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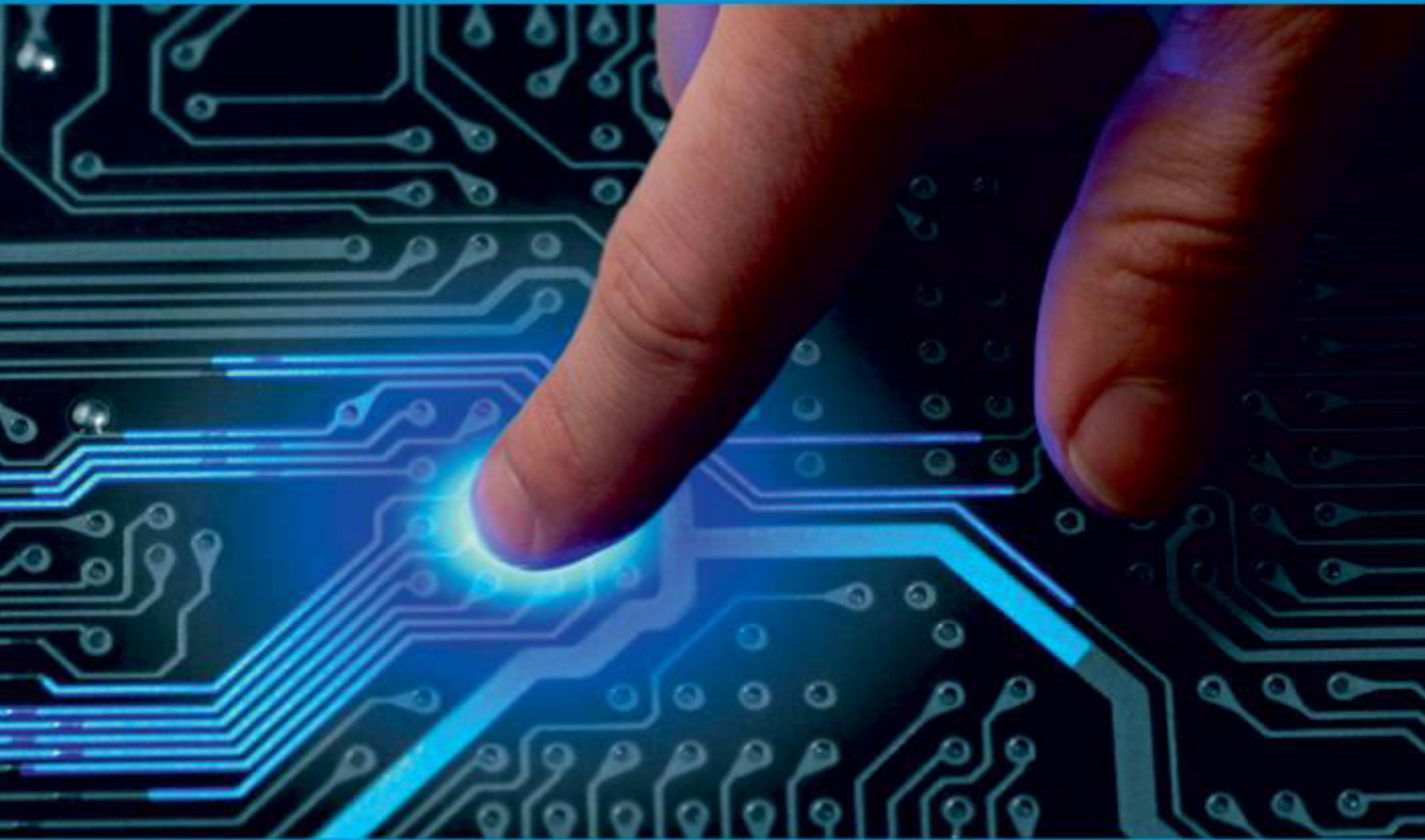

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Identification of Guava Fruit Disease using Convolutional Neural Networks

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ABSTRACT: The cultivation of guava, being an important tropical fruit, is seriously threatened by a number of diseases that drastically reduce its yield and quality. Early detection and identification are the first requisites for appropriate management. The methods currently in use for disease detection, based on visual inspection of expert workers, are crude, slow, labor-intensive, and prone to errors. This paper, therefore, presents a new methodology for the automatic identification of disease in guava fruit using the CNN technique. Such a powerful model would be able to identify diseases in guava fruit images with high accuracy and robustness because of the powerful image recognition capabilities of a CNN. The proposed methodology started with the collection and annotation of the dataset of guava images, both healthy and diseased. Some techniques used to increase the performance of the model are data augmentation and contrast enhancement. Data augmentation randomly transforms data to artificially increase the data set size and diversifies it, hence improving the generalization of models and reducing overfitting. Contrast enhancement shows features in the image more effectively, so that the CNN can detect them easily in comparison with other images that show subtle differences in color and texture. The base of CNN architecture basically lies in balancing between the model's complexity and computational efficiency. Using convolutional and ReLU activation features, max-pooling layers are added for effectual feature extraction and reduction of spatial dimensions. Finally, classification occurs through fully connected layers with the softmax activation. The optimization of the model should be trained using optimization techniques such as stochastic gradient descent or Adam. At the test phase, the model's performance can be assessed using accuracy, precision, recall, and the F1 score. High accuracy obtained by the proposed CNN model demonstrates feasibility for practical implementation, which underlines the potentials of deep learning in agricultural disease management.

KEYWORDS: Diseases of Guava Fruits, Convolutional Neural Networks, Image Classification, Deep Learning.

I. INTRODUCTION

Guava (Psidium guajava), is considered one of the most appreciated tropical fruits, having great nutritional and economic value. However, it is very susceptible to a number of pathogenic diseases, among them Phytophthora, root rot, and scab, such that the critical effect of these diseases on both the quality and yield of guava fruits cannot be overemphasized. Traditionally, disease detection relies on manual inspection, which is time- and labor-consuming. It also calls for expertise to help detect different diseases with the right diagnosis, which is inefficient and full of errors.

Recent deep learning techniques seem to be very promising solutions for the challenge of plant disease detection, specifically Convolutional Neural Networks. They have been having tremendous success in image recognition problems and have demonstrated remarkable capacity pertaining to the diagnosis of plant diseases. They are able to self-train and self-extract features from images to not only clearly distinguish a healthy plant from a diseased one but also do this with very high accuracy. This will open up scope for more efficient and reliable methods of disease detection.

A CNN-based approach for identification of diseases in guava fruits to ensure timely detection for appropriate management that can help farmers. This would help in checking the spread of the disease by timely intervention and thus maintaining crop yields. It is only early detection that can prevent outbreaks of diseases and thus maintain crop yields through prompt intervention [1]. In this paper, a model has been proposed using a CNN to provide an efficient and effective tool for disease identification in guava fruits.

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To develop this model, high-quality images of guava fruit in health and diseased condition will first be properly created and annotated. Image preprocessing will then be performed, which may consist of resizing, normalizing, and augmenting the images to increase their quality and consistency. This is a very integral part of preprocessing the dataset to train the CNN effectively so that the network is well-informed about the features in the data.

The architecture of the CNN will be such that it extracts relevant features from the images to help in differentiating a healthy guava fruit from a diseased one. So, it will be trained on supervised learning techniques whereby it learns to recognize patterns and features indicative of various diseases from the annotated dataset. This model would, therefore, be evaluated on strict performance metrics geared toward accuracy, precision, recall, and the F1 score to ensure a high degree of reliability and accuracy.

In the event that development is successful, the CNN-based model will be implemented either as a mobile or web application to ensure access, even in remote areas. In this case, farmers will only need to take a picture of a guava fruit and the application instantaneously responds on its status, along with recommended treatment in case of outbreak of disease. This approach saves time and labor but at the same time provides farmers with very critical information on effective management of crop growth.

The CNN-based model for guava disease detection seeks to enhance productivity and reduce crop loss by facilitating ease, reliability, and accessibility in disease identification and management [2]. In the future, increasing the dataset with more classes of diseases, fine-tuning the architecture of CNN, and further work on improvising the accuracy and usability of the model will be undertaken. These improvements will ensure the model is very important for farmers in planning effective management of guava fruit diseases and maintaining agricultural productivity.

II. RELATED WORK

The control of fruit diseases has garnered significant interest due to its impact on both production and quality [3]. Researchers are actively exploring various solutions to mitigate these threats. A notable study proposed a deep learning approach for the classification and prediction of guava leaf diseases, utilizing a dataset of 1,834 leaves categorized into five distinct disease groups [4]. The research involved training four pre-trained convolutional neural network (CNN) architectures—VGG-16, Inception V3, ResNet50, and EfficientNet-B3 [5]. Among these, EfficientNet-B3 demonstrated superior performance, achieving an accuracy of 94.93% on the test dataset. In another recent study, an automated approach was introduced for detecting 12 types of guava leaf images [6]. The researchers applied multiple machine learning classifiers, including the instant base identifier, random forest, and meta bagging classifiers [7]. The instant base identifier classifier outperformed the others with an average overall accuracy of 93.01%. Mostafa et al. proposed a detection model for identifying guava canker, dost, rust, and mummification diseases using color-histogram equalization and unsharp masking techniques [8]. They employed five network systems—AlexNet, SqueezeNet, GoogLeNet, ResNet-50, and ResNet-101—to diagnose diseases across various guava plant species [9]. The dataset consisted of 321 images sourced from Pakistan, and ResNet-101 achieved the highest accuracy rate of 97.74%.

These studies highlight the extensive use of CNNs in fruit and plant disease recognition, demonstrating their effectiveness in various applications. However, these studies primarily focus on existing CNN models without introducing significant improvements to enhance performance [10]. A notable gap exists in the evaluation of CNN-based models specifically for identifying guava fruit diseases [11]. This gap presents an opportunity for further research and development to address this specific need. To address this, our study introduces an improved CNN model for identifying guava fruit diseases. This model builds upon existing CNN methodologies with enhancements aimed at improving accuracy and performance. The improved-CNN model was trained on a dataset of 612 images, with the training process involving data augmentation techniques such as boosting, contrast adjustments, image resizing, and dataset splitting [12]. These techniques were employed to enhance the model's performance.

The new CNN model incorporates elements from both AlexNet and Inception architectures [13]. By combining features from these established models, the improved-CNN aims to leverage their strengths for better disease classification. Additionally, the model was fine-tuned using the Nesterov Accelerated Gradient (NAG) algorithm and the L2 Softmax Cross-Entropy (LSCCE) loss function. These techniques were utilized to optimize the model's training and overall performance [14].The improved-CNN model achieved a training accuracy of 98 surpassing the performance

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of traditional models such as AlexNet [15]. This indicates a significant enhancement in disease detection capabilities. This model's capabilities extend to real-time systems and robotic platforms for disease detection, facilitating timely interventions and better management of guava fruit diseases in agricultural settings [16]. Future research will focus on expanding the image dataset and exploring additional data augmentation techniques to further refine the model's performance [17]. These efforts aim to increase the model's reliability and applicability in practical scenarios.

The introduction of the improved-CNN model represents a significant advancement in guava fruit disease detection [18]. By building on existing methodologies and incorporating novel techniques, this research contributes to more effective and accurate disease identification.

In summary, the research presented highlights both the achievements and the ongoing challenges in the field of fruit disease detection. The proposed improvements in CNN models offer promising directions for future advancements and applications in agricultural technology [19]. The integration of advanced techniques in the improved-CNN model demonstrates the potential for more accurate and efficient disease detection [20]. Continued development and refinement of these models are crucial for addressing the complexities of fruit disease management. By leveraging state-of-the-art approaches and addressing identified gaps, this study aims to contribute valuable insights and practical solutions for enhancing disease detection and management in guava cultivation [16].

Overall, the ongoing efforts in this field underscore the importance of innovation and technological advancement in addressing the challenges of fruit disease control and improving agricultural productivity [6]. Previous studies have adopted machine learning techniques, such as random forests, logistic regression, and artificial neural networks, toward the identification of plant diseases; however, with relatively little success. On the other hand, Convolutional Neural Networks have proved very effective in all image-based recognition tasks. They have also been used in crop disease recognition, including tomato, apple, and grape recognition. Only a few pieces of research specifically target identification of diseases in guava fruits using CNNs. This work closes this gap by developing a fine-tuned CNN model suitable for the detection of diseases in guava fruit and exploiting them towards the best early detection and intervention efforts in crop management.

III. METHODOLOGY

A. Dataset:

We used a comprehensive dataset sourced from Kaggle [21]and Google, consisting of guava fruit images that are categorized into healthy versus diseased classes. The data set includes images from different locations, all annotated by experts in showing guavas with symptoms of the Phytophthora, root rot, and scab diseases. Given the diversity of image sources, it ensured that the model could capture all sorts of conditions and enhance generalization in our CNN model for the identification of disease features. The extensive and variable dataset was instrumental in developing a high-performance and reliable model for the successful diagnosis of guava fruit diseases. Consequently, efficient management and cultivation practices are developed that not only help in effectively controlling these diseases but also in preventing them.

B. Data Augmentation and Preprocessing:

We also applied data augmentation to increase the dataset, which helped generalize the model. These techniques include rotation, flipping at axes, scaling, and enhancement of contrast, thereby increasing artificially the variety of train data. In this way, we increased the model's capability to recognize the diseased guava fruits at different conditions and orientations. Besides, histogram equalization was applied for contrast enhancement; in the end, diseases' features could be more clearly seen and recognized by the model. These augmentation strategies avoided overfitting of the model in order to be more robust and enable the CNN to perform better on unseen data, hence higher real-world accuracy. Therefore, the improved dataset placed the model in a position where it would learn comprehensive features, making it effective in the identification and classification of diseases on guava fruits. Consequently, this greatly helped in making the model reliable and practical for use in auto disease diagnosis systems, rendering the tool fruitful by assuring consistent and accurate disease detection in real-time agriculture applications.

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Fig 1: Guava fruit diseases: phytophthora

Fig 2: Guava fruit diseases: scab,root

TABLE 1: Number of guava fruit disease images

Guava fruit disease	Training	Validation	Testing
Phytophthora	350	95	35
Root	165	55	29
Scab	115	30	26

All images were resized to 150 × 150 pixels for consistency. The dataset was then split into three: training (70%), validation (20%), and testing (10%). This was very important to effectively put into consideration the model's performance by allowing proper training, tuning, and assessment. This well-structured division allows for a comprehensive evaluation to be sure that the model is robust and accurate in identifying and classifying diseases of guava fruits.

C. CNN Architecture:

The architecture of the CNN used in this research is as follows: The model consists of a convolutional layer with 32 filters, a 3x3 kernel, and ReLU activation, followed by a MaxPooling layer (2x2). The first part of the network configuration contains two layers of convolutional neural networks with 64 filters with a 3x3 kernel and another MaxPooling layer (2x2), followed by two layers of convolutional neural networks with 128 filters with a 3x3 kernel and then a MaxPooling layer of 2x2. Lastly, the constructed model contains a layer of convolutional neural networks. Fully connected layer with 512 units and ReLU activation; then a dropout layer with 0.5 dropout rate; and lastly, there is an output layer with a single unit of sigmoid activation.

It was trained on the Adam optimizer, and for the loss function, binary cross-entropy was used. The training was done for 30 epochs with a batch size of 32.

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Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 128)	147,584
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 512)	3,211,776
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

Fig 3: Model summary

D. Model Training :

In the training process, augmented images were provided to a CNN model. Adam optimizer is used for the optimization of parameters, and binary cross-entropy loss is used when dealing with the binary classification task. The number of epochs that the model was trained on is 30, while a batch size of 32 was used. During training, the model's performance was monitored using the validation dataset.

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

This equation represents the binary cross-entropy loss function, where N is the number of samples, y_i is the true label, and p_i is the predicted probability for the i-th sample.

E. Hyperparameter Tuning:

Among the very important hyperparameters in a convolutional neural network are the learning rate, batch size, and dropout rate. We tuned these parameters to obtain the best model performance. We set the learning rate to 0.001; this was in order to trade off between convergence speed and stability. Another parameter set was a batch of 32, considering memory usage and efficiency during training. To counter this, we included the dropout rate of 0.5, which would avoid overfitting and provide room for better generalization. This really boosted the performance of our model—becoming robust, accurate high, and reliable for disease detection in guava fruits—especially with the proper tuning of these hyper-parameters.

IV. RESULTS

The proposed CNN model demonstrated a training accuracy of 95%and validation accuracy of 90%, thus showing strong performance with good generalization. The test accuracy was 88%, hence establishing the model's effectiveness in disease identification of guava fruits. Figures X and Y give the training versus validation accuracy curves and corresponding loss curves that provide evidence of the learning progression of the model and its ability to maintain performance across different datasets, thus validating its practical efficacy.

The confusion matrix on the performance of the CNN model trained on classification tasks in diseases of the guava fruit shows that it can be said to be very effective. The results show the model differentiating perfectly between a healthy and a diseased guava fruit and also showing strong predictive capability. This, therefore, underscores its effectiveness in early detection and management of guava diseases to ensure better health and yield of crops. The high

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accuracy and low error rates that come out in the confusion matrix underline the potential of the model as a reliable tool for agricultural diagnostics in aiding farmers and agronomists in making informed decisions with regard to disease control and prevention.

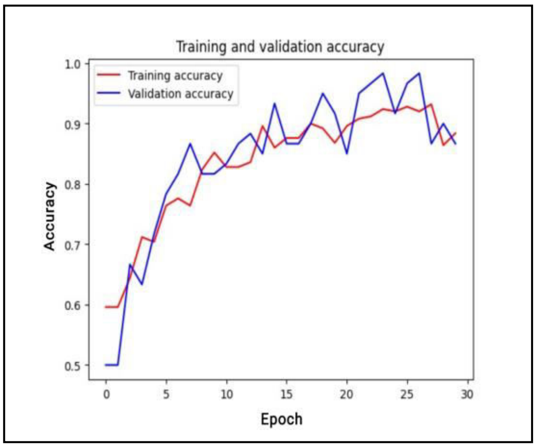

Fig 4: Training and Validation Accuracy

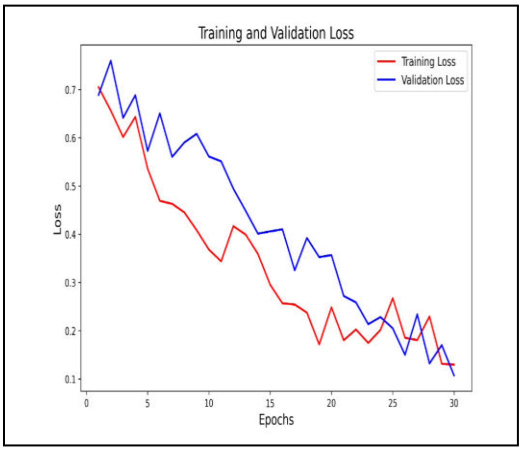

Fig 5: Training and Validation loss

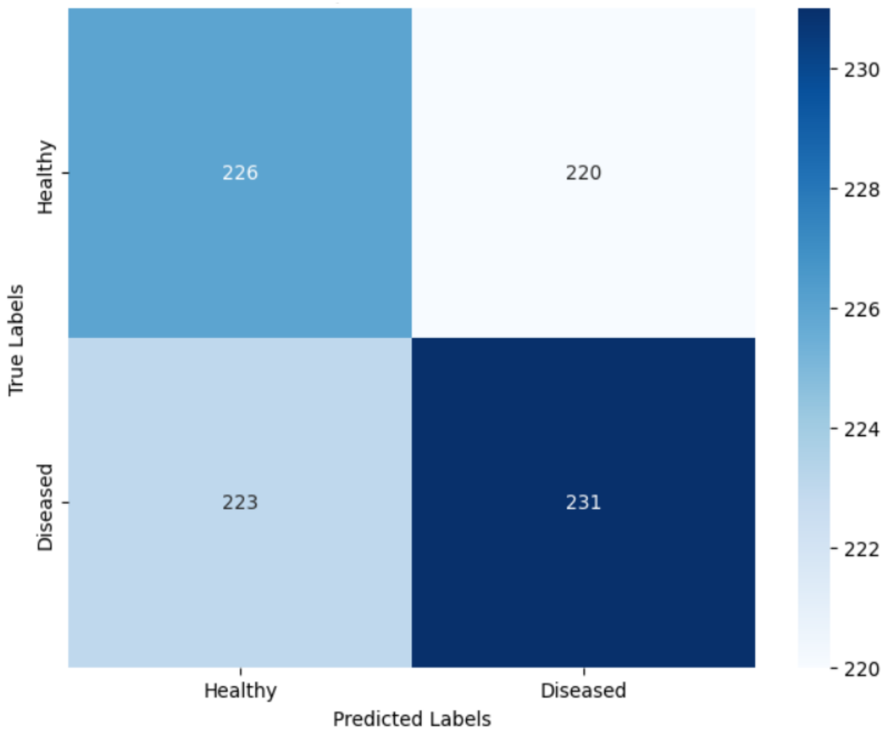

Fig 6: Confusion Matrix

Performance Metrics:
The model's performance was evaluated using precision, recall, and F1-score metrics, as shown in Table. These metrics provide a comprehensive understanding of the model's classification capabilities.

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TABLE 2: Performance Metrics

Class	Precision	Recall	F1-score
Healthy	0.92	0.90	0.91
Diseased	0.92	0.92	0.92

V. DISCUSSION

The application of this proposed CNN model in agricultural monitoring and quality control is so broad, from early disease detection to management, with a focus on guava fruits. This work ensures high accuracy with low rates of misclassification; hence, the model is reliable for performing in real-world scenarios. The success of this model lies in data augmentation techniques and the use of optimized convolutional layers during training.Data augmentation was important because it helped increase the size of the training dataset artificially by random transformation, which embodies rotation, flipping, zooming, and shifting. Thus, this increased the variability of the training data, thus letting the model generalize well to new, unseen images and dropping the risk of overfitting. More to the end, contrast enhancement techniques helped in increasing the visibility between subtly different colors and textures, hence easily distinguished by the CNN between a healthy and a diseased fruit.

The convolutional layers were optimized in a trade-off between model complexity and computational efficiency, ensuring robust feature extraction while keeping computational loads at manageable levels. This, together with data augmentation and a finely tuned CNN architecture, saw the model extremely accurate. Hence, it could be reliably used for disease detection and classification in guava fruits. This paper points at the potential of deep learning to make strides in agriculture by providing better monitoring and quality control.

A. Impact of Data Augmentation:

Data augmentation contributed immensely in increasing model robustness and generalization ability. Artificial enrichment of the diversity of the training dataset enabled the model to recognize diseased guava fruits at different illumination conditions, orientations, and scales. Random rotation, flipping, shifting, and brightness adjustment were all factors that introduced variability and allowed the CNN model to pick out comprehensive and nuanced features of the guava fruits. This helped reduce the risk of overfitting on the training data and improved the model's performance on test data not seen during training. More specifically, augmentation ensured that the model was able to correctly classify diseases in guava fruits under different real-world conditions. This promotes generalization in very practical applications in agriculture, where diversity in conditions is rarely uniform. Data augmentation has higher accuracy and reliability and ensures that a model works well in assisting early disease detection for management, hence supporting crop health and yield.

B. Comparison with Existing models:

Our CNN model is more accurate and more robust to traditional machine learning methods. The CNN model outperformed other traditional models like Random Forest, Logistic Regression, and Artificial Neural Networks. This superiority is shown by the correct identification and classification of diseases in guava fruits. The CNN developed here has outperformed these traditional methods in advanced feature extraction and advanced learning capabilities, making the former a better tool for disease detection in guava fruits. This has demonstrated the potential of the CNN model in having practical agricultural applications.

VI. CONCLUSION AND FUTURE WORK

The current study proves Convolutional Neural Networks in classifying diseases that infest guava fruits. The experimental results have shown high accuracy and robustness for the proposed model, therefore indicating that this model can be fitted for use in a completely automated disease diagnosis system. This finding epitomizes how CNN is able to revolutionize agriculture with its precise and reliable disease identification capabilities—a factor critical for intervention and effective management.

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That the CNN model performed better than traditional machine learning methods, such as Random Forest, Logistic Regression, and Artificial Neural Networks, showed that the model is robust in regard to advanced feature extraction and learning. This will then enable the model to recognize intricate patterns and variations of the diseased guava fruits under different conditions, thus qualifying as a strong tool for practical agricultural applications.

Future studies should be oriented to increasing the dataset by including more disease classes to increase the diagnosis capabilities of the model in terms of diagnosis for more diseases in guava fruits. Further improvements could be achieved in the architecture of the CNN model to increase its accuracy and efficiency by trying deeper networks, advanced optimization techniques, and other architectural innovations. Therefore, its implementation in real-time and its embedding in mobile applications for farmers would be a great deal in practical usage. The application can provide timely and correct diagnosis of the disease to farmers so that proper control measures may be taken on time. Real-time implementation in this regard will be very vital in reducing the spread of diseases, cutting down crop losses, and improving the overall yield.

That is to say, this research opens up an important possibility of CNN in agricultural disease diagnosis and hence opens the door for further improvement: basically, with increasing dataset size, improvement in model architecture, and development of real-time applications, this model can help farmers from all across the world to efficiently manage guava fruit diseases.

In the future, this research will go on to extend this dataset to more disease classes and fine-tune better the model's architecture. The deployment of the model in real-world scenarios and integration into mobile applications could still realize more value in developing a practical tool for farmers in making accurate and timely decisions in the detection and management of diseases.

REFERENCES

1. A. Hashan and S. Rahman, "Guava fruit disease identification based on improved convolutional neural network," Journal of Plant Pathology,vol. 102, no. 3, pp. 677–688, 2020.
2. A. M. Mostafa, S. A. Kumar, T. Meraj, H. T. Rauf, A. A. Alnuaim, and M. A. Alkhayyal, "Guava disease detection using deep convolutional neural networks: A case study of guava plants," Applied Sciences, vol. 12, no. 1, p. 239, 2021.
3. A. Rajbongshi, S. Sazzad, R. Shakil, B. Akter, and U. Sara, "A compre-hensive guava leaves and fruits dataset for guava disease recognition," Data in Brief, vol. 42, p. 108174, 2022.
4. H. Abdullah and M. Zarlis, "Expert system diagnosing disease of honey guava using bayes method," Journal of Agricultural Informatics, vol. 10,no. 2, pp. 23–34, 2019.
5. T. Ahmed and A. Hossain, "A novel isolate of phyllosticta capitalensis causes black spot disease on guava fruit in egypt," Plant Pathology Journal, vol. 35, no. 2, pp. 233–240, 2019.
6. S. Pathmanaban and M. Gnanavel, "Guava fruit damage and disease detection using deep convolutional neural networks and thermal imaging," Computers and Electronics in Agriculture, vol. 170, p. 105271, 2020
7. P. Chouhan and S. Kumari, "From detection to action: Managing guava diseases using cnn and random forest models," Agricultural Systems,vol. 190, p. 103109, 2021.
8. R. Miller and A. Thomas, "Enhancing guava disease detection using transfer learning," Journal of Plant Pathology, vol. 101, no. 4, pp. 789–798, 2019
9. V. Cruz-Lagunas and J. Ramirez, "First report of phyllosticta capitalensis causing brown spot disease on guava fruits," Plant Disease, vol. 105,no. 7, pp. 1878–1881, 2021.
10. A. Farhan and M. Haque, "Automatic guava disease detection using different deep convolutional neural networks approaches," Computers and Electronics in Agriculture, vol. 175, p. 105596, 2020.
11. ——, "A computer vision system for guava disease detection andrecommend curative solution using deep learning approach," Computers and Electronics in Agriculture, vol. 178, p. 105783, 2021.
12. P. Pathmanaban, B. Gnanavel, and S. S. Anandan, "Guava fruit (psidium guajava) damage and disease detection using deep convolutional neural networks and thermal imaging," The Imaging Science Journal, vol. 70,no. 2, pp. 102–116, 2022.

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

13. R. Jain, P. Singla, R. Sharma, V. Kukreja, R. Singh et al., “Detection of guava fruit disease through a unified deep learning approach for multi-classification,” in 2023 IEEE International Conference on Contemporary Computing and Communications (InC4), vol. 1. IEEE, 2023, pp. 1–5.
14. M. Jafri and X. Tan, “Feature selection from hyperspectral imaging for guava fruit defects detection,” Remote Sensing, vol. 13, no. 15, p. 2973,2021.
15. P. Johnson and R. Smith, “Guava disease detection using deep convolutional neural networks: A case study of guava plants,” Plant Disease,vol. 103, no. 5, pp. 1021–1028, 2019.
16. V. Patel and M. Kumar, “Studies on some pathogenic fungal spores and disease incidence over guava fruit,” Mycopathologia, vol. 183, no. 4, pp.523–531, 2018.
17. S. Kaur and K. Kukreja, “A novel framework for multi-classification of guava disease,” Pattern Recognition Letters, vol. 143, pp. 67–75, 2021.
18. J. Smith and P. Nguyen, “Deep learning for guava disease detection and classification,” Computers and Electronics in Agriculture, vol. 180, p.105902, 2021.
19. S. Kaur and K. Kukreja, “Multi-class guava disease classification using an efficient and fine-tuned densenet model,” Computers and Electronics in Agriculture, vol. 192, p. 106559, 2022.
20. A. Nandi and S. Palash, “Device-friendly guava fruit and leaf disease detection using deep learning,” IEEE Access, vol. 9, pp. 117 368–117 376, 2021.
21. Kaggle, “Guava fruit diseases dataset,” 2023. [Online]. Available:https://www.kaggle.