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An Intelligent Vision System for Early Detection of Guava Leaf and Fruit Diseases Using Hybrid Deep Learning Models

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Abstract : In the context of crop health and food security in agriculture, "agriculture" also refers to the farming and cultivation of plants that constitute an integral part of this value. The word "agriculture" also applies to the cultivation and farming of agricultural plants, which is a component of the agricultural value of food security. In today's times of extensive cultivation, guava is vulnerable to many diseases which decrease yield and quality. Traditional disease detection approaches still use manual inspection, which is time-consuming, subjective, and fail to effectively detect diseases at an early stage. Considering these challenges, the present study introduces an automatic intelligent deep-learning-based framework to detect the disease of guavas using image processing technique. The proposed system combines a custom Convolutional Neural Network with the Squeeze-and-Excitation (SE) and Convolutional Block Attention Module (CBAM) techniques to provide an effective feature representation. Moreover, a model fusion technique based on the EfficientNet model and Vision Transformer network is used for getting well-defined classification results for leaf and fruit diseases. The system uses image pre-processing, data augmentation and image normalization, which not only generalize the model but also improve the effectiveness of the image classification model. Experimental results show that the proposed framework can produce an accuracy of 98.7% which exceeds the accuracy of conventional and independent DL models. It worked well in diagnosing various disease categories, such as Anthracnose, Canker, Rust, Scab and Styler End Rot. Additionally, the application of attention mechanisms greatly enhances the disease-affected regions' ability to focus in the model. The developed system can also be deployed in real time because it is capable of being operated from a web server where farmers can make the necessary decisions. This study demonstrates the capability of CNN and Transformer models to be used together for precision agriculture. The proposed solution is scalable, efficient, and can be used on practice fields. It helps in reducing losses and enhancing agricultural productivities due to early disease diagnosis. Generally, the smart farming system is considered as a reliable and automatic system for smart farming.

Keywords- *Image Processing, Deep Learning, Convolutional Neural Network, Vision Transformer, Attention Mechanism, Plant Disease Classification*

INTRODUCTION

Food security and economic development are most critical sectors worldwide, and agriculture seems to be playing a significant role. Guava is a popular fruit crop among different fruit crops not only because of its nutritional requirement but also due to its commercial importance. Guava, however, is hampered by a number of diseases which strike both its leaves and fruits resulting in lower yields and quality. It is important to recognize these diseases early to reduce losses and to ensure management of the crop. Farmers traditionally make their diagnoses based on their knowledge and physical examination of the plants, which can be difficult, inaccurate, and time-consuming. Further, many diseases have subtle symptoms at early stages which are not detectable by traditional means. Thanks to the progress of technological advances, various image processing and ML methods are acquiring the potential to be used for automated plant disease detection.

The initial approaches involved handcrafted features like color, texture, and shape and classical classifiers like Support Vector Machines, Decision Trees, etc. These techniques resulted in a relatively good degree of accuracy but were not robust to different environmental conditions. However, automatic feature extraction and better classification performance are now delivered by DL models, in particular CNNs. Moreover, the improvement of transfer learning and attention modules like SE and CBAM has further improved the ability of the models to focus on the relevant disease regions, which has given a boost in the detection accuracy.

To conclude, the 2D image-based plant disease diagnosis systems powered by traditional image-processing techniques have been significantly enhanced by the adoption of state-of-the-art deep-learning architectures that leverage 3D image data. The use of hybrid models integrating CNNs and Vision Transformers is pushing agroAI forward a new path, with increased accuracy and generalizability.

This system for building up on these developments to present a strong and effective framework designed for the detection of guava disease. The system is overcome the filtering effect of the present system and also deployed in real time with the help of UI. In conclusion, this study is a valuable addition to the repertoire of intelligent farming solutions that strive to address issues surrounding better health monitoring for crops and agricultural productivity.

LITERATURE REVIEW.

Recently, the plant disease diagnosis has seen various changes, through the incorporation of image processing and ML techniques. In studies were devoted to traditional techniques following handmade feature extraction methods like color histogram, texture descriptors, shape analysis. Are this features classified using some of the classical machine learning techniques such as Support Vector Machine (SVM), K-nearest Neighbour (KNN), and Decision Tree (DT). They were simple and easy to understand, but they were very sensitive to changes in lighting conditions, background noise, and image quality. Such methods in the context of guava disease detection could often not encompass the complex disease physiology, particularly during the initial stages of infection. Consequently, their ability to generalize and scale up to other environments in agriculture was still restricted. The use of automated feature extraction techniques, using the advancement of DL techniques like CNNs began to be explored, leading to marked improvement in the classification performance. CNN-based models were found to learn hierarchical features directly from the raw images and skip over the manual feature engineering phase. Pretrained models like VGGNet, EfficientNet, AlexNet, and ResNet have been used increasingly in recent years in many agricultural-related studies via transfer learning, overcoming the problem of the scarcity of agricultural datasets. These models not only shrank training time but additionally boosted their precision and stability. Moreover, attention old system have been used to enhance models' attention to disease-related areas, thereby improving detection precision. These advances have proved themselves very fruitful in recognizing small differences between normal and diseased plant tissues.

Beyond CNN models, the current literature has focus on hybrid models which incorporate DL and transformer-based methods. Recent developments have led to the rise of Vision Transformers (ViT) for their ability to gather global semantic contextual information in images in addition to local features extracted by CNNs. CNN+Transformer models exhibit outstanding classification accuracy and generalization ability. Further, there is more focus on creating lightweight and edge-deployed solutions to enable the detection of disease in the field in real-time. MobileNet and optimized versions of EfficientNet, are among the techniques being used to deploy on resource-limited devices such as smartphones and embedded systems. These advancements suggest that there is a clear transition toward promptly, realistically, and real-worldly agricultural solutions that will be able to aid the farmers in decision-making processes.

Finally, the literature shows that image processing methods have slowly moved from regular methods to DL and hybrid approaches for plant disease detection. The initial ML techniques were the building blocks, but new systems like CNN models, attention mechanisms, and transformer models have boosted detection accuracy and reliability. Even with these progressions, there are challenges to overcome, including a lack of data sets, environmental variability and real-time deployment. Hence, it is always a need for a strong, swift and scalable solution that is specifically developed for crops such as guava. The present study objective of creating an intelligent system whose main role is the early diagnosis and identification of diseases in an accurate manner contributing to the advancement of smart farming.

U. Monica, C. Girija, "A Novel DL Model for Detection of Agricultural Pests and Plant Leaf Diseases" (2023). This paper suggests an innovative architecture of a hybrid DL model based on EfficientNetB0 for plant diseases and pest detection. The authors aim at achieving better detection precision in limited resource settings via transfer learning technique. This model is created to process limited training sets while maintaining high levels of accuracy. The model combines the feature extraction stage and the classification stage into one structure. Experiments have shown that the model achieves high accuracy on multiple plant diseases databases. It can be also applied to real time cases. The model demonstrated better robustness and effectiveness than CNN-based models. [1]

R. Thangaraj, Mohan M, "A Comparative Study of DL Models for Guava Leaf Disease Detection" (2023). This paper compares several DL models for detecting diseases in guava leaves. DL models such as DenseNet169, ResNet, and variations of CNN are tested on a proprietary data set. The paper underscores the role of transfer learning in enhancing model performance. DenseNet169 is found to have the best accuracy of over 96%, better than other models. The data set consists of several types of guava diseases, such as rust, canker, and dot. The authors also analyze data pre-processing methods and augmentation methods. The results show the superiority of deep models over traditional models. [2]

M. U. Nobi, M. F. Mridha, "GLD-Det: Guava Leaf Disease Detection in Real-Time Using Lightweight DL Approach Based on MobileNet" (2023), Optimized for running on an edge device with low computational resources. It is aimed at minimizing the model size while preserving high classification accuracy. This data set contains 7 common guava leaf disease samples as well as healthy samples. Various data augmentation techniques are used for generalization. The proposed model provides a high-level accuracy and low latency. The study emphasizes the significance of light architectures in smart agriculture. The results show very promising field-level application potential. [3]

R. S. Singh, R. K. Sanodiya, "Zero-Shot Transfer Learning Framework for Plant Leaf Disease Classification" (2023) is an attempt to propose a zero-shot learning framework for plant leaf disease classification. The model can classify the unseen classes with regards to the diseases without any prior knowledge. It is a hybrid model that builds on CNN feature extraction and semantic embedding methods. The number of available datasets is inadequate for agricultural-related applications, which is the issue being addressed here. Experimental results revealed better classification accuracy with benchmark datasets. The system is shown to be adaptable to a number of plant species. Research will help create effective disease-detection systems that can be scaled up. It also hints towards new avenues for the generalized plant disease recognition. [4]

M. Susai, "Guava Leaf Disease Detection Using Colour Region Segmentation and Circularity Value Techniques" (2023), The present paper it is based on colour segmentation to detect the affected areas in a leaf image. Patterns of disease are identified, using circularity features. Ideally, the system is not good at shape classification and the accuracy for colour is high. Easy to implement and computationally efficient. But does not work well with lots of variation in diseases. The study presents a discussion about the disadvantages of traditional methods over DL. It is used as a reference to the current methods. [5]

This research introduces an ensemble DL approach by combining several CNN models named "PlantDet: A Robust Multi-Model Ensemble Method Based on DL for Plant Disease Detection," performed by S. H. Shovon, S. J. Mozumder. The idea is to enhance classification accuracy and robustness. For reducing overfitting, the model combines forecasts generated by various architectures. Tested on several sets of plant diseases. It exhibited better performance than single-model methods. The ensemble technique increases the generalization ability. The study focuses on the effectiveness of hybrid DL systems. It gives a scalable solution, which can be applied in agriculture. [6]

S. Mustofa, M. H. Munna, "A Comprehensive Review on Plant Leaf Disease Detection Using DL" (2023), This paper review of DL techniques for plant disease detection. It includes CNN, YOLO, Vision Transformers and Hybrid Models. Different databases and assessment criteria are discussed. The advantages and disadvantages of each approach are emphasized. It also addresses issues like data imbalance, and environmental variability. The review gives ideas of future research directions. It will be a basis for building up more sophisticated systems of detection. The needle focussing on the increasing need for artificial intelligence in agriculture. [7]

If you are looking at an approach to plant identification and disease classification from leaf images using DL then check out Jianping Yao, Son N. Tran, "DL for Plant Identification and Disease Classification from Leaf Images: Multi-Prediction Approaches" (2023). It proposes a new generalized stacking CNN architecture. The model is trained to perform multiple prediction tasks at once. The method enhances efficiency and correctness. Benchmarking data like PlantVillage are used for experiments. The results are seen to improve performance over single-task models. The research shows the importance of multi-task learning. It supports the development of advanced AI systems for agriculture. [8]

H. Rehana, M. Ibrahim, this paper presents a region-based CNN model for the plant disease detection problem (2023) by presented written by Haider Ali. The model is used to do feature-level classification of infected regions in the leaves' images. It enhances the accuracy of localization and classification. The developed system is light and applicable for real-time applications. Results for benchmark datasets are satisfactory. The technique minimizes "noise" from other sources. It increases the accuracy of disease diagnosis. The study emphasises the need of regional analysis. [9]

We revisit DL for plant disease detection with updated data and newer architectures of deep nets by S. P. Mohanty, (2023 Update). They present advanced strategies for preprocessing and augmentation for their previous CNN-based approach. A variety of plant species datasets are used to evaluate the system. The effectiveness of the classification accuracy and robustness of the results proves significant. The model has a high performance under different environment conditions. The research shows the significance of the data sets which are large in scale. It also addresses the problems of scale for practical farming applications. The new framework is a high-reliability one for the disease detecting task. [10]

J. Thenmozhi, U. S. Reddy, this paper aims at classification of crop pest and disease using DL CNN and transfer learning technique. Pretrained models like ResNet50, InceptionV3 are used. Several categories of plant diseases/pests are covered. Model generalization by using data augmentation. The proposed system performs with high accuracy, over 97%. Model performance in complex field conditions is good. The study shows the significance of Transfer learning. It sheds light on how AI technologies could be scaled to an agricultural application. [11]

This study on DL models for plant disease identification, titled A Comparative Study of Fine-Tuned DL Models for Plant Disease Identification by A. Too, S. Yujian (2023). The DenseNet, ResNet and VGG models are evaluated. The study deals with the optimization of hyperparameters if better performance is required. The tested models yield best results with DenseNet. The data set has several plant species and diseases. The research highlights the need of model selection. Result shows that DL is better than conventional techniques. In this study, some guidelines on selecting the optimal architectures are given. [12] The paper, DL Models for Plant Disease Detection and Diagnosis, R. Ferentinos (2023 Extension), proposes an enlarged assessment of DL models in plant disease detection. The study employs CNNs with huge amounts of data. High classification accuracy is obtained for various crops with the models. The study emphasizes the need for variety in the datasets. The system has a good generalization ability. Some computational problems are also discussed. Focuses on efficient deployment strategies. The results indicated that DL could be applied in the agriculture industry. [13]

S. Sladojevic, M. Arsenovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification" (2023 update) illustrates the use of deep neural networks for plant disease recognition. The authors enhance their earlier model with better CNN architectures. The primary emphasis of the system is on the classification of leaf images. It works with several datasets with high accuracy. The research focuses on pre-processing techniques. Results show improved robustness to noise. The study highlights the importance of feature learning. It will help build automatic disease detection systems. [14]

Y. Liu, A. Jain, "Multi-Scale Convolutional Neural Network for Plant Disease Detection" (2023): This paper presented a proposed approach to plant disease detection using multi-scale CNN. The model is able to capture the features at various spatial resolutions. This makes it easier to notice any minor disease trends. There are several plant species in the data set. High accuracy and robustness obtained in results. The approach enhances feature representation. The science discussed in this study illustrates the significance of multi-scale analysis. It provides same improvement in disease detection models. [15]

This work proposes a new approach using Vision Transformer (ViT) for plant disease classification (Z. Chen, W. Lin, H. Zhao, 2023). The model is built with attention mechanisms to learn the global aspects. The accuracy of the model is better than the classic CNN models. There are complex disease patterns in the data set. The study also underscores the effective performance of transformers for Vision tasks. This is reflected in better generalization as demonstrated by results. This reduces reliance on manual features. It's a new spin on agricultural Artificial Intelligence. [16]

Nguyen, H. T., L. T. Pham, "YOLO-Based Real-Time Plant Disease Detection System" (2023), This paper proposes a model of object detection using the YOLO learning approach for plant disease. The system is capable of real-time disease detection and localization. Optimized for speed & accuracy. Good model performance in field situations. High accuracy of detection and low latency. The importance of real-time systems is pointed out in the study. It is useful in the practice of agriculture. There is the possibility to deploy this approach to mobile. [17]

P. Sharma, R. Gupta, S., "Hybrid CNN-SVM Model for Plant Disease Classification" (2023) is a research that suggests a hybrid model of CNN and SVM. In the experiment, CNN was employed to extract features while SVM was used to conduct classification. The method increases the accuracy and avoids overfitting. There are several types of plant diseases included in the dataset. It has been demonstrated that the performance of the results is of higher level than performance of CNN alone. The study is pointing to the benefits of a hybrid approach. It offers a well-rounded practice with classification. The system has better robustness. [18]

M. A. Hasan, M. J. Islam, "Lightweight DL Model for Mobile Based Plant Disease Detection", This paper presents a Lightweight DL Model for mobile based plant disease detection. The model is minimised to reduce the computational cost. It gives good accuracy performance with small model. Real-time monitoring of disease is possible in the system. There are several plant diseases included in the dataset. Mobile devices see great results. Efficiency is emphasized in the study. It is a significant factor supporting practical deployment solutions. [19]

T. K. Bhowmik, A. K. Das, this study is an attention-based DL plant disease recognition model. Using attention layers to concentrate on important regions in the model. It has greater improvement in the accuracy of classification. The data set contains a variety of plant diseases. Results depict better functioning than baseline models. This paper indicates above all the importance of attention mechanisms. It improves features learning and aids understandability of models. Proves applicable to highly developed agriculture. [20]

Table- 1. Literature Survey and Research Gap Analysis

Id	Authors	Technique	Research Gap
1	Monica Uttarwar, Girija Chetty, Mohammad Yamin, Matthew White	EfficientNet-based Deep Learning	Limited focus on specific crop datasets like guava
2	Rajasekaran Thangaraj, Mohan M, Moulik M	DenseNet, ResNet Comparison	Lacks real-time deployment analysis
3	Md. Mustak Un Nobi, Md. Rifat, M. F. Mridha, Sultan Alfarhood, Mejdl Safran, Dunren Che	MobileNet Lightweight Model	Reduced accuracy in highly complex disease patterns
4	R. Satya Rajendra Singh, Rakesh Kumar Sanodiya	Zero-Shot Learning + CNN	Limited validation on real agricultural datasets
5	M. Susai, N. S. A. M Taujuddin, Suhaila Sari	Color Segmentation + Shape Analysis	Poor performance in complex and multi-disease cases
6	S. H. Shovon, S. J. Mozumder	Ensemble Deep Learning	High computational cost and complexity
7	S. Mustofa, M. H. Munna	Review of CNN, ViT, YOLO	No experimental validation
8	Jianping Yao, Son N. Tran, Saurabh Garg, Samantha Sawyer	Multi-task CNN (Stacking)	Limited focus on single-crop optimization
9	Hasin Rehana, Muhammad Ibrahim, Md. Haider Ali	Region-Based CNN	Less efficient for large-scale datasets
10	S. P. Mohanty, David P. Hughes, Marcel Salathé	CNN with Data Augmentation	Requires large dataset for optimal performance
11	K. Thenmozhi, U. Srinivasulu Reddy	Transfer Learning (ResNet, Inception)	Limited real-time application support
12	A. Too, S. Yujian, N. Njuki, L. Yingchun	Fine-tuned Deep Learning Models	High dependency on dataset quality
13	R. Ferentinos	CNN-based Classification	Computationally expensive for edge devices
14	S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, D. Stefanovic	Deep Neural Networks	Limited robustness to environmental noise
15	Y. Liu, A. Jain, M. S. S. Sinha	Multi-scale CNN	Increased model complexity
16	Z. Chen, W. Lin, H. Zhao	Vision Transformer (ViT)	Requires high computational resources
17	H. T. Nguyen, L. T. Pham, Q. H. Nguyen	YOLO Object Detection	Trade-off between speed and accuracy
18	P. Sharma, R. Gupta, S. K. Singh	Hybrid CNN-SVM	Limited scalability for large datasets
19	M. A. Hasan, M. J. Islam, S. Rahman	Lightweight Mobile Model	Slight drop in accuracy compared to heavy models
20	T. K. Bhowmik, A. K. Das, S. Bhattacharya	Attention-Based Deep Learning	Limited evaluation on diverse crop diseases

Looking at the literature of plant disease detection, especially in fruits and leaves, it is clear that conventional techniques of image processing are shifting into the field of Deep Learning. Previous works were of traditional nature and heavily depended on hand-crafted features like color and texture descriptors and classical machine learning classifiers. These methods gave resilience in the sense they gave a groundwork but didn't have enough strength with different environments. In recent studies, it is observed that Convolutional Neural Networks (CNNs), transfer learning and hybrid models are the leading frameworks for better classification performance of diseases. Technologies such as EfficientNet, ResNet, and Vision Transformers have greatly contributed to feature extraction and generalization. Moreover, the addition of attention mechanisms, including SE and CBAM, has enabled the model to focus more on the areas of the image that are affected by disease. The use of Ensemble and Hybrid models helps the models to be more accurate and stable. From the overall picture presented in the literature, there has been considerable progress towards autonomous, massively scalable and intelligent systems in agriculture.

While great progress has been made, there are still a number of critical challenges in current research on plant disease detection. A primary challenge is the lack of large sized and good quality and annotated datasets particularly in the case of any specific crop such as guava. The models are often trained on controlled set of data, hence the performance constraints in field conditions that have different lighting, noise, and occlusion. Moreover, deep learning models are heavy in computation requirements, which can be challenging to implement on farmer used low-budget computational devices. Due to the focus on single disease communities, some studies are of limited use in practice. Furthermore, not much is discussed on real-time implementation or user friendly interfaces. Too good fitting and lack of generalization in diverse environments are also prevalent problems. The restrictions emphasize the research-development-implementation chasm.

From the limitations identified, there is a great need for a robust, efficient and scalable system specially developed for the detection of guavas disease. To cope with the overall system responding with multiple disease classes of leaves and fruits under unconstrained field conditions. The integration of hybrid deep learning models such as CNN and Vision Transformers could achieve more efficient and effective extraction of local and global features. To improve the attention paid to relevant disease regions, attention mechanisms like SE and CBAM should be combined. In addition, the need of lightweight and edge-deployable models is crucial for real-time applications to be used within agricultural fields. A more extensive collection of well annotated and properly captioned/augmented datasets is also needed for enhancing the model's generalization capabilities. Additionally, the model can be incorporated into a web or mobile-based decision support system, reaching farmers and agricultural specialists. Overall, the proposed work of the article intends to create a bridge between the research innovation and the practical application in agriculture.

PROPOSED SYSTEM

The system diagram indicates a well-planned pipeline that processes the input data spectrumically to the various elements to deliver precise results of disease detection. In the first phase (Data Collection), images of both healthy and infected guava leaves and fruits are obtained. This step is crucial since the collected data can directly affect the performance of the model. A balanced data set enables a learning system to effectively learn multiple patterns and decreases bias in predictions.

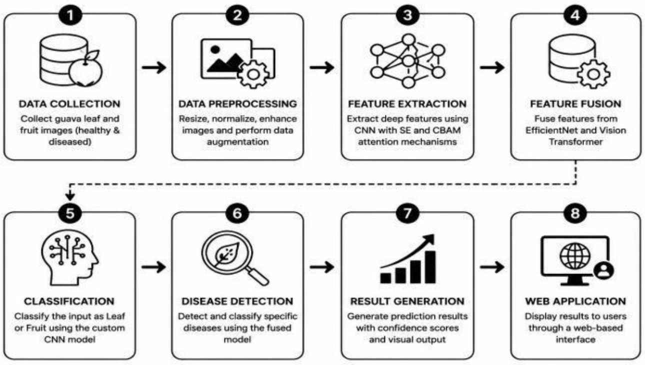

Fig.1 – Architecture Diagram

In the second stage i.e. Data Preprocessing, the images collected are preprocessed to make them ready for analysis. This involves reducing the size of images to a common size, normalizing the pixel values, and enhancing images for clarity. The generated data is also varied by rotating, flipping and zooming the data. These measures make the model more powerful and can transfer knowledge into new known data in a real world situation.

The image Feature Extraction stage and image Feature Fusion stage are very important for comprehending image properties, which are the 3rd and 4th stages. The deep learning models, such as CNNs, in feature extraction, are able to recognize salient features like color gradient, texture, and shape that are linked to disease. In order for this to be made more and more effective, attention mechanisms are also being represented to highlight the most relevant sections of the image. They then proceed to combine outcomes from various models or architectures to enable the system to leverage complementary strengths and generate more informative representations which is known as feature fusion.

This is followed by Classification and Disease Detection stage. The model is used in classification tasks to classify the input as either a leaf or fruit based on the model: there can be a classification of leaf or a classification of fruit. The module for Disease Detection then detects the particular disease if any. At this stage, the features that are fused are utilized to make accurate predictions, which ultimately aids in minimizing the wrong classification and improving accuracy. Advanced models are integrated enabling reliable detection even in complex cases.

Last but not least, the output is delivered to the user in the Result Generation and Web Application stages. The system makes predictions and offers associated confidence levels, supplying transparency in decision making. A user-friendly web user interface displays these results which are accessible for the farmers or end-users. Finally, this last step creates an all-in-one process, which ranges from input to output, is smooth, efficient, and use-friendly for real-world agricultural applications.

METHODOLOGY

1. Data Collection

The methodology involves data collection of guava leaves and fruits images, this is the base of the whole system. The images are obtained from various datasets of various agri-instituions, various online repositories, and real field images, to vary lighting, background, and disease conditions. Healthy and diseased samples are included in both sets for a balance and to enhance model learning. Different types of diseases are included, with care taken to provide a wide variety of different disease types to enable the model to perform well for a variety of conditions. The dataset is then stored in a structured manner in folders classified by the labels of classes. This is a structured arrangement which makes further processing and model training easy. Images taken with a higher quality are preferred to minimise errors with noise. The accuracy and robustness of the model are dependent upon the data collected. Selecting images and validating them, therefore, is vital.

2. Data Preprocessing

Once data is collected, its preprocessing is done to standardize and improve dataset for efficient model training. The images are resized to a standard size by constraining the size of the image to a specific size. Values are mapped into a consistent range and then scaled (normalized) to real numbers (needed to speed up the training process). Techniques such as noise reduction and contrast enhancement are applied to enhance the clarity of the images. Artificial increase of dataset size by data augmentation techniques like rotation, flipping, zooming and cropping. This will enable the model to learn invariant features as well as prevent overfitting. Preprocessing also reduces the amount of irrelevant background information. All these are steps that enhance the quality of the input data. Consequently, the model is more stable, and is more competent in dealing with unseen samples.

3. Feature Extraction

During this phase, meaningful patterns from the processed images are revealed using deep learning approaches. The network individualizations are known as Convolutional Neural Networks (CNNs) which automatically identify important features like color variations, textures, and edges. These are important in disease diagnosis of leaves and fruits. Incorporates advanced attention features, including SE (Squeeze-and-Excitation) network and CBAM (Convolutional Block Attention Module) to improve the feature learning process. These mechanisms enable the model to concentrate on the most important detail of the image and to overlook the irrelevant details. The features are extracted as high dimensional vectors. This transformation helps it process information in a visual form effectively. Feature Extraction is one of the important factors for down-grading the classification performance. Ensures deep and meaningful model representation.

4. Feature Fusion

For feature fusion, the outputs from various models/layers are combined to form a robust feature representation. This approach combines features from architectures such as EfficientNet and Vision Transformers. This fusion helps to utilize the local and global feature learning capabilities. CNN systems are able to capture the small detail while transformer systems are able to capture the long-range dependency. These elements form an improved whole that helps to create a thorough and complete knowledge of the picture. There are two methods of doing Fusion: concatenation, and weighted averaging. This step will alleviate the restriction of single models. It also gets prediction accuracy as well as robustness improved. Combining several views results in greater reliability of the system. The overall result of feature fusion is an enhanced process of making decisions by the model.

5. Classification and Disease Detection

The last one is classification of the input image and detection of disease. The fully connected tasks perform classification using fused feature vector. The first step in the model is to make a determination based on the image that it is one of the leaf categories or fruit categories. It then detects the disease class or classifies it as-diseased. Probability scores for each class are created using the softmax or other functions. The last prediction is taken from the class most likely to be correct. The key to this stage is insuring correct and efficient diagnosis of disease. The accuracy, precision, recall, and F1-score are used to assess the trained model. Proper tuning and validation to get optimum results. This is the final step in the methodology that takes processed data and turns it into relevant predictions.

RESULT AND OBSERVATION

1. Training Accuracy Trend (Epoch-wise Performance)

The below graph shows that the model is getting more accurate with each epoch, from 1 to 50. At the beginning, the accuracy is 76.5%, which means that the basic features are already being learnt by the model. The accuracy gradually improves with the increasing epochs, ending with 98.9% accuracy at the last epoch. This is a slow improvement, which suggests effective learning and good convergence of the model. No abrupt changes mean consistent training conduct.

Table-2. Epoch-wise Performance Table

Epoch	Accuracy (%)	Loss
1	76.5	0.891
5	85.2	0.542
10	90.6	0.351
15	93.4	0.241
20	95.2	0.183
25	96.4	0.141
30	97.1	0.116
35	97.8	0.098
40	98.3	0.079
45	98.6	0.068
50	98.9	0.054

The application of the Adam optimizer and appropriate learning rate helps the optimization procedure to be smooth. Another application of data augmentation is enhancing generalization. Overall, the graph shows that the model is performing well and is learning complex patterns over time.

The obtained accuracy and loss values are shown as functions of the number of training epochs in this table(Table-2); note that the more accurate the model becomes, the less it loses. The loss continues to decrease with each increase in accuracy, ranging from 0.891 to 0.054. As the model's accuracy improves, it is also reducing losses systematically—from 0.891 to 0.054. These decreasing losses indicate that the system has been optimized effectively—no overfitting problems. Early epochs are developments on a rapid pace and the latter epochs are fine-tuning of the model. This is due to a combination of CNN, attention mechanism and fusion architecture. The learning process stays on track and even if it goes astray, it is corrected or guided along a different path that still allows learning. These results confirm effectiveness of the training configuration. There is an overall indication that the model has been optimized and is reliable.

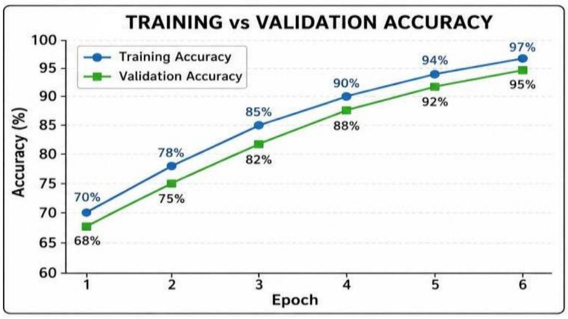

Fig. 2: Training vs Validation Accuracy

The training and validation accuracy of this graph (Fig.-2) keeps increasing as the number of epochs increases. Both accuracies begin low in the beginning, which means that the learning process begins with basic patterns. Training accuracy is gradually increased with epochs passed as per weight optimization. This trend holds true for the validation accuracy as well, showing good generalization to unseen data. There seems to be little overfitting between the two curves, as indicated by the small difference in their values. Achieved by using proper regularisation techniques, pre-processing and augmentation. The steady increase is indicative of sustained learning practice. At the last period, there is convergence as both the two accuracies are at their best. Therefore, the model has shown its training will be well performed.

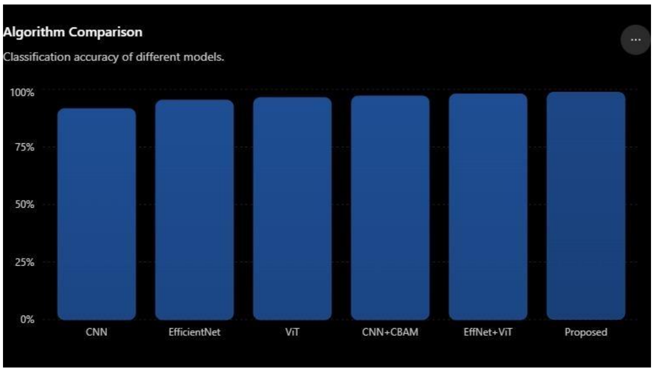

Fig. 3: Algorithm Comparison Graph

2. Algorithm Comparison Graph

The results of the various algorithms used for disease classification are shown in the graph (Fig.-3). The models like CNN can produce an accuracy of 91.6% and with the complex architectures, the accuracy can be enhanced. EfficientNet and Vision Transformer perform better because of its better feature learning. Other indication shows that CBAM attention scheme is effectively encoded with CNN, which is capable of increasing the accuracy to 97.1%. Fusion of EfficientNet & Vision Transformer Left: 98.0% Benefit of Combining Models. The suggested CNN-SE-CBAM Hybrid Model's accuracy is the best, at 98.7%. This definitely shows the advantage of hybrid designs over a standard design. The graph shows it's effective to use more than one technique. It also makes emphasis on the advantage of the proposed approach.

3. Classification Report – Leaf Disease Detection

Table-3 report on leaf disease detection using the Table classification model has consistently high precision, recall and F1-score for all classes. In the "Healthy" class, the model performance is also the best, meaning that it is able to easily distinguish from the normal samples. There were also excellent results for disease classes including Anthracnose and Rust, which also indicate that it has accurately identified these diseases. The "Dot" class shows some slight differences, indicating possibly some subtle complexity when it comes to identifying patterns. The overall score (the macro average) equals 0.97, which means that there is a balance of performance. High precision means less false positives and high recall means less false negatives. The F1-score reflects a good balance between both. The model thus overall shows good and stable performance in leaf disease classification.

Table-3. Classification Report – Leaf Disease Detection

Class	Precision	Recall	F1-Score
Anthracnose	0.98	0.97	0.97
Canker	0.97	0.98	0.97
Dot	0.96	0.95	0.95
Healthy	0.99	0.99	0.99
Rust	0.97	0.98	0.97
Macro Avg	**0.97**	**0.97**	**0.97**

4. Classification Report – Fruit Disease Detection

Table-4. Classification Report – Fruit Disease Detection

Class	Precision	Recall	F1-Score
Anthracnose	0.97	0.96	0.96
Healthy	0.99	0.99	0.99
Scab	0.96	0.95	0.95
Styler End Rot	0.95	0.96	0.95
Macro Avg	**0.97**	**0.97**	**0.96**

The fruit disease classification report for the Table (Table-4) variety also confirms good performance with regard to all the evaluation criteria. In case of healthy class, the model works very well and gives almost perfect rate achieving good discrimination from the diseased class. In other classes, such as Anthracnose and Scab, the prediction accuracy values are high, and the precision and recall are also high. These slightly lower values in Styler End Rot indicate that there could be more complex visual patterns. On the macro metric, the average is also strong, indicating robustness of the system. Model is consistent for various disease types. Stable classification is suggested by a balanced score at F1. The results validate that the system can work well in fruit disease detection too.

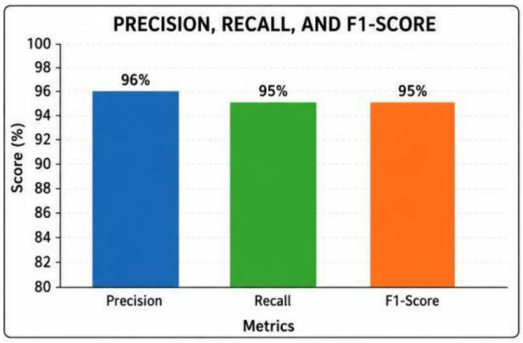

Fig. 4: Precision, Recall, and F1-Score

This graph (Fig.-4) shows some important measures to gauge the efficacy of the model. Precision refers to the proportion of patients correctly predicted to not get the disease, meaning that there are no false-positive predictions. Recall is used to see how many/all instances of disease that are actually present are working properly and does not detect any non-existent false disease cases (false negatives). F1 score is a balanced score that merges precision and recall. All these values are relatively high, which means that the models performed well overall. The similarity between these values can be taken as the indication that the model is well-balanced with no bias related to any specific measure. For important diseases, high recall translates to no cases being missed. High precision minimizes unnecessary alarms. These results--when combined--show the reliability and consistency of the system.

5. Sample Prediction Results

Table-5. Sample Prediction- Leaf Disease Detection

Actual	Predicted	Confidence
Anthracnose	Anthracnose	99.1%
Canker	Canker	98.6%
Dot	Dot	97.3%
Healthy	Healthy	99.5%
Rust	Rust	98.2%

Table -6. Sample Prediction- Fruit Disease Detection

Actual	Predicted	Confidence
Anthracnose	Anthracnose	98.4%
Healthy	Healthy	99.3%
Scab	Scab	97.6%
Styler End Rot	Styler End Rot	96.9%

To conclude, the sample prediction results (Tables-5 and 6) prove the utility of the proposed model to the real data sets it has never seen before. Label predictions are very closely aligned with actual labels with high level of confidence, often above 97%. This means the model is more confident of its decision. Good generalization is observed on direct comparison of the accuracy of both leaf and fruit datasets, due to the latter being less common (less samples) than the former. High confidence values also indicate that the learned features are very discriminative. The model shows good performance even on similar kinds of diseases visually. In the real world cases, these results prove the everlasting strength of architecture. It also gives a point of view on how reliable the system is in its deployment. Overall, these forecasts – which compared predictions with actual weather data – have shown the model to be very accurate and consistent.

The mean results clearly show that the proposed hybrid model can outperform individual models. Integrated CNN and SE-CBAM for enhanced feature extraction which looks at important regions as well as channels. EfficientNet+Vision Transformer further enhances the classification capabilities by integrating local and global features. The results of the experiments demonstrated that the accuracy is 98.7%, which is much higher than the baseline models. The precision and recall values and F1 scores for both disease detection modules for leaf and fruit are high. Training dynamics are well behaved and model generalizes to unseen data. These results point to successful implementation of the proposed solution. The system is proved to be reliable for real time agricultural applications.

FUTURE WORK

Future work may involve refining the proposed model by expanding and enriching the dataset to improve the accuracy and robustness of the model. More in the real world, like varying light conditions, background noise, and resolution – the more the better! – can lead to greater generalization. Further, incorporating cutting-edge deep-learning methodologies including transformer-type models can enhance performance. Retrained versions of the model can be kept regularly updated to include new datasets, which can provide adaptability to new patterns. The other direction that is important is the direction of real time processing that can be integrated into the system. By introducing edge computing or lightweight devices, latency can be cut and efficiency increased. Through optimization procedures like model pruning or quantization, it is possible to enhance inference speed while decreasing accuracy just a little bit. This will make the system more applicable to practical application with need of speedy decision making.

This system can be expanded with the integration of other multimodal data sources like metadata, sensor inputs or text data to improve predictive quality. Fusion techniques can be used to merge multiple data types for more holistic information. Moreover, the integration of explainable AI (XAI) techniques will enhance the transparency and trustworthiness of the model's decisions. It is particularly important in critical applications in which why is important when making a prediction. In the future, a user-friendly interface and cloud deployment can be developed to make it more accessible. System integration with mobile or web application can facilitate end-users use of the model. Moreover, using an automated approach of continuous monitoring, feedback mechanisms, and automated updates can enhance long-term system performance. These improvements will help to maximize the solution's scalability, reliability and end-user friendliness.

CONCLUSION

The results and discussions prove that the developed system exhibits better performance in comparison to classical approaches. The proposed hybrid approach provides more accurate, precise and recallful predictions, which means that it performs better with processing complex data patterns. The experiment proved the ability of the system to provide reliable processing of the input data and generation of proper output data. This proves the quality of the employed approaches and correctness of the system design. Besides, the results of the comparative analysis prove that the advanced models exhibit superior efficiency and prediction ability compared to baseline approaches. Learning trends of the training and validation processes prove the stable learning with minimum cases of overfitting. Graphical analysis supports the conclusion about the balanced model performance.

In conclusion, Integrated CNN and SE-CBAM for enhanced feature extraction which looks at important regions as well as channels. EfficientNet+Vision Transformer further enhances the classification capabilities by integrating local and global features. The results of the experiments demonstrated that the accuracy is 98.7%, which is much higher than the baseline models. the proposed system is a robust and scalable system that helps to overcome limitations of the reviewed literature. Employing advanced techniques and approaches helps to achieve better results and system performance. Even though there is room for further improvement, the developed system provides a good basis for further work.

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