BANANA LEAF DISEASE DETECTION USING CNN

Teammates

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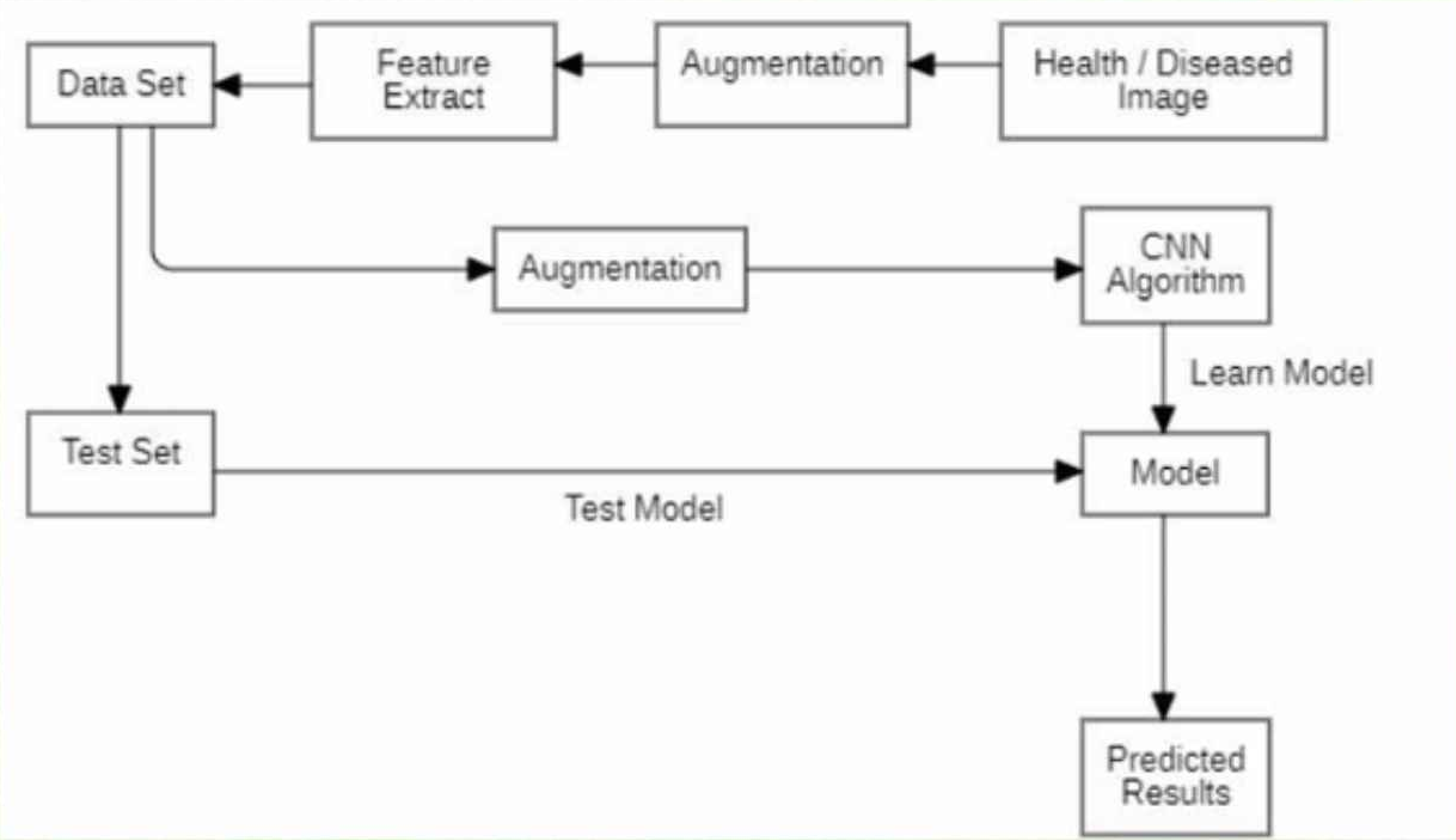
INTRODUCTION

This project focuses on utilizing Convolutional Neural Networks (CNNs) and deep learning techniques to detect and classify banana leaf diseases. Common diseases affecting banana plants, such as Black Sigatoka, Fusarium Wilt, and Bacterial Wilt, significantly impact growth and yield. Early and accurate detection of these diseases is essential to minimize crop losses. By developing a robust model to differentiate healthy banana leaves from diseased ones, this initiative aims to empower farmers with a reliable tool for timely disease identification and management. Ultimately, it contributes to improving productivity and quality in precision agriculture.

OBJECTIVE



Data Set
Feature Extract
Augmentation
Health / Diseased Image
Augmentation
CNN Algorithm
Learn Model
Test Set
Test Model
Model
Predicted Results

- Banana farmers often face significant financial losses due to diseases such as Black Sigatoka, Fusarium Wilt, and Bacterial Wilt. Early detection of these diseases is critical for effective treatment and minimizing crop damage. Since different diseases require specific treatments, accurately identifying the disease type is essential. This project leverages advanced technologies like Convolutional Neural Networks (CNNs) and Deep Learning to provide a reliable solution for detecting and classifying banana leaf diseases. The objective is to equip farmers with an efficient tool to identify diseases promptly, reduce crop waste, and prevent financial losses.

METHODOLOGY

Convolutional Neural Networks (CNNs) play a crucial role in detecting banana leaf diseases from images. CNNs, with their layered architecture, are highly effective in processing complex data. The methodology involves several steps: collecting images of banana leaves, converting them into arrays, organizing the dataset, training the CNN model, testing it with new images, and providing insights on disease detection and treatment. Consistency is critical, ensuring all images are standardized in size and accurately labeled. The model's performance depends on factors such as the number of layers, filter sizes, and hyperparameter tuning, ensuring precise and reliable disease identification.

IMAGE PREPROCESSING

Preprocessing in banana leaf disease detection using CNN involves crucial steps like scaling, data augmentation, and normalization to enhance the model's ability to analyze image details. Scaling adjusts image pixel values, typically setting them between 0 and 1 using a rescaling layer in a Sequential model. Data augmentation, such as flips, rotations, and resizing, improves the model's robustness by expanding the training dataset. Normalization ensures data consistency, enhancing training accuracy. These preprocessing techniques prevent overfitting, enabling the model to generalize well on new data. Overall, preprocessing is essential for optimizing the model's performance in accurately classifying banana leaf diseases.

DATA AUGMENTATION

Data augmentation is a technique used to expand training datasets by generating new data from existing samples. For banana leaf disease detection using CNN, data augmentation was implemented using the Keras Sequential model with multiple image augmentation layers. These included Random Flip, Random Rotation, Random Zoom, Random Height, and Random Width layers to diversify the dataset. For instance, the Random Flip layer enhances the model's ability to recognize features regardless of image orientation by randomly flipping images horizontally or vertically. This approach creates a more robust and varied training dataset, improving the model's capacity to generalize and identify patterns effectively.

FEATURE SELECTION

- The architecture used for banana leaf disease detection employs a Convolutional Neural Network (CNN) for feature extraction. The model consists of multiple convolutional layers with varying numbers of filters, sizes, and activation functions. These layers are followed by max-pooling layers to down-sample the feature maps, effectively reducing the spatial dimensionality of the input data. This architecture enables efficient feature extraction by leveraging convolutional and pooling layers to identify patterns and spatial relationships within the images, ensuring precise and reliable disease classification.

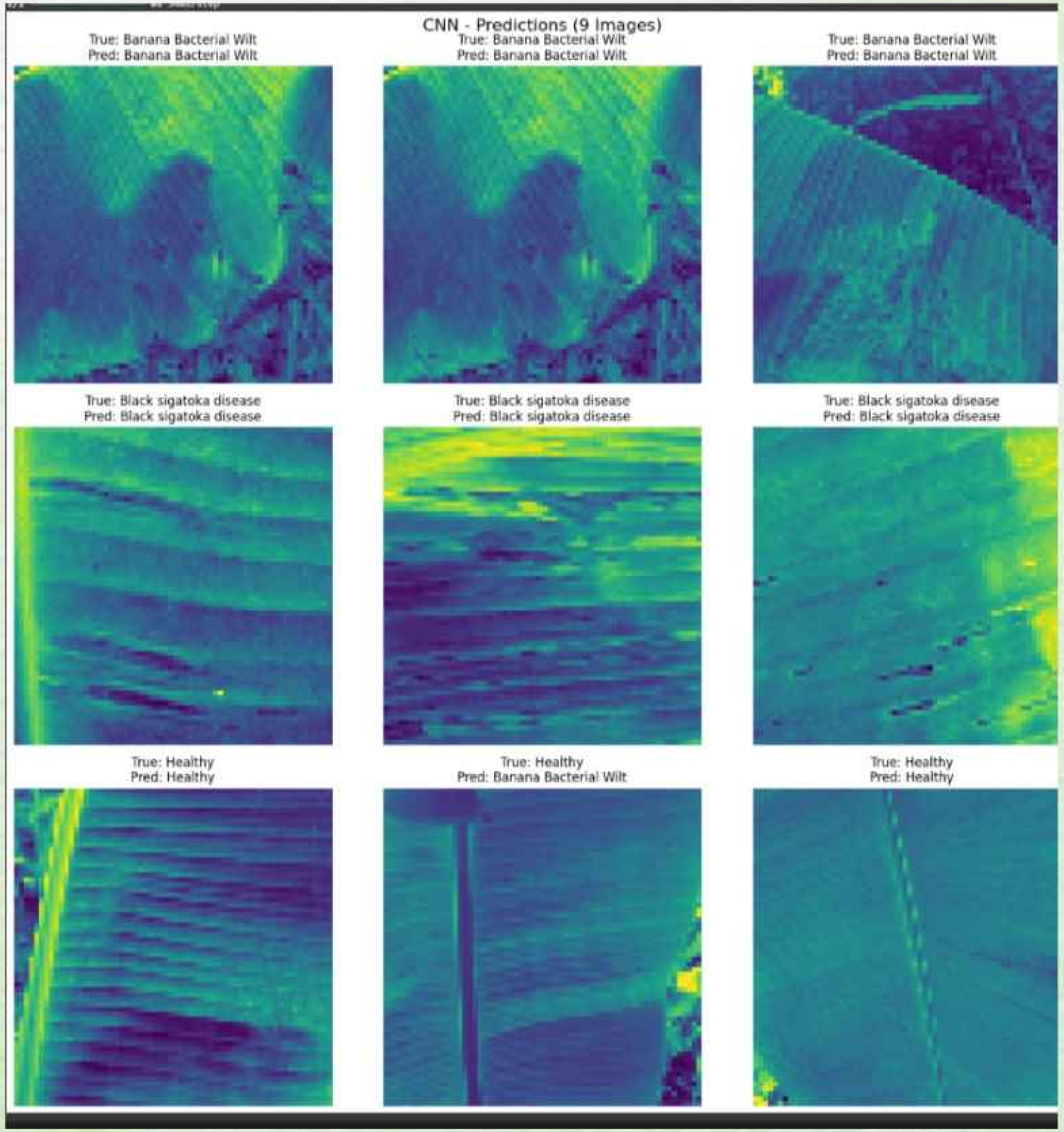
CLASSIFICATION CNN

The CNN architecture for banana leaf disease detection consists of six convolutional layers with filter counts of 32, 256, 256, and 32, each extracting distinct image features. A max pooling layer follows these convolutional layers to reduce spatial dimensions, aiding computational efficiency. Rectified Linear Unit (ReLU) activation functions are applied across all convolutional layers, introducing non-linearity for enhanced feature learning. The output of the final convolutional layer undergoes global average pooling to further reduce dimensions before reaching a fully connected output layer. This layer utilizes softmax activation to predict disease classes based on probabilities. This architecture is optimized for efficient feature extraction and precise classification, enhancing the model's effectiveness in detecting and categorizing banana leaf diseases.

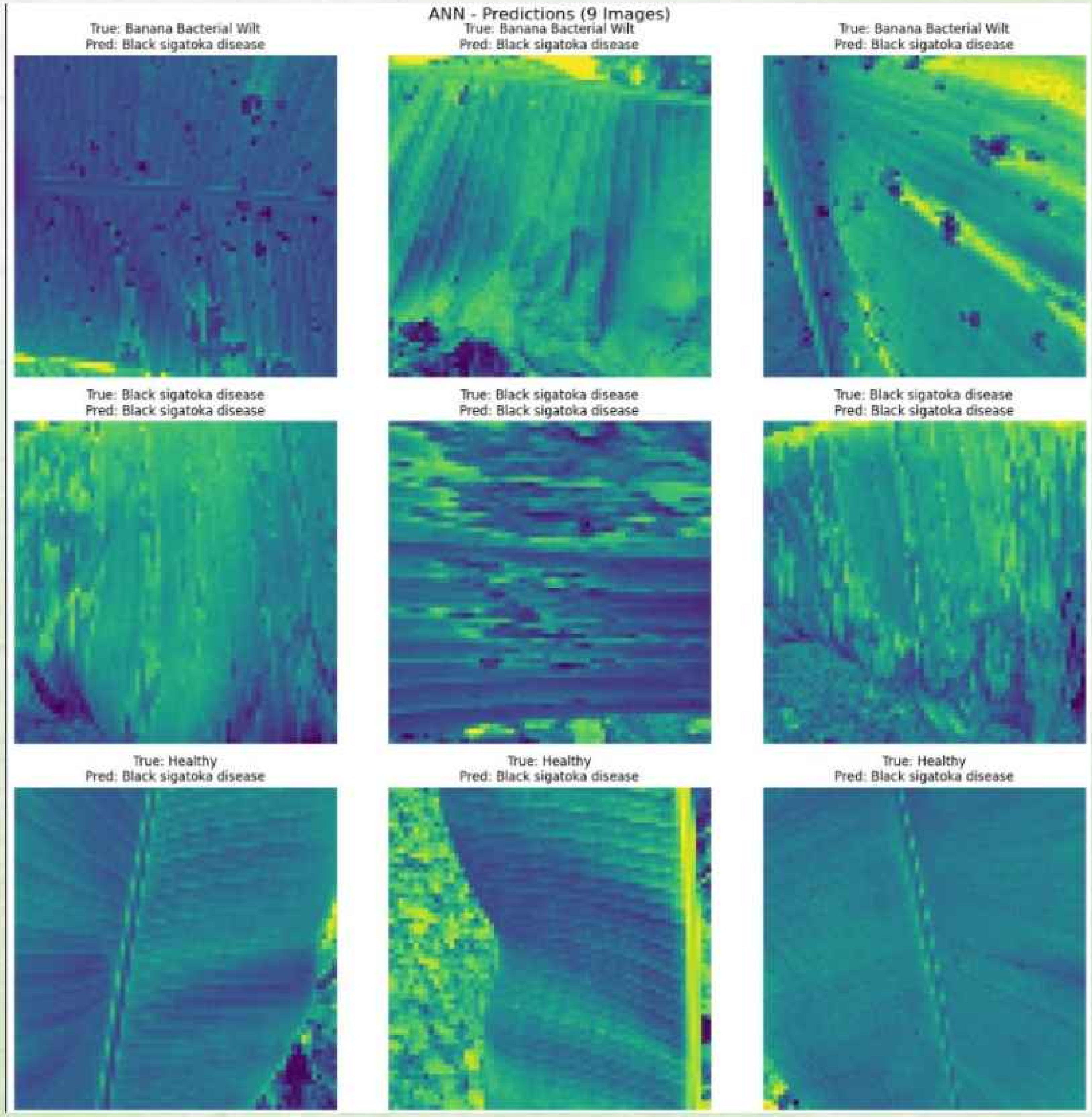
CLASSIFICATION ANN

The ANN architecture for banana leaf disease detection comprises six densely connected layers with neuron counts of 32, 256, 256, and 32 in each layer. A dropout layer with a 0.25 rate is incorporated to prevent overfitting by randomly deactivating neurons during training. Rectified Linear Unit (ReLU) activation functions are applied throughout the network to enable learning of intricate patterns from input data. The output from the final dense layer is passed to a fully connected output layer with softmax activation, which predicts class probabilities. This architecture ensures effective feature extraction, prevents overfitting, and enhances the model's ability to understand complex patterns for accurate disease classification.

RESULTS FOR CNN



RESULTS FOR ANN

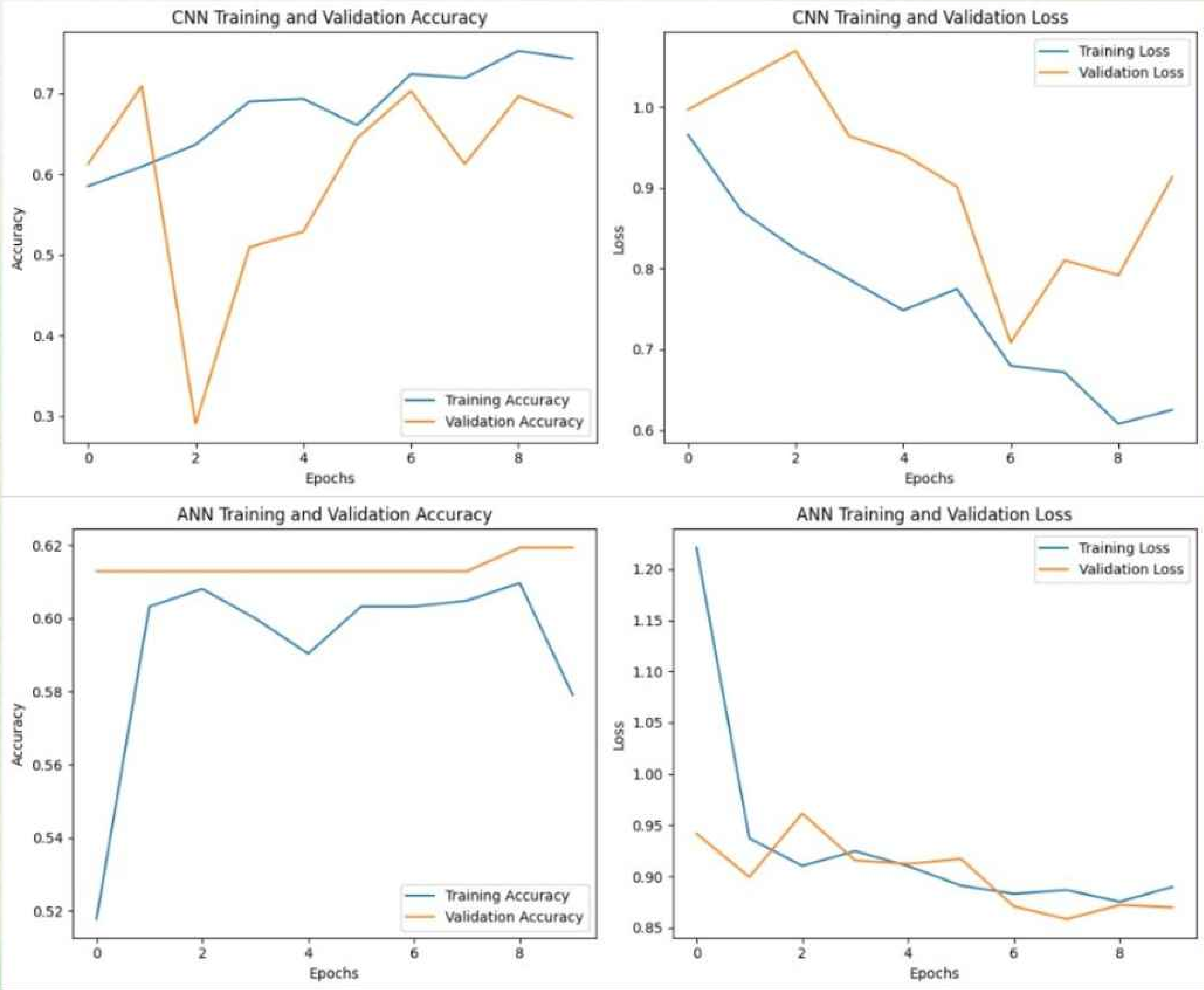


MODELANALYSIS

Model Performance Comparison Table:

Metric	ANN	CNN
Training Accuracy	0.579032	0.743548
Validation Accuracy	0.619355	0.670968
Training Loss	0.889759	0.625116
Validation Loss	0.869760	0.913477

MODELANALYSIS



FUTURE WORK

A specialized mobile application can be developed to assist farmers, particularly those who are illiterate, by offering a voice-guided interface for ease of use. This app will focus on identifying and managing banana leaf diseases, providing a comprehensive list of diseases with visual representations to show the extent of leaf damage. Farmers can use these features to quickly understand the severity of the disease and take appropriate action. This innovative tool aims to empower farmers by simplifying disease management, improving crop health, and increasing their earnings, serving as a valuable, accessible assistant for better farm management.

CONCLUSION

The primary goal is to assist farmers in accurately detecting and identifying diseases affecting banana leaves. Leveraging neural networks, a novel method has been developed, surpassing traditional approaches. A CNN model with exceptional accuracy has been designed to identify banana leaf diseases effectively. With the integration of GPU, the model operates faster and more efficiently, reducing reliance on costly expertise. This approach is cost-effective, enabling rapid disease identification and providing actionable solutions. Easily accessible, the solution can be deployed as a mobile application, allowing farmers to capture images of banana leaves and quickly diagnose issues. This innovation empowers farmers with a practical and accurate tool to enhance plant health management.

THANK YOU