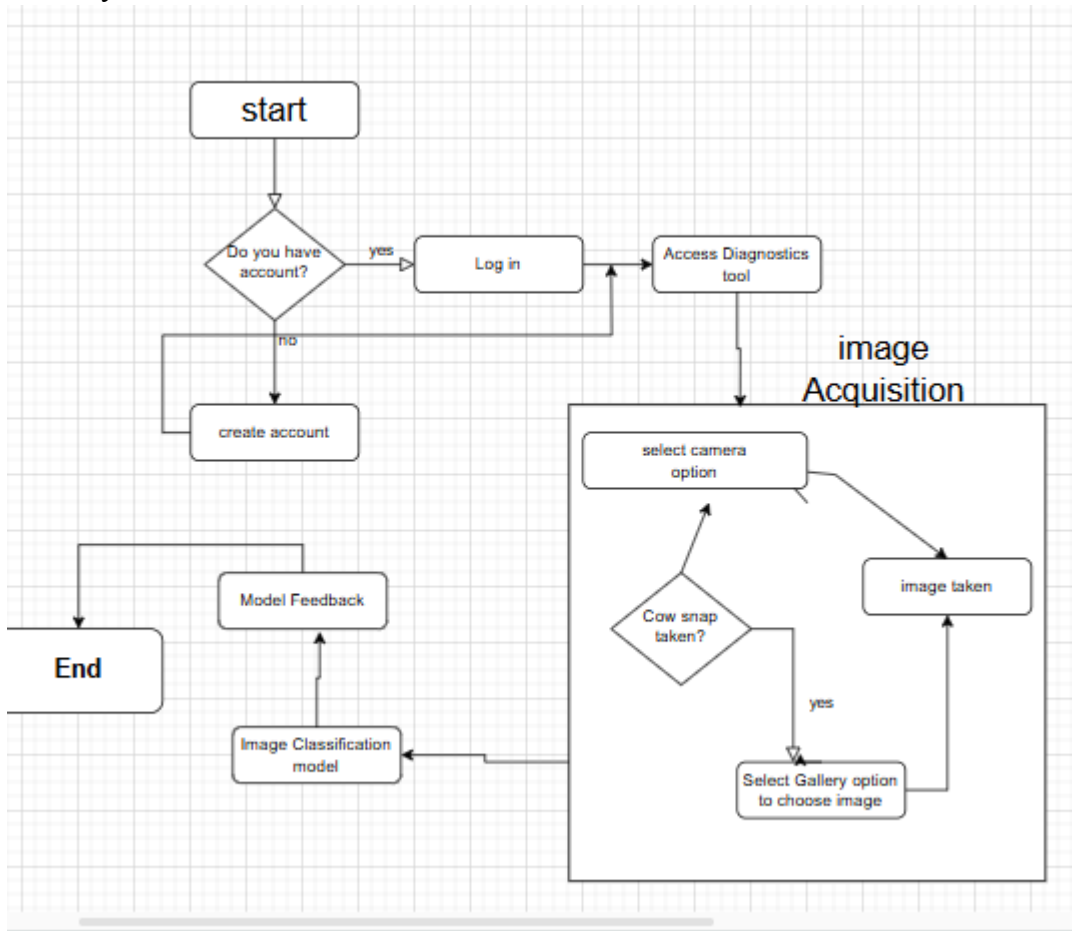
Diagnosis results were presented alongside probability scores to indicate the model's confidence level. In addition to viewing the results, users had access to a dedicated module within the app for locating nearby veterinary doctors. This allowed farmers to search for professional veterinary assistance if needed.

3.4.4.2 System Block Diagram for Data Flow

The following block diagram illustrates the primary data flow within the application system:



3.5.4 System Flow chart



3.5 METHODOLOGY FOR VALIDATING AND TESTING MOBILE APPLICATION AND COMPUTER VISION MODEL.

3.5.1 Model Validation

The computer vision model was evaluated to determine its performance in diagnosing Foot-and-Mouth Disease (FMD) and Lumpy Skin Disease (LSD) from cattle images.

The dataset had already been divided into training, validation, and test sets during the model development phase. Therefore, testing was carried out using

the test set, which consisted of previously unseen images.

The model's performance was assessed using various metrics including:

- Accuracy: Measuring the proportion of correct predictions.
- Precision: Indicating the correctness of positive predictions.
- Recall (Sensitivity): Measuring the model's ability to detect actual cases.
- F1-Score: A balance between precision and recall.
- ROC-AUC (Receiver Operating Characteristic - Area Under Curve): To evaluate the model's overall classification ability.

These metrics provided a comprehensive understanding of the model's effectiveness in real-world conditions, especially in distinguishing between healthy cattle and those affected by FMD and LSD.

3.5.2 Mobile Application Testing

Testing of the mobile application focused on both functional and non-functional requirements.

Functional testing was conducted to ensure that all core features of the app were working correctly. These included:

- Image upload functionality.
- Disease diagnosis display.

Non-functional testing covered performance, usability, and responsiveness.

User Acceptance Testing (UAT) was performed with a small group of farmers and veterinary officers who interacted with the application and provided feedback on:

- Ease of navigation.
- Speed of diagnosis.
- Reliability and stability of the application under normal usage.

Additionally, cross-device testing was performed on different Android devices to ensure compatibility and consistent user experience across varying hardware specifications.

3.5.3 Integration and End-to-End Testing

End-to-end testing was conducted to validate the integration between the computer vision model and the mobile application.

This process ensured that:

- Images captured or uploaded via the app were correctly processed by the model.
- Diagnosis results were accurately displayed to the users.

Field testing was also performed in a real environment with selected farms to verify system behavior under practical conditions.

3.5.4 Summary of Testing and Validation Approach

This table summarizes the testing techniques adopted for validating both the computer vision model and the mobile application.

Component	Testing Technique	Purpose
Computer Vision Model	Test Set Evaluation, Metrics Assessment	To measure accuracy, precision, recall, F1-score, and AUC

Mobile Application	User Acceptance Testing (UAT), Functional and Non-Functional Testing	To assess usability, functionality, stability, and responsiveness
End-to-End System	Integration Testing, Field Testing	To ensure seamless operation between the model and the application

4 Budget

Creating a proposed budget for this mobile application project involved careful consideration of all necessary components, resources, and services required throughout the development lifecycle. This includes software tools, hardware components, testing, personnel, and miscellaneous costs. The budget ensures that the project remains cost-effective while delivering a high-quality solution for early cattle disease diagnosis and veterinary support.

The table below presents the estimated budget breakdown:

ITEM	COST	
Softwares	200000	
Image Data	300000	
Cellular data	50000	
RAM(16GB)	120000	
Transport	240000	
miscellaneous	60000	
Grand Total	970,000	

4.9 Work Plan

A Gantt chart is a project management tool that visually represents a project's timeline, showing tasks, their duration, and when they will be completed. It helps in organizing and tracking the progress of each task, identifying task dependencies, and ensuring timely delivery of the project milestones.

Below is the Gantt chart showing the development phases of the mobile application for early cattle disease detection and veterinary support:

WORK PLAN.

NO	ACTIVITIES	August	September	October	November	December	January	February	March	April
1	IDENTIFICATION OF PROJECT TITLE									
2	LITERATURE REVIEW									
3	PROPOSAL WRITING									
4	PROJECT PROPOSAL PRESENTATION									
5	COMPILATION OF NECESSARY DATA									
6	IMAGE VISUALISATION AND ANALYSIS									
7	MODEL DEVELOPMENT									
8	MODEL EVALUATION									
9	CONSULTATION									
10	FINAL YEAR PROJECT PRESENTATION									

Appendix

Below are the links to the;-

<https://colab.research.google.com/drive/1fDVZ1jeHx4Hg8SdOwUiQnZrICakL6TeW?usp=sharing> - Notebook used to train the computer vision model.

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