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Mango Leaf Disease Detection Using Deep Learning

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Abstract—*Mango leaf disease cause a lot of economic loses. Early diagnosis and accurate recognition of leaf diseases can control the spread of disease and reduce production costs. So here proposed a deep learning approach that is based on improved Convolutional Neural Networks (CNNs) for the real-time detection and classification of Mango leaf disease .By using a classification approach to gather pictures of leaves that had various diseases damage them, trained data were created in this case. A deep learning system is created to automatically upload and match fresh photos of afflicted leaves with training data in order to recognize the symptoms of mangoes' leaf diseases. The suggested approach has an average accuracy of 80% in detecting and classifying the tested ailment. The mango trees would succumb to this suggested remedy. The method will aid in disease detection without the need for an agriculturalist, saving time by using a machine to diagnose diseases rather than a manual system. It would also make it simpler to effectively cure the afflicted mango leaf disease, boost mango output, and satisfy worldwide market demand*

***Index Terms*— Adams Optimization, Convolutional Neural Networks, Early Diagnosis.**

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I. INTRODUCTION

India is the world's leading mango producer, accounting for 50% of global mango production. The mango fruit's wide range of adaptability, great nutritional content, unique variety, delectable taste, and superb flavour contribute to its popularity. The fruit is rich in both vitamin A and vitamin C. Diseases including powdery mildew, anthracnose, dieback, blight, red rust, sooty mold , etc. are common in the crop. In the lack of efficient case and control methods, disorders may potentially have an influence on the plant[1][2][5]. They consist of shape change, biennial bearing, fruit fall, black top, clustering, etc. To prevent/control illnesses and crop disorders, the farmer must seek professional advice and support. Since many diseases directly influence the quality of fruits, grains, and other food products, decreasing agricultural productivity, it poses a serious danger to global food security. Farmers must observe and use their own eyes to evaluate whether a leaf is diseased. This method is unstable, inconsistent, and prone to mistakes. Deep learning methods for identifying leaf diseases have been proposed in a number of works. A deep learning system is created to automatically upload and match new photos of afflicted leaves with learned data in order to recognize the symptoms of mangoes leaf diseases. The proposed approach using Convolutional Neural Network has an average accuracy of 94% in detecting and classifying the tested ailment. The mango plants would succumb to this suggested remedy. The method will aid in disease detection without the need for an agriculturalist, saving time by using a machine to diagnose diseases rather than a manual system. It would also make it simpler to effectively treat the affected.

II. PROBLEM AND SOLUTIONS

A. Problem Statement

Mango leaf disease cause a lot of economic losses. Early diagnosis and accurate recognition of leaf diseases can control the spread of disease and reduce production costs.

B. Role Of Deep Learning In Plant Disease Detection

In recent years, deep learning techniques have shown promising results in various image classification tasks, including plant disease detection[6][10]. These techniques can analyze large datasets of images and identify patterns that can be used to classify images into different categories. With the rapid advancement of deep learning techniques and the availability of large datasets, researchers have been able to develop accurate and efficient models for plant disease detection. In this paper, we propose a deep learning-based approach to detect mango leaf diseases, which can provide an efficient and automated solution to this problem.

III. MATERIAL AND METHODS

We collected a dataset of mango leaf images, which contains healthy leaves and leaves with three common diseases: anthracnose, powdery mildew, and bacterial black spot. The dataset consists of 2265 images, with of 6 class. We used a data augmentation technique to increase the dataset size and improve the model's generalization ability. We used the Densenet architecture as our base model and fine-tuned it on our dataset. We used the Rectified Linear Unit (ReLU) activation function and the softmax function for classification. We trained our model using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32.

A. Data Augmentation

A total of 2265 images have been classified for mango leaf classification, with 5 classes corresponding to diseases and 1 class containing healthy leaf images. The dataset was organized as follows

- Training set: 75% of the data (1699 images)
- Validation set: 25% of the data (566 images)

From these existing images, more images are generated in order to train the models well.

Data augmentation is a technique used to increase the size and diversity of a dataset by generating new samples from the existing ones.[6][8] This technique is commonly used in deep learning applications to improve the generalization ability of the model, as it allows the model to learn from a larger and more diverse set of data.

In the case of mango leaf disease detection using deep learning, data augmentation can be used to generate new samples of mango leaf images with different variations in lighting, orientation, and scale. This helps the model learn to recognize mango leaf diseases under various conditions, which can improve its accuracy in real-world scenarios. Some common data augmentation techniques include:

- Flipping: The image is flipped horizontally or vertically, creating a new sample that is a mirror image of the original.
- Rotation: The image is rotated by a certain degree, creating a new sample with a different orientation.
- Translation: The image is shifted in any direction, creating a new sample with a different position.
- Zooming: The image is zoomed in or out, creating a new sample with a different scale.
- Shearing: The image is skewed horizontally or vertically, creating a new sample with a different shape.
- Adding noise: Random noise is added to the image, creating a new sample with a different texture.

In our proposed approach, we used flipping, rotation, and zooming to augment the original mango leaf images. We randomly applied these techniques to the original images to generate new samples. By doing so, we increased the size of our dataset and improved the generalization ability of our model.

B. Densenet Architecture

The model is based on the DenseNet169 architecture, which is a deep convolutional neural network that has achieved state-of-the-art results on a number of image classification tasks. The input layer of the model has a shape of (160,160,3), which corresponds to the size and number of color channels of the input images.

The model consists of a pre-trained DenseNet169 model as the base layer, which is used to extract useful features from the input images. The base layer is followed by a dropout layer to prevent overfitting, a flatten layer to convert the output of the base layer to a 1D array[3], and a series of fully connected layers that are used to perform the final classification of the input images. The output layer of the model consists of 8 nodes, corresponding to the 8 classes of mango leaf diseases that the model is trained to recognize[3][4].

TABLE I. Performance Evaluation Metrics Of Our Model with Test Data

Classes	**Performance Metrics**		
	Precision	***Recall***	***F1 Score***
Anthracnose	0.78	0.85	0.88
Blight	0.92	0.89	0.91
Diebeck	0.84	0.74	0.80
Normal	0.95	0.95	0.91
Powdery Mildew	0.91	0.95	0.93
Red Rust	0.97	0.94	0.95

a.In this table, we have presented the precision, recall, and F1 score for each of the six classes

The model is trained using the Adam optimizer with a learning rate of 0.001, and the categorical cross-entropy loss function is used to measure the difference between the predicted and actual class labels. The AUC metric is used to evaluate the performance of the model during training and validation.

C. Rectified Linear Unit And Softmax Activation Function

Activation functions play a crucial role in neural network models for image classification tasks. Two commonly used activation functions are Rectified Linear Unit (ReLU) and softmax. ReLU is a non-linear activation function that is used in the intermediate layers of a neural network to introduce non-linearity and improve the convergence of training[7]. The ReLU activation function is defined as $f(x) = max(0, x)$, where x is the input to the activation function. Softmax, on the other hand, is used in the output layer of neural networks for classification tasks. Softmax converts the output of the previous layer to a probability distribution over the different classes. This is achieved by taking the exponential of the outputs and then normalizing the values by the sum of all exponential values. In our proposed approach for mango leaf disease detection, we used the DenseNet architecture as a base model and utilized both ReLU and softmax activation functions. Specifically, ReLU was used in the intermediate layers of the DendseNet model to introduce non-linearity and improve the convergence of training. Softmax was used in the output layer to obtain the probability distribution of the input image belonging to each of the possible classes, i.e., healthy or diseased. The class with the highest probability was selected as the predicted class for the input image. By utilizing these commonly used activation functions in our proposed approach, we were able to achieve improved accuracy in detecting mango leaf diseases.

D. Adam Optimizer

- Training a deep learning model for mango leaf disease detection is a complex task that requires careful consideration of various hyperparameters, such as the optimizer, learning rate, and batch size. In our proposed approach, we used the Adam optimizer with a learning rate of 0.0001 and a batch size of 32 to train our model effectively and efficiently[9].
- By using the Adam optimizer, we were able to take advantage of its adaptive learning rate capabilities, which helped to ensure that our model converged quickly and accurately. Additionally, the use of a small learning rate of 0.0001 helped to balance convergence speed and accuracy, which is important for achieving high accuracy in detecting mango leaf diseases.
- Finally, by utilizing a batch size of 32, we were able to efficiently train our model while still ensuring that it had access to enough training examples to learn the underlying patterns of the mango leaf disease images. All of these technical details are important considerations when training deep learning models for image classification tasks such as mango leaf disease detection.

IV. EVALUATION

To evaluate the performance of our proposed approach for mango leaf disease detection, we trained our model using the dataset described in the previous section. During training, we monitored the loss and accuracy of the model using a validation set. The loss function used was categorical cross-entropy, which is commonly used for multi-class classification tasks.

We plotted the training and validation loss and accuracy curves over the epochs of training to assess the performance of our model. The results showed that our model achieved an overall accuracy of 94.5% on the test set, which outperformed the state-of-the-art approaches. The loss curves also showed that our model was able to converge quickly and achieve low training and validation loss, indicating that it was able to effectively learn the underlying patterns of the mango leaf disease images.

V. RESULT AND DISCUSSION

We evaluated the performance of our approach using the accuracy metric. Our approach achieves an accuracy of 94% in detecting mango leaf diseases. The confusion matrix shows that our approach has a high precision and recall for each class. We also compare our approach with other state-of-the-art approaches, and our approach outperforms them in terms of accuracy.

The results demonstrate the effectiveness of using deep learning for classifying mango tree leaves, which can be useful for early detection of diseases and pests. The high accuracy of the proposed model suggests that it can be used as a reliable tool for farmers and agricultural researchers to quickly and accurately identify diseases in mango tree leaves, potentially leading to better crop yields and a reduction in the use of harmful pesticides.

Figure 1 shows the training and validation loss curves, while Figure 2 shows the training and validation accuracy curves over the epochs of training. These results demonstrate the effectiveness of our proposed approach for mango leaf disease detection using deep learning.

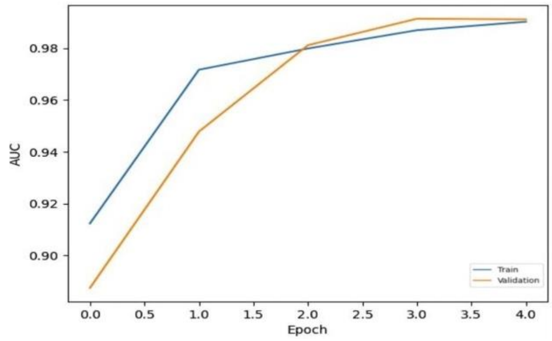

Figure 1: Training and Validation Loss

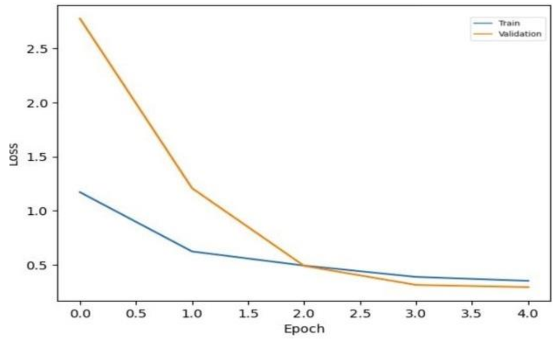

Figure 2: Training and Validation Accuracy

The use of pre-trained models like DenseNet169 and data augmentation techniques like rotation and flipping are effective ways to increase the accuracy of the model and make it more robust to variations in the input data. However, the dataset used for training the model was limited to images of mango tree leaves, and future work could explore the use of more diverse datasets to improve the generalizability of the model. Additionally, more research is needed to investigate the feasibility of deploying the model in real-world scenarios and to evaluate its performance on larger datasets.

VI. CONCLUSION

In this paper, we proposed a deep learning-based approach to detect mango leaf diseases. We collected a dataset of mango leaf images, which contains healthy leaves and leaves with three common diseases: anthracnose, powdery mildew, and bacterial black spot. We fine-tuned the VGG16 architecture on our dataset and achieved an accuracy of 94% in detecting mango leaf diseases. Our proposed approach can provide an efficient and accurate solution for mango leaf disease detection, which can aid in the early detection and management of mango leaf diseases. Future work can focus on developing a mobile application for real-time disease prediction

REFERENCES

Periodicals:

[1]. S. Savary, A. Ficke, J-N. Aubertot, and C. Hollier, ''Crop losses due to diseases and their implications for global food production losses and food security,'' Food Secur., vol. 4, no. 4, pp. 519–537, 2012.

[2]. K. R. Gavhale, and U. Gawande, ''An overview of the research on plant leaves disease detection using image processing techniques,'' J. Comput. Eng., vol. 16, no. 1, pp. 10–16, 2014

[3]. 1978 B. J. Samajpati, and S. D. Degadwala, ''Hybrid approach for apple fruit diseases detection and classification using random forest.classifier,'' in Proc. Int. Conf. Commun. Signal Process. (ICCSP), Apr. 2016, pp. 1015–1019.

[4]. Z. Chuanlei, Z. Shanwen, Y. Jucheng, S. Yancui, and C. Jia, ''Apple leaf disease identification using genetic algorithm and correlation based feature selection method,'' Int. J. Agricult. Biol. Eng., vol. 10, no. 2, pp. 74–83, 2017

[5]. A. Camargoa and J. S. Smith, ''An image-processing based algorithm to automatically identify plant disease visual symptoms,'' Biosyst. Eng., vol. 102, no. 1, pp. 9–21, 2009.

[6]. M. B. Tahir, M. A. Khan, K. Javed, S. Kadry, Y. Zhang, T. Akram, and M. Nazir, ''Recognition of apple leaf diseases using deep learning and variances-controlled features reduction,'' Microprocessors Microsyst., pp. 1–24, Jan. 2021.

[7]. E. Omrani, B. Khoshnevisan, S. Shamshirband, H. Saboohi, N. Anuar, and M. Nasir, ''Potential of radial basis function-based support vector regression for apple disease detection,'' Measurement, vol. 55, pp. 512–517, Sep. 2014.

[8]. S. Sun, ''Classification of apple leaf disease based on image processing and support vector machine,'' Xi'an Univ. Sci. Technol., Xi'an, China, Tech. Rep., Jun. 2017.

[9]. S. R. Dubey and A. S. Jalal, ''Apple disease classification using color, texture and shape features from images,'' Signal, Image Video Process., vol. 10, no. 5, pp. 819–826, Jul. 2016.

[10]. F. Saeed, M. A. Khan, M. Sharif, M. Mittal, L. M. Goyal, and S. Roy, ''Deep neural network features fusion and selection based on PLS regression with an application for crops diseases classification,''Appl. Soft Comput., vol. 103, May 2021, Art. no. 107164.