A PRELIMINARY PROJECT REPORT ON

PREDICTING LUMPY SKIN DISEASE IN CATTLES THROUGH MACHINE LEARNING

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY,
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SAVITRIBAI PHULE PUNE UNIVERSITY

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CERTIFICATE

This is to certify that the project report entitled
"**PREDICTING LUMPY SKIN DISEASE IN CATTLES THROUGH MACHINE LEARNING**"

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ABSTRACT

Lumpy Skin Disease (LSD) is a concerning and contagious viral disease affecting cattle, distinguished by symptoms like fever, reduced milk production, and infertility, leading to major financial repercussions. To predict LSD infection in cattle with high precision, we aim to deploy machine learning. To achieve an F1 score of 98% and makethem the most effective in detecting infected cattle, approximately ten classifiers will be trained on disease data withRandom Forest and Light Gradient Boosted Machine (LGBM).

For evaluating an accurate prediction of LSD occurring due to environmental conditions, we will feed these features (raw images of cattle) into machine learning models. A machine learning model called the Convolutional Neural Network (CNN) and ANN will be used for predicting LSD in cattle through their visual data that is images. This model will provide a robust framework for predicting Lumpy Skin disease in cattle using machine learning.

Keywords: Lumpy Skin Disease (LSD), Random Forest, Light Gradient Boosted Machine, Artificial Neural Network (ANN), Forecasting, Disease Prediction.

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Abbreviations

ML – Machine Learning

CNN – Convolutional Neural Networks

ANN – Artificial Neural Networks

LSD – Lumpy Skin Disease

LGBM - Light Gradient Boosted Machine

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CHAPTER 1

INTRODUCTION

1.1 Background and Basics:

The pre-requisites which are needed to understand the entire project are:

1. Lumpy Skin Disease (LSD).
2. Convolutional Neural Networks (CNNs).

1.1.1 Lumpy Skin Disease:

LSD is a viral disease that affects cattle, caused by a virus from the Capripoxvirus genus. The disease causes nodules that are essentially lumps found in the skin, mucous membranes, and sometimes the internal organs.

It poses significant threats to cattle health, leading to economic losses by reducing milk and meat production, affecting hide quality, and causing reproductive issues like abortions and infertility. Transmission occurs through direct contact, contaminated environments, medical equipment, or via insect vectors. There is also potential for vertical transmission.

1.1.2 Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) are a specialized form of artificial intelligence (AI) model, particularly well-suited for image classification and object detection tasks. By processing images through multiple layers, CNNs can detect and learn distinctive features such as shapes, patterns, textures, and even complex, hierarchical relationships within the visual data. These unique capabilities make CNNs ideal for applications where subtle visual distinctions are key to accurate categorization or diagnosis, such as in medical imaging, facial recognition, and, as in this case, veterinary disease identification.

In this study, a CNN model has been employed to analyze cattle skin images to classify them into two categories: infected with Lumpy Skin Disease (LSD) and non-infected. LSD, a viral disease affecting cattle, leads to significant skin lesions, which the CNN can detect early on by learning to recognize specific patterns associated with these lesions. The ability of CNNs to automatically learn and detect these visual patterns enables the model to identify signs of LSD with high accuracy, often earlier than traditional methods. This early detection is crucial for initiating timely treatment and containment measures.

1.2 Literature Survey:

1.2.1 Title: Predicting and Analysing Lumpy Skin Disease using Ensemble of Machine Learning Models.

Publisher:

E. Chandralekha V. DeepJemin MT. Anitha Ravikumar S, IEEE (2023)

Methodology:

The paper explores the use of ensemble machine learning models to predict and analyze the spread of Lumpy Skin Disease (LSD) in cattle, focusing on the integration of geographical, climatic, and historical outbreak data.

1.2.2 Title: Lumpy Skin Disease Detector.

Publisher:

Vidur Sharma, Kushal Kanwar, IEEE (2023)

Methodology:

To automate the early detection of Lumpy Skin Disease (LSD) in cattle. This approach aims to improve disease management and reduce economic losses associated with manual inspections by leveraging image data for diagnosis.

1.2.3 Title: An Explainable Machine Learning Model For Lumpy Skin Disease Occurrence Detection.

Publisher:

Anuj Kumar Jain, Raj Gaurang Tiwari, Neha Ujjwal, IEEE (2022)

Methodology:

To predict the occurrence of Lumpy Skin Disease (LSD) in cattle and water buffalo based on climatic and geographical data. The Random Forest algorithm, which achieved the highest accuracy, is further explained using SHAP visualizations to enhance model interpretability.

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1.2.4 Title: Lumpy Skin Disease Detection Using Deep Learning.

Publisher:

Tejaswani Velugoti, Suresh Babu Dasari, Shaik Sheeba Sultana, IEEE (2023)

Methodology:

In order to detect lumpy skin illness, we suggested a convolution neural network model in this study, leveraging the powerful DenseNet169 architecture. The implementation begins by initializing the base model with pre- trained weights. The input shape is set to (256, 256, 3), aligning with the dimensions of our dataset images.

1.2.5 Title: Machine Learning Diagnosis of Lumpy Skin Disease in Cattle Herds.

Publisher:

Nimmagadda Kumar Krishna, Ruth Moly Benjamin, Nimmagadda Tejaswi, IEEE (2023)

Methodology:

One of the most widely used supervised learning techniques for both classification and regression issues is support vector machine, or SVM. SVM has the benefit of efficiently handling high-dimensional data, which is important when examining the complex datasets that are frequently involved in the detection of disease in cow herds.

1.3 Project Undertaken:

1.3.1 Problem Definition

This project aims to develop a machine learning model that accurately predicts Lumpy Skin Disease (LSD) outbreaks using visual data with the help of Convolutional Neural Networks (CNN) and Artifical Neural Networks (ANN), for better identification of disease by raw images of cattle.

1.3.2 Scope Statement

The project aims to develop a CNN-based model for accurately detecting Lumpy Skin Disease (LSD) incattle using image data.

The model can be adapted and expanded to detect other skin diseases in cattle or livestock, improvingoverall animal health management.

This project can serve as a foundation for creating automated veterinary tools using AI for remote and on-site disease detection.

1.4 Organization of the Project Report

The project report is divided into four sections:

Chapter 1 : Explains the structure of the overall project. It explains the prerequisites i.e., the background and basics. The problem statement and the complete scope of the project are also explained in this chapter.

Chapter 2 : Project planning and management with software requirement specification (SRS). It covers functional, non-functional, and external interface requirements. The cost efforts estimate, and process modeling are explained in this chapter as well.

Chapter 3 : Visually demonstrates the functionalities of the project. The IDEA matrix and mathematical model are used to show the competency of the application. The feasibility analysis and necessary UML diagrams are also included to better understand the assignment.

Chapter 4 : Focuses on testing to be performed on the modules and includes test cases for Unittesting, Integration testing, and Acceptance testing. The references, operational and implementational understating of the project is also covered in this section.

Chapter 2

SOFTWARE REQUIREMENTS AND SPECIFICATION

2.1 Introduction

This chapter covers the project planning and management details. It also covers Software Requirement Specification. SRS is considered as the base for the effort estimations and project scheduling.

2.2 Software Requirement Specification (SRS)

2.2.1 System Overview:

Develop a machine learning system to predict the likelihood of Lumpy Skin Disease (LSD) in cattle for early detection and intervention.

1. **Data Collection**: Gather veterinary records, visual data, and cattle health records.

2. **Data Preprocessing**: Clean and prepare data, engineer features, and handle missing values.

3. **Model Selection**: Use supervised learning models like Random Forest, Logistic Regression, CNN, and ANN for binary classification (infected vs. not infected).
4. **Model Training**: Train models on historical data, tune hyperparameters, and split data into training/testing sets.

5. **Evaluation Metrics**: Measure performance using accuracy, precision, recall, F1-score, and ROC-AUC curve.

6. **Deployment**: Integrate the model into a cloud-based system and mobile application for real-time predictions and alerts.
7. **Continuous Learning**: Retrain periodically to improve predictions as new data becomes available.

2.2.2 Functional Requirements:

Main flow:

User will select Opinion analysis from the interface. User will input an image.

Model shall feature select and analyze the input.

Model will give the output whether the identification is Positive or Negative.

1. **Data Input**
   - Farmers/veterinarians input cattle health data (visual input) through dataset.
2. **Data Preprocessing**
   - The system cleans the input data, fills missing values, and applies necessary transformations (e.g., scaling, encoding).
3. **Prediction Request**
   - The dataset forwards the preprocessed data to the machine learning model for prediction.
4. **Model Prediction**
   - The model processes the input data and generates a prediction (probability of infection).
5. **Results Display**
   - The system displays the prediction result to the user.
6. **Action**
   - Based on the prediction, farmers/veterinarians take preventive or treatment measures (e.g., vaccination, quarantine).
7. **Model Retraining**
   - Periodically, the system retrains the model using new data to improve accuracy.

Exceptional Flow:

If the image inputted is in a format other than jpg-jpeg-png, the model won't process the image.

1. **Data Inconsistency**

- **Issue**: Input data contains significant missing or invalid values.
- **Handling**: The system prompts the user to correct the data or auto-fills missing values based on past patterns or averages.

2. **Network/Server Failure**

- **Issue**: Connection issues or server downtime during data submission or prediction.
- **Handling**: The system saves the input data locally and retries once the connection is restored or notifies the user to try again later.

3. **Model Failure**

- **Issue**: The model fails to generate a valid prediction (e.g., due to corrupted data).
- **Handling**: The system falls back to a simpler rule-based system or triggers a warning to seek manual veterinary intervention.

4. **Outlier Detection**

- **Issue**: Input data appears to be an outlier (e.g., extremely unusual symptoms or location data).
- **Handling**: The system flags the case for manual review by a veterinarian.

5. **Incorrect Predictions**

- **Issue**: The model gives false positives/negatives repeatedly.
- **Handling**: The system retrains the model more frequently and adjusts thresholds to minimize incorrect classifications.

2.2.3 Deployment Requirements:

Operating System (Windows)

Tools: Python3 (with Libraries), Jupyter Notebook

Editor: Jupyter Notebook

2.2.4 External hardware requirements:

Minimum intel i5 Processor

Minimum 4GB RAM

2.3 Project Process Modeling

1. Project Initiation

Define the problem and gather requirements from stakeholders (farmers, veterinarians).

2. Data Collection

Collect veterinary records, environmental, and geographical data via IoT devices, databases, and reports.

3. Data Preprocessing

Clean the data, create features, and split them into training

4. Model Development

Select and train machine learning models (e.g., RandomForest).
Tune hyperparameters for optimal performance.

5. Model Evaluation

Measure performance using accuracy, precision, recall, and ROC-AUC.

6. Deployment

Deploy on a cloud-based platform with a mobile interface for real-time predictions.

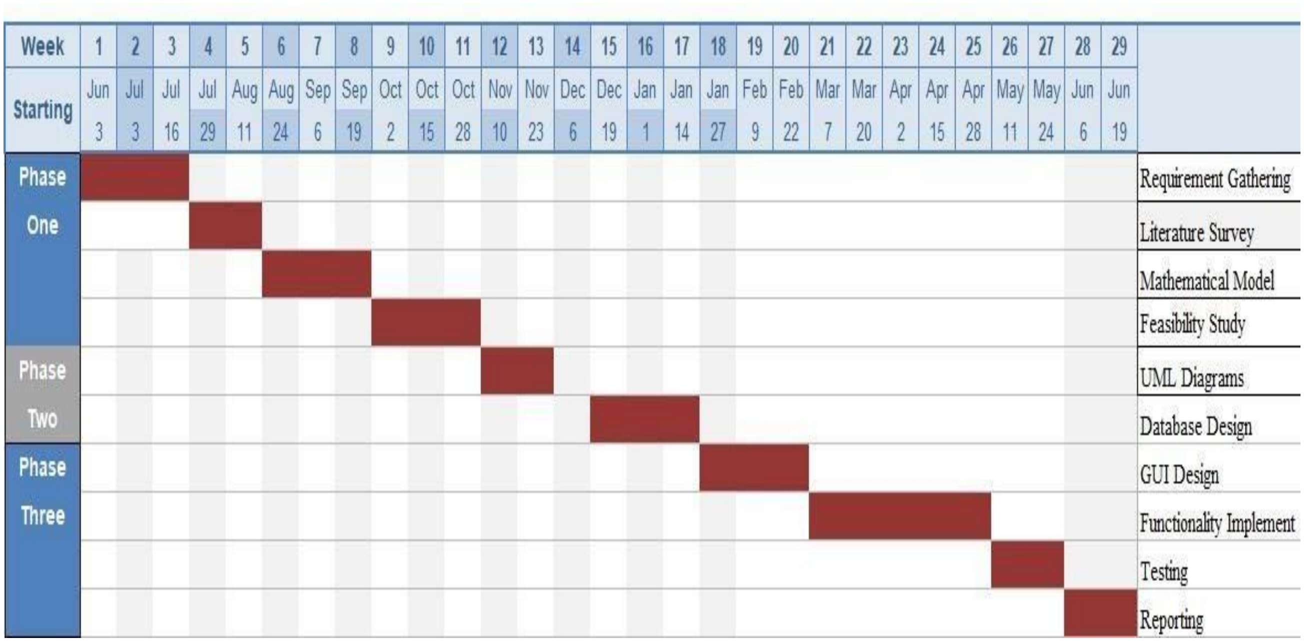
7. Monitoring and Maintenance

Continuously monitor performance, retrain models, and update the system.

8. Final Review

Gather user feedback for improvements and refine the system.

2.4 Project Scheduling:



CHAPTER 3

ANALYSIS AND DESIGN

3.1 Introduction

This chapter covers the analysis and design of the considered system.

3.2 IDEA Matrix:

I matrix

I	Deliverable	Parameter Affected
Increase	Increasing functionalities Increase the result accuracy	Reliability Accuracy
Input	Input image file.	Checking Efficiency
Impact	Analyses the features in the image. Checks whether the following image is clear or not. Classifies the disease prediction based on content	Accessibility
Innovation	Utilize real-time environmental and cattle health data integrated with machine learning models to predict Lumpy Skin Disease outbreaks.	Motivation Time
Ignore	Blurry Images Corrupted Images	Time Detection

E matrix

E	Deliverable	Parameter Affected
Eliminate	Noisy images. Blurry images.	Accuracy Performance
Educate	Educate project members and users of the project (Writers, Students, Teachers etc.)	Project members Stakeholders
Evaluate	Evaluate summary and concept map from document	Purpose

3.3 Mathematical Model

Considering S to be the closed system defined as,

S= {Ip, Op, Ac, Su, Ex, Fa}

Where,

Ip = Set of Inputs

Op = Set of Outputs

Ac = Set of Actions

Su = Success States

Ex = Exceptions

Fa = Failure States

Ip: Set of inputs =

A Where,

A = Image

Op: Set of outputs-Op1, Op2 Where,

Op1 =True Op2 = False

Su: Set of success = S1 Where,

S1 = Uploaded image is in correct format

Fa: Set of Failures = F1 F1 = Wrong input

3.4 Feasibility Analysis

NP Problem:

The NP problem is a set of problems whose solutions are hard to find but easy to verify and are solved by Non-Deterministic Machine in polynomial time.

NP-Hard Problem:

Any decision problem Pi is called NP-Hard if and only if every problem of NP (say P<subj) is reducible to Pi in polynomial time.

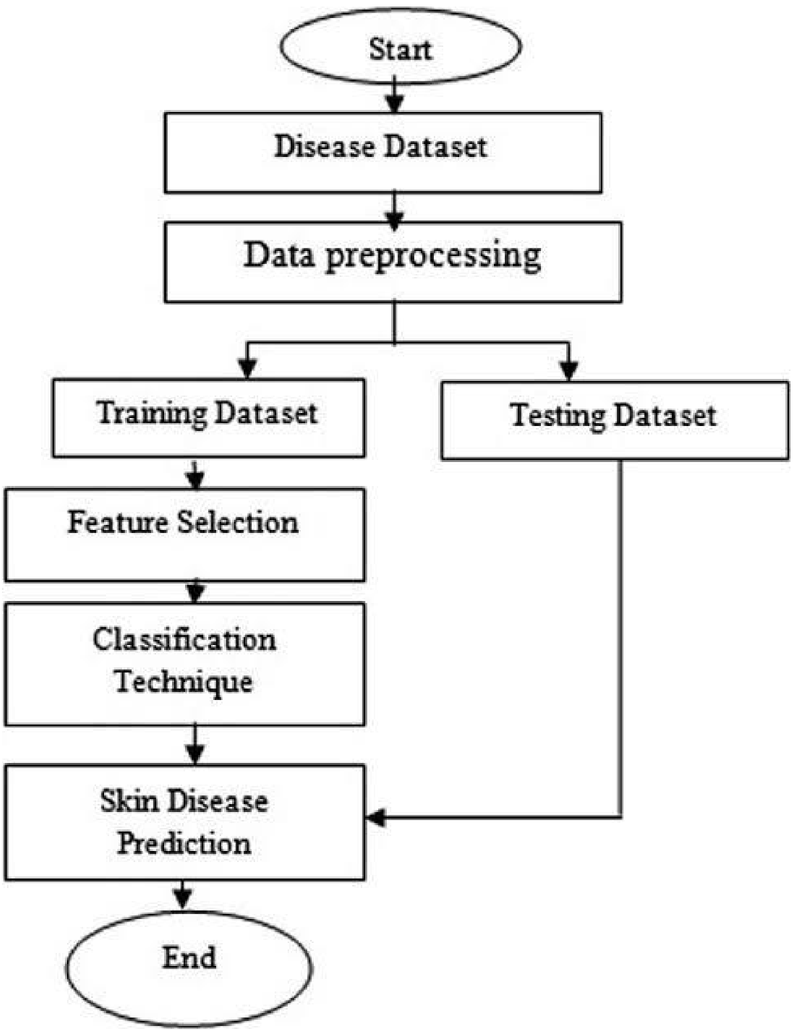
NP-Complete Problem:

Any problem is NP-Complete if it is a part of both NP and NP-Hard Problem.

3.5 Architecture Diagram :

An architecture diagram is a graphical representation of a set of concepts, that are part of an architecture, including their principles, elements, and components. It gives the overall structure of the application.

Figure 3.1: System Architecture

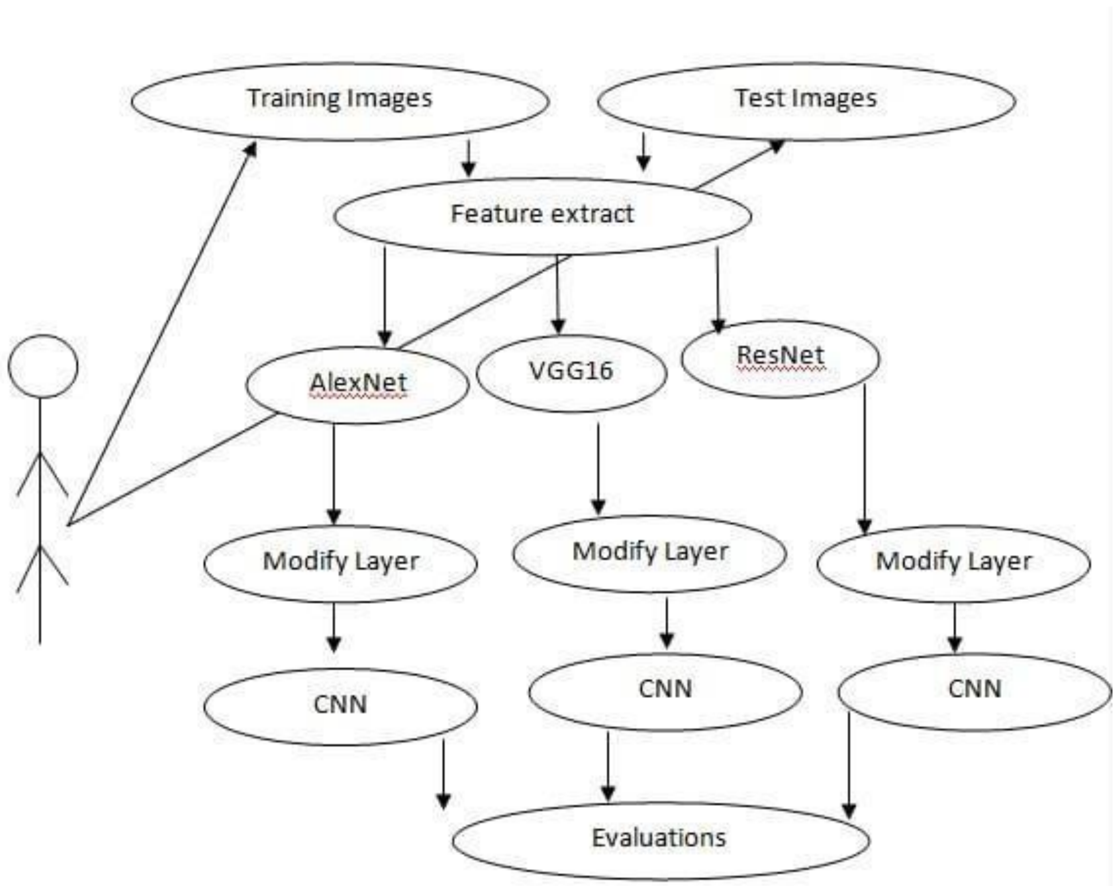


3.6 UML Diagrams:

3.6.1 Use Case Diagram:

This use case diagram is used to determine the flow of the system. The user and the server are the actors in this scenario. After the home page is loaded, the user selects one of the features of the application. after selection of the features, the system asks for the text to be performed the function upon. The system then processes the text and tokenizes it, to give the required output.

Figure 3.2: Use Case Diagram



3.6.2 Activity Diagram:

Activity diagram is essentially an advanced version of flow chart that modeling the flow from one activity to another activity. Activity Diagrams describe how activities are coordinated to provide a service which can be at different levels of abstraction. The following diagram shows the flow of the application, wherethe user can select one of the features and the corresponding functions are performed. And after the functions are performed the system stops.

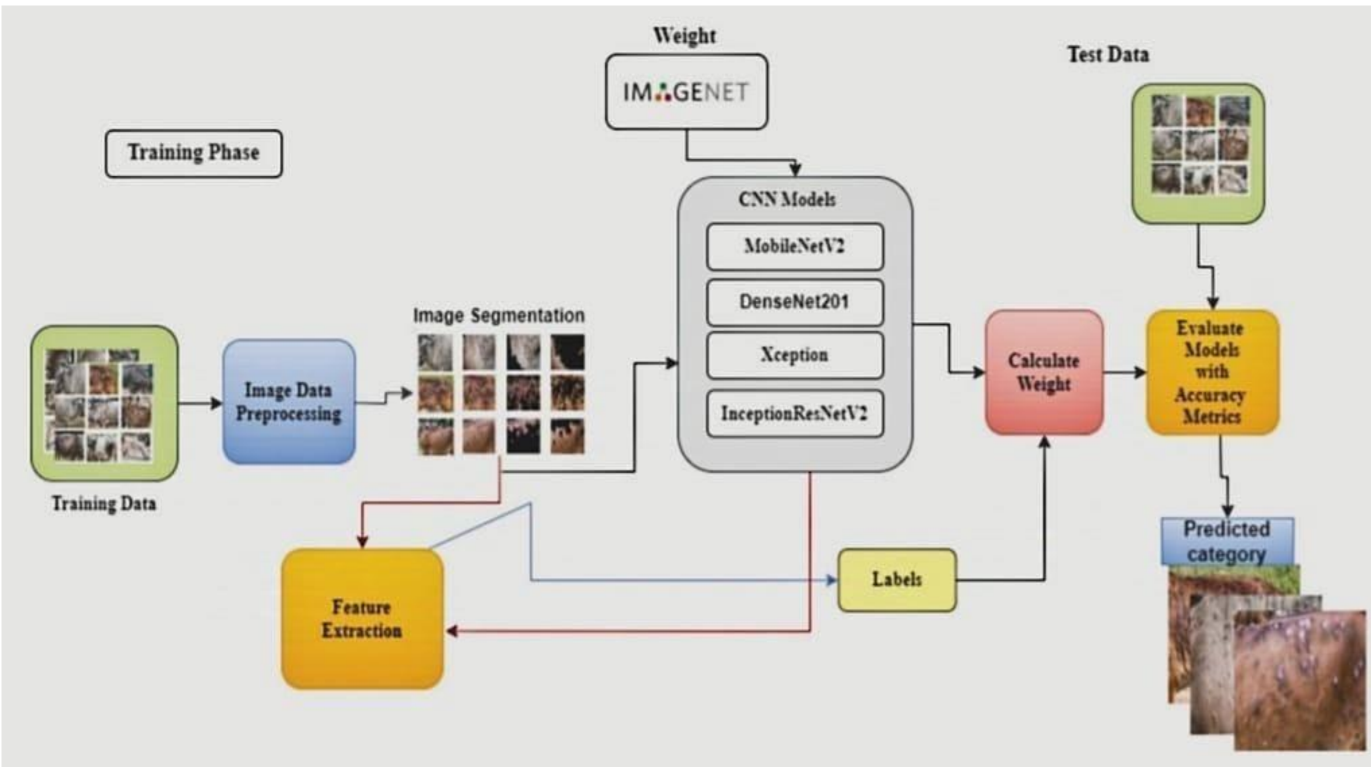
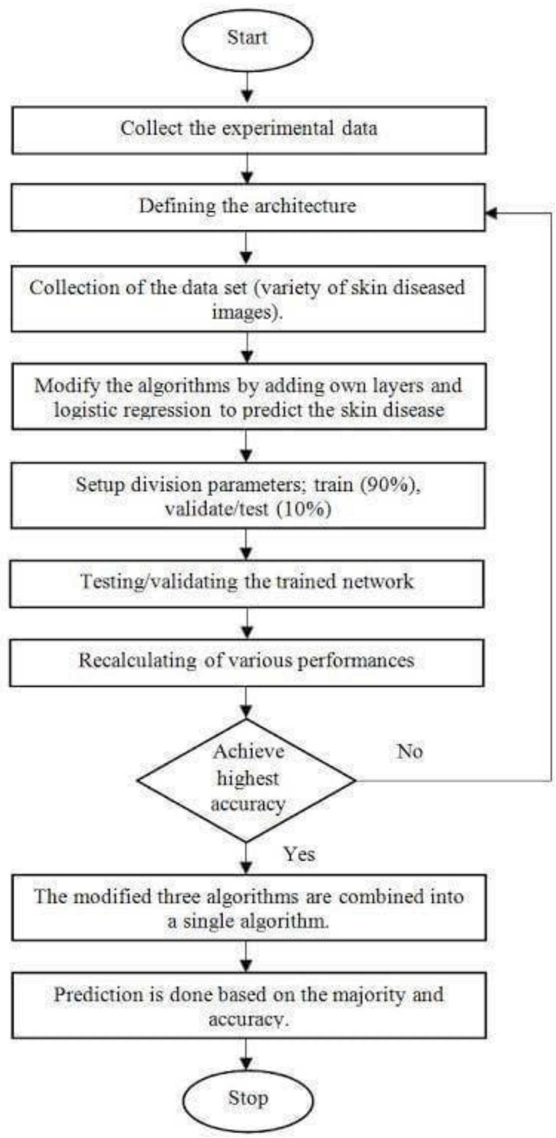


Figure 3.3: Activity Diagram

3.6.3 System Flow diagram

A flowchart is a method of showing how information flows through a system and how decisions are made to control events. Symbols are used to explain this. They are connected to each other to show what is happening to the data and where it is going. Again, we see the work shown in the picture here and we do the work on it.

Figure 3.4: System Flow



CHAPTER 4

IMPLEMENTATION CODING

4.1 Introduction

This chapter covers the role of various subsystems/modules/classes along with implementation details listing of the code for the major functionalities.

4.2 Operational Details

1. Data Collection Module

Functionality:

(i) Input Data: Farmers or veterinarians input cattle health data.

(ii) Data Validation: Thesystem validates the input data for completeness and correctness.

2. Data Preprocessing Module

Functionality:

(i) Data Cleaning: The system cleans the input data by removing duplicates and handlingmissing values.

(ii) Feature Engineering: Features are extracted and transformed, such as encoding categorical variables and normalizing numerical data.

3. Prediction Module

Functionality:

(i)Model Selection: The user can select from multiple machine learning models (e.g., Logistic Regression, Random Forest) for prediction.

(ii) Model Training: The selected model is trained on the training dataset to learn patterns associated with LSD.

(iii) Prediction: The trained model predicts the likelihood of LSDbased on new input data. (iv) Display Results: The system displays the prediction results (True/False).

4. Monitoring and Feedback Module

Functionality:

(i)Performance Monitoring: The system continuously monitors model performance usingreal-time data and feedback.

(ii) User Feedback: Farmers and veterinarians can provide feedback on predictions, which is recorded for future model improvements.

(iii) Model Retraining: The model is periodically retrained with new data to enhance accuracy and adapt to changing conditions.

4.3 Code Listing

Code 1

```
from keras.layers import Input, Lambda, Dense, Flatten
from keras.models import Model
from keras.applications.mobilenet_v2 import MobileNetV2
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing import image
from keras.preprocessing.image import
ImageDataGenerator from keras.models import Sequential
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
```

The provided code imports necessary libraries and functions for building a convolutional neural network (CNN) model using Keras. It utilizes pre-trained models like MobileNetV2 and VGG16 for image classification tasks, enabling efficient feature extraction. The code also includes functions for image preprocessing and data augmentation to enhance model performance during training.

Code 2

```
IMAGE_SIZE = [224, 224]
train_path = 'D:/CowLumpyDiseases/Dataset/TrainData/'
valid_path = 'D:/CowLumpyDiseases/Dataset/TestData/'
```

The provided code specifies the **image size** to be used for model input, setting it to 224x224 pixels, which is a common dimension for many CNN architectures. It also defines the **file paths** for training and validation datasets, pointing to directories that contain images of cows with and without Lumpy Skin Disease. This setup is essential for loading and processing images for training and evaluating the machine learning model.

Code 3

```
r =  model.fit(
  training_set,
  validation_data=test_set,
  epochs=5,
  steps_per_epoch=len(training_set),
  validation_steps=len(test_set)
)
```

model.fit(...): Trains the model on the training_set.

validation_data=test_set: Evaluates performance on unseen validation data.

epochs=5: The model iterates through the training data five times.

steps_per_epoch=len(training_set): Sets the number of training batches per epoch.

validation_steps=len(test_set): Sets the number of validation batches per epoch.

Code 4

```
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
```

plt.plot(r.history['accuracy'], label='train acc'): Plots the training accuracy from the model's training history.

plt.plot(r.history['val_accuracy'], label='val acc'): Plots the validation accuracy from the model's training history.

Code 5

```
from sklearn.metrics import classification report
print (classification_report(actual, predicted)
```

classification_report (actual, predicted): Generates a report that includes metrics such as precision, recall, F1-score, and support for each class based on the actual and predicted labels.

CHAPTER 5

TESTING

5.1 Selenium Testing

TEST ID	TEST CASE	TEST SCENARIO	TEST INPUT	EXPECTED OUTPUT	ACTUAL OUTPUT	TEST RESULT
1.	Detection of Lumpy Skin Disease	Check if the given image of cattle shows signs of lumpy skin disease	Image of cattle with lesions	Positive for lumpy skin disease	Positive for lumpy skin disease	Passed
2.	Healthy Cattle Detection	Check if the given image of cattle shows no signs of lumpy skin disease	Image of healthy cattle	Negative for lumpy skin disease	Negative for lumpy skin disease	Fail

5.2 Acceptance Testing

TEST ID	TEST CASE	TEST SCENARIO	TEST INPUT	EXPECTED OUTPUT	ACTUAL OUTPUT	TEST RESULT
1.	Disease Detection	Detect the presence of lumpy skin disease in cattle	Cattle Image	System successfully detects the disease	System successfully detected the disease	Passed
2.	Disease Detection	Detect the presence of lumpy skin disease in cattle	Cattle Image	System successfully detects the disease	System failed to detect the disease	Fail

CHAPTER 6

Discussion and Purpose of Project

6.1 Discussion

Machine learning has brought a paradigm shift in the prediction and management of livestock diseases like lumpy skin disease (LSD) in cattle. The process involves utilizing vast amounts of image data, coupled with sophisticated algorithms, to accurately detect and classify LSD. One of the key benefits of this approach is its ability to provide rapid and reliable diagnostics, which is crucial for timely intervention and treatment. Moreover, the continuous learning aspect of machine learning models means they can adapt and improve over time, enhancing their accuracy and efficiency. This technological advancement not only aids in better disease management but also significantly contributes to the overall health and productivity of cattle, thereby safeguarding the agricultural economy.

6.2 Purpose of Project

The primary aim of this project is to utilize machine learning technologies to predict lumpy skin disease (LSD) in cattle. By analyzing vast amounts of image data, our automated system can accurately identify the presence of LSD, facilitating timely and effective treatment interventions. This can significantly reduce the impact of the disease on cattle health and farmer livelihoods.

The implementation of this technology is expected to revolutionize veterinary diagnostics by providing a quick and reliable tool for disease detection. Machine learning algorithms, known for their adaptability, will continuously improve in accuracy as more data is processed, ensuring a robust and scalable solution to managing LSD. This project not only enhances animal health management but also contributes to the broader goal of a more sustainable agricultural sector.

In addition to immediate health benefits, the project underscores the transformative potential of artificial intelligence in traditional farming practices. By integrating advanced AI technologies, we can create more resilient agricultural systems capable of responding swiftly to emerging health threats. This proactive approach not only protects the economic interests of farmers but also promotes animal welfare on a larger scale.

CHAPTER 7

CONCLUSION

In conclusion, harnessing machine learning predict and manage lumpy skin disease (LSD) in cattle marks a significant advancement in veterinary science and animal husbandry. The implementation of an automated system capable of analyzing vast datasets and accurately diagnosing LSD is transformative, offering timely and reliable detection that is crucial for effective disease management. The use of image classification algorithms notonly improves the precision of diagnostics but also ensures that interventions can be implemented swiftly, thereby impact of LSD on cattle health and farmer livelihoods.

This project underscores the immense potential of artificial intelligence in revolutionizing traditional farming practices. Machine learning models, with their ability to continuously learn and improve, offer a scalable and adaptable solution to the challenges posed by LSD. As more data is collected and processed, the models become increasingly accurate, enhancing their efficacy in identifying and managing the disease. This adaptability is particularly valuable in the agricultural sector, where rapid and reliable disease detection can make a significant difference in maintaining the health and productivity of livestock.

Moreover, the integration of AI technologies into animal health management systems represents a broader shift to wards more sustainable and resilient agricultural practices. By harnessing the power of machine learning, we can build better relationships and create more jobs that protect the agricultural industry and support animal husbandry. The program not only addresses the urgent need for disease control, but also supports the long-term goal of developing sustainable and profitable agriculture.

The success of this project will demonstrate the transformative power of AI and pave the way for future innovations in this field.

CHAPTER 8

FUTURE WORK

- **Enhanced Data Collection**:

Expand the dataset by incorporating more diverse cattle breeds, geographic locations, and varying environmental conditions to improve model generalization.

Utilize IoT sensors for real-time monitoring of cattle health metrics and environmental factors.

- **Model Improvement**:

Explore advanced machine learning techniques, such as deep learning models (CNNs, RNNs) and ensemble methods, to enhance prediction accuracy.

Implement transfer learning with pre-trained models to leverage existing knowledge and improve performance on limited datasets.

Incorporate climate data (e.g., temperature, humidity) to understand their impact on disease spread and susceptibility.

- **User-Friendly Interface Development**:

Develop a mobile application for farmers and veterinarians, allowing them to easily input data, receive predictions, and access disease management resources.

Integrate a dashboard for monitoring trends in disease outbreaks and predictions across different regions.

Utilize machine learning algorithms for anomaly detection to identify sudden spikes in infection rates.

- **Continuous Learning and Model Updating**:

Establish a feedback loop for continuous model improvement based on user input and new data, ensuring the model adapts to changing patterns.

Periodically retrain the model with updated datasets to maintain accuracy over time.

- **Collaboration with Veterinary Services**:

Collaborate with veterinary professionals to validate predictions and refine disease management strategies based on the model's insights.

Conduct training sessions for farmers and veterinarians on using the system effectively.

CHAPTER 9

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