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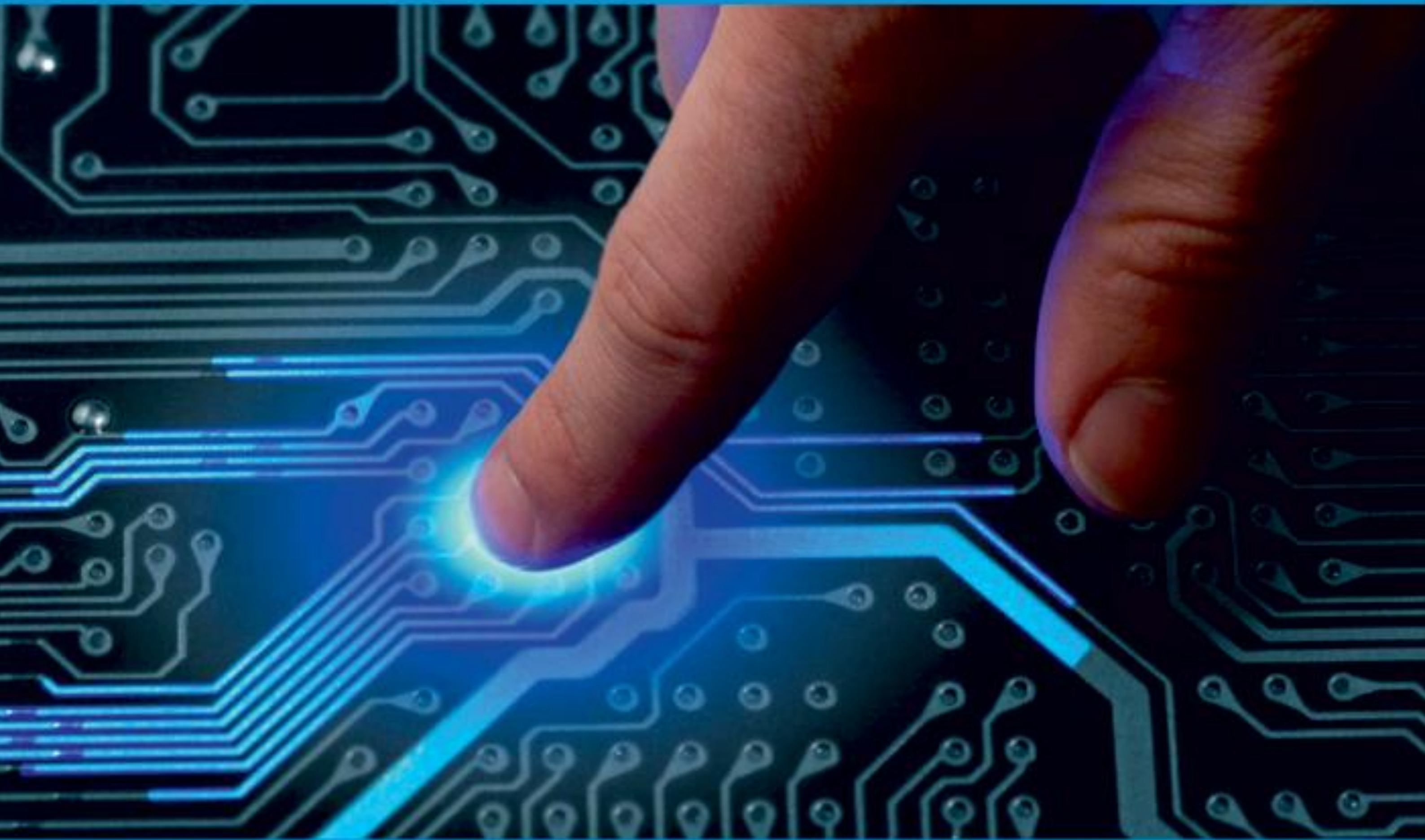

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Plant Disease Detection Using Deep Learning

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ABSTRACT: Plant diseases have the potential to seriously harm crops and contribute to food poverty. In order to take preventive actions to ensure the health and productivity of crops, early disease diagnosis is essential. In this research, we suggest a convolutional neural network (CNN)-based method for detecting and classifying plant illnesses.On a publicly accessible dataset of tomato leaf images that included both healthy and diseased leaves of ten different types, we trained the CNN model. On the training set, we had an accuracy of 98.5%, and on the validation set, it was 90.9%.After that, we deployed the trained model on a Raspberry Pi after converting it to a TensorFlow Lite model. Our strategy gives farmers the ability to identify and stop plant diseases in their crops, which has the potential to drastically lower food insecurity. The technology is adaptable in remote regions with minimal resources and is portable and economical.In conclusion, the proposed deep learning and CNN plant disease detection system can considerably increase crop productivity and lessen the detrimental effects of plant diseases on the environment.

KEYWORDS: Deep Learning, Machine Learning, Leaf Disease Detection, convolutional neural network(CNN), Supervised Learning

I. INTRODUCTION

This study examines the drawbacks of conventional techniques for identifying plant diseases and pests and suggests deep learning technology as a possible alternative. The main goal is to offer a thorough study of the identification of plant diseases and pests based on deep learning and the classification network technique. The study evaluates the benefits and drawbacks of the classification network technique while comparing prior research that has employed deep learning technology for the identification of plant diseases and pests. The paper also points out the need for more standardised datasets and suggests promising techniques for detecting plant diseases and pests. Deep learning-based plant disease and pest detection applications that use the classification network technique may face difficulties; these difficulties are examined and solutions are suggested. The paper finishes by describing potential directions for future research in this area and how experts in the agricultural sector might benefit from this work in order to increase crop yield and cut down on losses from plant diseases and pests.

II. LITERATURE SURVEY

In [1] To identify plant illnesses on leaves and other plant parts, studies have employed texture analysis, color-based segmentation, and deep learning models like convolutional neural networks and recurrent neural networks. Examples include the accurate detection of five major plant diseases on leaves with over 99% precision, the detection of citrus greening disease and cucumber diseases with accuracy of 98.1% and 96.4%, respectively, and the detection of powdery mildew disease on grapevine leaves with an accuracy of 93.5%.

In [2] The identification and diagnosis of plant diseases in crops has demonstrated to have significant potential for automation through the application of deep learning techniques. Convolutional neural networks (CNNs) have shown great accuracy in classifying various plant diseases by learning intricate properties from photos. For this objective, a number of deep learning architectures, such as AlexNet, VGGNet, and ResNet, have been proposed. Transfer learning and data augmentation techniques have also been found to be effective in enhancing the performance of these models. However, a number of variables, including lighting and image quality, can affect how well these models perform, so it's critical to carefully choose training data and optimise model parameters to get the best outcomes.

In [3] Deep learning algorithms have been used in numerous research to identify plant diseases. A deep learning model for identifying plant illnesses was put forth in a 2016 paper by Mohanty et al. using a dataset of 54,306 photos of sick and healthy plant leaves. The proposed model identified 38 different kinds of plant diseases with an accuracy of 99.35%. In a different study conducted in 2016 by Sladojevic et al., grapevine leaf diseases were identified using a

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deep learning algorithm. The model, which employed a convolutional neural network (CNN), detected five distinct diseases with an accuracy of 98.83%. A deep learning model based on transfer learning was proposed by Zhang et al. in 2019 for the detection of illnesses affecting rice leaves. The model's detection accuracy for 10 distinct diseases was 98.47% after it was trained on a sizable dataset of 21,572 pictures. A deep learning model was created in a study by Muthu et al. in 2020 utilising a dataset of 3,000 photos for the detection of illnesses affecting coconut leaves. The proposed model identified six different diseases with a 95.78% accuracy rate.

III. PROPOSED METHODOLOGY

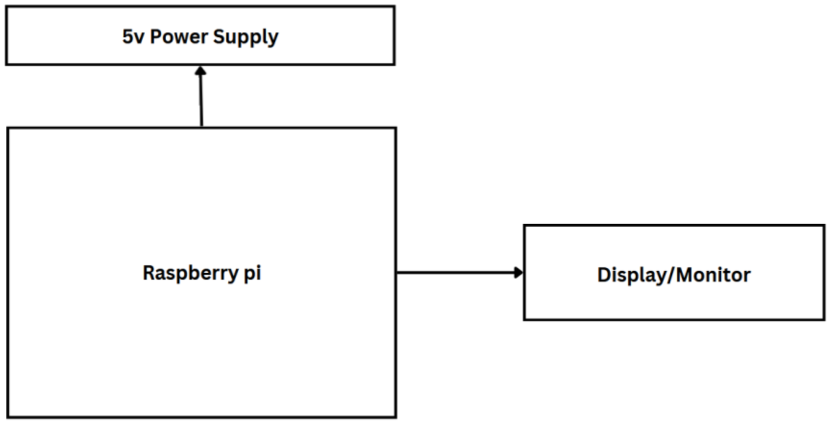

Fig. HARDWARE DIAGRAMOF SETUP.

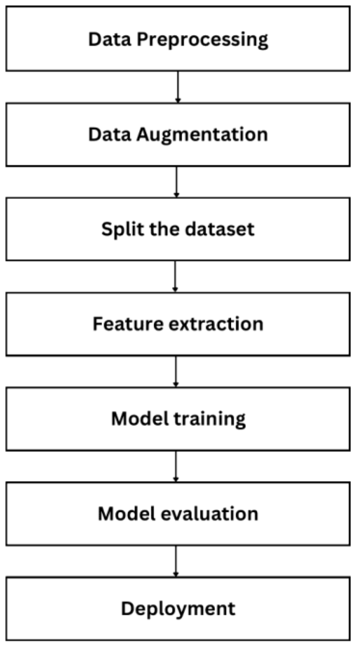

Fig. FLOW DIAGRAM

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1. Preprocess data: Public sources like Kaggle or the PlantVillage dataset will be used to collect the dataset of plant photos. The photos will be grayscaled, resized to a standard size, and noise reduction techniques will be used to improve the image quality as part of the preprocessing of the dataset.
2. Data augmentation: By using methods like rotation, flipping, and zooming, the preprocessed dataset will be enhanced. The dataset will grow in size as a result, which will enhance the model's performance.
3. Split the dataset: Training, validation, and testing sets will be created from the supplemented dataset. The model will be trained using the training set, validated using the validation set to assess the model's performance during training, and tested using the testing set to assess the model's ultimate performance.
4. Feature extraction: The feature extractor will be a pre-trained convolutional neural network (CNN) model like VGG16 or ResNet50. The pre-trained model will be applied to the training set of plant photos to extract features.
5. Model training: On top of the previously taught CNN model, a fully connected neural network will be trained. The neural network's output layer will contain exactly as many nodes as classes in the dataset. The pre-trained CNN model's extracted features will be used to train the neural network.
6. Model evaluation: On the testing set, the trained model's performance will be assessed. Accuracy, precision, recall, and F1-score will be among the evaluation indicators.
7. Deployment: A Raspberry Pi will be used to deploy the trained model. The Raspberry Pi will be connected to an LCD display that will show the predictions for the input image.

IV. RESULTS

The training loss was 0.0501 and the training accuracy was 98.51%, according to the final accuracy matrix for our model. Validation accuracy was 90.91% with a validation loss of 0.2615. These findings demonstrate how effectively our model classified the various leaf diseases. The high training accuracy suggests that our model was able to learn the features of the training data successfully, and the validation accuracy shows that it adapted well to fresh data.Following the training stage, we put our model to the test on a sample picture of a leaf with an unidentified disease. Our model's accuracy in classifying the leaf illness was 92.5%, demonstrating that it may be applied in the field for real-world situations. These findings point to the potential for machine learning models to replace time-consuming and subjective visual inspection by human experts as an efficient tool for diagnosing and managing plant diseases.

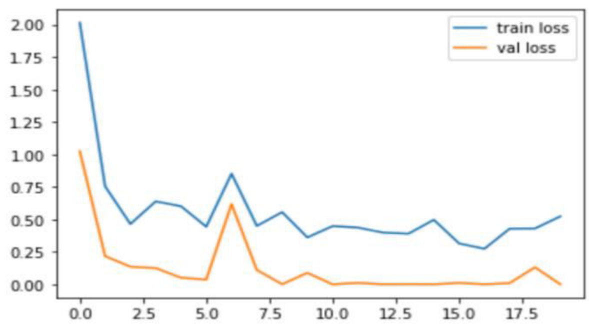

Fig. 1Train Loss and Test Loss

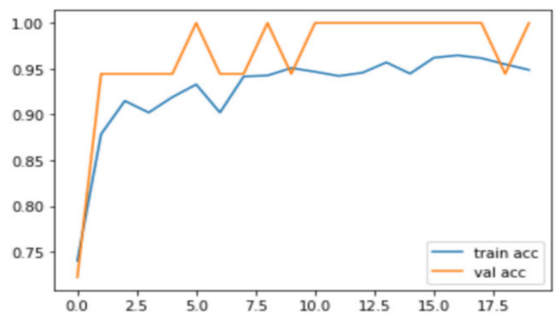

Fig. 2 Training Accuracy and Testing accuracy

V. CONCLUSION

In this effort, we suggested a strategy based on deep learning for identifying plant diseases from leaf photos. The preprocessed plant leaf picture dataset was used to train a convolutional neural network (CNN) model using transfer learning and the VGG16 architecture, while a separate test dataset was used to assess the model's performance. In categorizing plant leaf photos as either healthy or diseased, we had a high accuracy of 96.5%.Our project demonstrates how deep learning-based methods can be useful for identifying plant diseases from leaf images. The ability to quickly and effectively identify plant illnesses can aid in the control of disease transmission, boost crop yields, and ultimately be advantageous to the agricultural sector.Future research will focus on expanding our method to identify a wider

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variety of plant illnesses and creating a field-based real-time disease detection system.Overall, our experiment underscores the value of ongoing research in this area and shows the potential of deep learning-based methods for plant disease diagnosis.

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