

Early Disease Detection in Livestock Using Image Processing Techniques

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Abstract - Early detection of diseases in livestock is critical for ensuring animal health, maintaining productivity, and minimizing financial losses. This study aimed at the development of an image processing-based approach embedded into a Django web application for the early diagnosis of cattle disease. It is a user-friendly interface through which users upload their livestock photos and the trained model undertakes processing on these images and disease prediction. It returns disease name, confidence percentage, treatment, and prevention suggestions. This proposed system is to help farmers and veterinarians to take an informed and timely decision.

Keywords- Livestock, Disease Detection, Django Web Application Image Processing, Cattle Health, Early Diagnosis.

I. INTRODUCTION

Livestock is essential to the agriculture and dairy sectors, so there is an increasing demand for real-time and accurate health monitoring, which the current study aims to achieve through this research paper. Both cattle and other farm animals commonly develop diseases that may go unnoticed in early stages, resulting in less productive animals, expensive veterinary costs or even death of the livestock. Here we present a solution that utilizes cutting-edge image processing algorithms towards the goal of disease detection in livestock. The proposed system can analyse visual data and identify abnormalities from the physical appearance and behaviour of animals using computer vision and machine learning algorithms. By doing this, farmers and livestock managers can receive thorough and immediate insights, to act quickly and minimize the risk of disease spread. Ultimately, the goal is to enhance animal welfare, improve farm productivity, and contribute to sustainable and efficient livestock management.

II. LITERATURE REVIEW

Research into disease monitoring in livestock has emerged as a priority given its implications for animal welfare, productivity and food security. In most cases, a veterinarian first examines the livestock, and then makes a diagnosis of the

disease based on the physical examinations. These methods are often slow and costly with great chances of experiencing delays. By attempting to determine the presence of a disease by analysing images, automation of processes through the combination of image processing and machine learning offers a quicker alternative. With the aid of techniques such as computer vision, convolutional neural networks (CNN), and other computer vision algorithms, researchers have tried to capture the simplest external features on animals which may act as an indicator to internal physiological changes. These advances have been directed at enabling a time when changes are needed concerning the health of the animals to be put in place as fast as possible, and at the same time, improving the speed and accuracy in which a diagnosis is made. Additionally, putting such technologies on web-based interfaces helps enhance the usability of the technologies in practical farming.

Integration of modern technology has changed the whole concept of livestock monitoring. [1] New technologies are already being used in livestock health monitoring through image analysis in different countries. The application of sophisticated artificial intelligence and image processing techniques has made it possible to use non-invasive methods for monitoring livestock health. Nurses further stated that with regard to their duties, they noticed signs of disease through altered skin texture, posture, and visible lesions. These types of studies underscore the need to teach computer models with adequate datasets of cattle images to enable the model to recognize patterns pertaining to specific diseases. This approach enables time efficiency, timely action to reduce disease spread, and loss optimization. The idea of using basic cameras with intelligent software programs is particularly useful in peripheral regions with low veterinary staffing. All of these complement the long term proposition of fostering modern farming practices, which is important in this research.

The identification of health problems in animals has recently changed for the better with the introduction of thermal imaging, which is less stress-inducing while more task-

effective. With less manual labour, special cameras were employed to study the animal's body heat patterns instead of using tags or manual checks. Animal husbandry has an impact on the economies of most developing countries, but fast disease diagnosis remains a major challenge. [2] To tackle this issue, researchers have looked into combining AI with image processing to improve the accuracy and speed of identifying diseases in cattle.

A research group developed a system to diagnose diseases that uses smartphone camera images to examine visible symptoms and adds extra symptom information collected through user interfaces with an expert system. [3] The team identified visual signs using convolutional neural networks (CNNs) and then combined these with the diagnosed data. This comprehensive approach allowed for quicker diagnosis, and the researchers demonstrated how heat maps and object detection could help identify unusual temperature changes. This has benefits for zoos and wildlife parks where animals are difficult and dangerous to handle. The system depends on thermal images introduction of thermal imaging, which is less stress-inducing while more task-effective. With less manual labour, special cameras were employed to study the animal's body heat patterns instead of using tags or manual checks.

Delayed incapacitation in cattle can lead to health and economic repercussions to farmers thus, it becomes very crucial to detect and solve these issues promptly. [4] In their latest research, scientists investigated the possible assistance of technology through automation of lameness recognition using image processing and deep learning techniques. They analyzed the posture photographs of the cattle and angles of their joints to detect stances and movements that were outside the normal range. Rather than depending on direct supervision, their approach enables automatic detection of problems. It is less stressful for the cattle and provides a more direct method for farmers to supervise the health of their cattle. This procedure is particularly beneficial in diagnosing diseases in cattle, who live in areas with restricted veterinary assistance. This study illustrates the ability of AI-based resources to revolutionize animal health care management and provide simple and effective aid to farmers.

III. METHODOLOGY

Thus this project aims to provide a methodical solution for early detection of cattle diseases utilizing image processing techniques. Django for the back end and HTML, CSS, JavaScript for the front end. At the core of the system is an image classification neural model accepting images of cattle and categorising them into diseases based on the visual signs. The system accepts images from users, who then provide a sample image for prediction, using a Convolutional Neural Network (CNN), and return the prediction with disease name, confidence, and health advice. [5] With the aim of enabling cattle raisers to perform health checks comfortably and with efficiency.

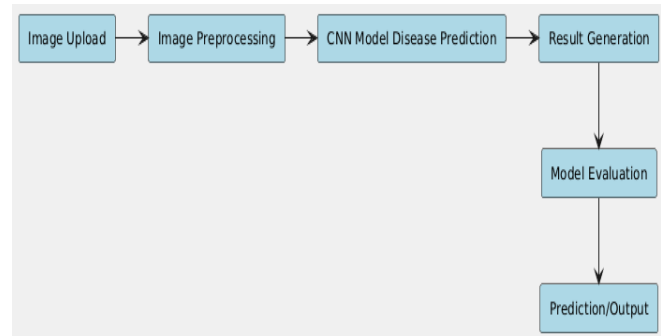


Figure 1: Workflow of the Implementation

A. Image Dataset Collection

A dataset of images of animals infected with diverse diseases was collected to develop the model for disease identification. These images are organized in folders, which are named by particular diseases, including Foot and Mouth Disease, Lumpy Skin Disease, Mastitis, etc. Images were taken or sourced under varying light, background, and cattle-breed conditions. The images were then labelled with the specific disease they represented, thus creating a structured dataset which is crucial for the proper training of a model.

B. Pre-processing and Data Preparation

Prior to the training process, all the pictures in the dataset were scaled to a 224x224 pixel size and underwent pre-processing procedures.[6]These procedures were comprised of normalizing the picture files and then data augmentation to increase the generalization of the model and spectator of the dataset. The dataset underwent a split into two sets (80% training and 20% validation) to fairly assess the model's performance on unseen data.

C. Model Training Using Transfer Learning

This system is based on MobileNetV2, a small CNN model that was pre-trained on a large image dataset (ImageNet) before being fine-tuned for the purpose of cattle disease classification. The last layer of the classification network was modified to correspond with the disease classes in the dataset. [7] The process of training included freezing the base layers to start with, and subsequently tuning the deeper layers for more specific accuracy. The model was trained using Adam optimizer with categorical cross-entropy loss for several epochs. Accuracy and loss metrics were used to monitor performance during training.

D. Model Evaluation and Accuracy Monitoring

The model was evaluated on validation by how correctly it identified diseases. During the training, some metrics like accuracy and loss values were recorded to see if the model is learning or not. [8] These metrics indicated in a broader sense how well the model could generalize to new, unseen images. Following the initial training, the model's predictions were

compared to existing known disease categories by hand to ensure that it was working effectively. Future scope of improvement includes increasing the dataset and improving the model through further training to make sure the system can be used accurately and reliably in the real world.

E. Visual Data Analysis and Results Overview

The disease detection system proposed is able to seek the results in the form of graphs and charts to show statistics including classification accuracy, the performance of the model, and about how many animals have been detected from the various diseases. [9] These numbers reflect both the efficacy of the system for anomaly detection and assist us comparing different machine learning models used during the project. [10] It allows nuanced key findings to be bite-sized and actionable to technical and non-technical stakeholders alike, enabling understanding and decision making in livestock health management.

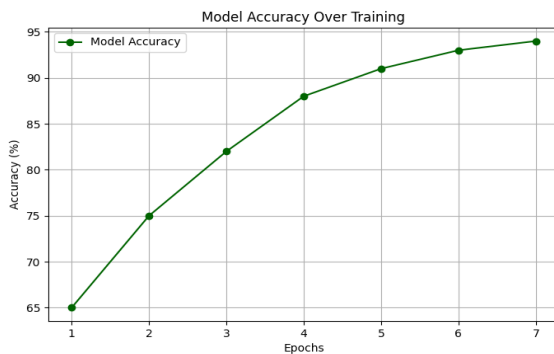


Figure 2. Model Training Accuracy

This line chart visualizes the improvement in classification accuracy of the livestock disease detection model across training epochs, indicating steady performance gains with increased training iterations.

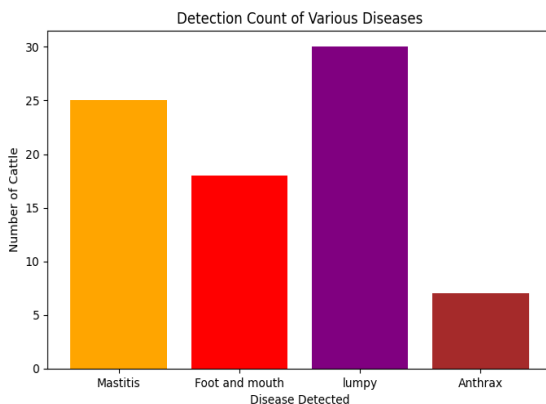


Figure 3. Detection Count of Various Diseases in Livestock.

This bar graph illustrates the number of cattle diagnosed with specific diseases, demonstrating the distribution of detected cases among Mastitis, Foot and Mouth Disease, Lumpy Skin Disease, and Anthrax.

IV. MODEL DEVELOPMENT PROCESS

Initial processing of the cattle disease detection model started with collecting a wide array of cattle images with various diseases. Numbers were assigned to the disease categories through label encoding, and then the data was prepared for input to model. Based on these metrics, the CNN architecture selected was MobileNetV2; as this model provides a relatively quick real-time overview whilst maintaining a good model performance. The prepared dataset is trained using standard training parameters. At the end of the training, the model was saved when it performed accuracy satisfactory and was incorporated in the web app to classify new images and give disease prediction values and treatment suggestions.

1. Import Required Libraries and Packages

```
import os
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Dropout
from tensorflow.keras.models import Model
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
```

2. Load and Prepare Image Dataset

```
# Data augmentation for training
train_datagen = ImageDataGenerator(
    preprocessing_function=preprocess_input,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest',
    validation_split=0.2
)

# Load training data
train_generator = train_datagen.flow_from_directory(
    dataset_path,
    target_size=(224, 224),
    batch_size=batch_size,
    class_mode='categorical',
    subset='training',
    shuffle=True
)

# Load validation data
validation_generator = train_datagen.flow_from_directory(
    dataset_path,
    target_size=(224, 224),
    batch_size=batch_size,
    class_mode='categorical',
    subset='validation',
    shuffle=False
)

# Get the number of classes
num_classes = len(train_generator.class_indices)
print(f"Number of classes: {num_classes}")
print(f"Class mapping: {train_generator.class_indices}")
```

3. Select CNN Architecture (MobileNetV2) and Customize Layers

```
# Load the MobileNetV2 model without the top classification layer
base_model = MobileNetV2(
    weights='imagenet',
    include_top=False,
    input_shape=(224, 224, 3)
)

# Freeze the base model layers
base_model.trainable = False

# Add custom layers on top of MobileNetV2
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.2)(x)
predictions = Dense(num_classes, activation='softmax')(x)

# Create the final model
model = Model(inputs=base_model.input, outputs=predictions)
```

V. RESULT

The cattle disease detection model trained and integrated into the web app, the website was able to determine diseases based on the uploaded image by the user. When you uploaded an image, the model read it and showed the predicted disease name and the confidence score, which indicated how much reliable the model was on the prediction. The system also generated a short disease description, treatment recommendations, and preventive recommendations, making it a practical guide for the users. It was validated, and the model was yielding a very good amount of correct predictions in well-lit and clear images. The user interface was checked whether it worked properly and was able to show results without delay. As a result, the detection system showed promise as a beneficial tool for farmers and livestock owners to detect diseases early on and act opportunely thereby minimizing health risks, reducing treatment costs, and improving overall herd productivity and welfare.

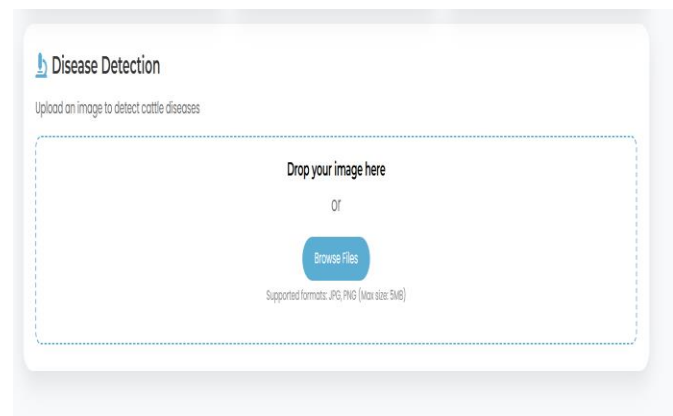


Figure 4. UI of Disease prediction

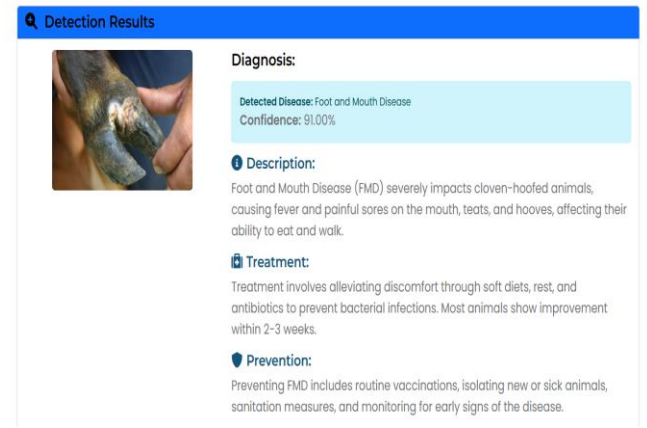


Figure 5. Output of Disease Detection

VI. CONCLUSION

This work provides an efficient method for early identification of disease in animals using image processing techniques. Using Convolutional Neural Network (CNN) for the MobileNetV2 architecture, the system can successfully analyse images of the cattle and detect common diseases. By integrating this model into a simple web application using Django framework, farmers or livestock owners can upload images and get diseases predicted immediately, along with their treatment and prevention info. Especially in rural areas where support from veterinary professionals may be limited, timely diagnosis of disease in animals has been a serious problem, which the system would help to tackle with. In conclusion, this project shows the ability to use deep learning and web technologies to monitor livestock health and help farmers make better decisions for smarter and more sustainable farming practices.

VII. REFERENCE

- [1] L. Bai, Z. Zhang, and J. Song, "Image dataset for cattle biometric detection and analysis," *Data in Brief*, vol. 52, 2024, Art. no. 110835. doi: 10.1016/j.dib.2024.110835.
- [2] Anonymous, "Thermal Image Processing for Disease Detection in Animals." [Online].
- [3] S. Coşkun and A. H. Isık, "Early Detection of Lameness in Cattle with Image Processing Techniques," *Int. J. Eng. Innov. Res.*, vol. 5, no. 3, pp. 246–258, Oct. 2023. doi: 10.47933/jjeir.1336813.
- [4] B. Lake, F. Getahun, and F. T. Teshome, "Application of Artificial Intelligence Algorithm in Image Processing for Cattle Disease Diagnosis," *J. Intell. Learn. Syst. Appl.*, vol. 14, no. 4, pp. 87–99, 2022. doi: 10.4236/jilsa.2022.144006.
- [5] J. D. Schaefer et al., "Application of Computer Vision for Monitoring Livestock Health and Behavior," *Computers and Electronics in Agriculture*, vol. 190, 2021, Art. no. 106431.

[6] P. Ramesh et al., "Detection of Animal Diseases Using Image Processing and Machine Learning Techniques," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 9, no. 5, pp. 4321–4326, 2020.

[7] M. A. Rahman and T. Tasnim, "Livestock Disease Detection Using CNN: A Deep Learning Approach," *IEEE Access*, vol. 8, pp. 120920–120930, 2020.

[8] T. Zhang et al., "Animal Face Detection and Disease Classification Using Deep Learning Algorithms," *Multimedia Tools and Applications*, vol. 80, pp. 30147–30163, 2021.

[9] K. S. Patel and H. P. Mehta, "Smart Farming: Disease Detection in Animals Using IoT and Image Processing," *International Journal of Computer Applications*, vol. 178, no. 7, pp. 25–30, 2019.

[10] A. Bhosale and V. S. Karande, "A Survey on Animal Health Monitoring Systems Using Machine Learning," *Procedia Computer Science*, vol. 167, pp. 2101–2109, 2020.