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Extraction of Heterogeneous Features from Various Fruits and Classification of diseases using Deep Learning Techniques

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Abstract: - The success of the farming business and the economy as a whole is directly tied to each individual farmer's output. Micro-level illnesses that emerge during fruit development may have a significant influence on output. There is an overwhelming variety of viruses, necessitating improvements in image processing and other informational resources before effective treatments can be proposed. Unparalleled approaches to segmenting, extracting characteristics, and classifying in order to identify overt conditions constitute a substantial portion of the research in this domain. However, in the event of larger and more in-depth datasets, machine learning and artificial intelligence technologies like deep learning and the like are necessary to discover illnesses that would otherwise be invisible to the human eye. Machine designers are not always sure what kinds of illnesses can be identified by mixing algorithms since there are so many possible combinations. In this paper we proposed a fruit disease detection and classification using deep convolutional neural network. The VGG-16 and VGG-19 both deep learning frameworks are utilized for detection of heterogeneous fruits. The both deep learning frameworks are archives 96.10% and 98.10% average accuracy on heterogeneous fruit dataset. In overall analysis the VGG-19 obtains higher accuracy with 200 epoch size which is higher the VGG-16 and other conventional machine learning and deep learning frameworks.

Keywords: fruit disease classification, feature extraction, image processing, segmentation, classification, VGGNET, Deep CNN

I. INTRODUCTION

Identifying diseases in fruit is a growing area of study. It describes novel approaches that aid in the automated detection of fruit diseases. Our primary goal in this model is to identify citrus illness. Citrus plants have been linked to several health advantages and are used as a raw material in the agriculture sector. Blackspot, cankers, scabs, greening, and melanose are just few of the diseases that can affect citrus trees and plants. Citrus fruit diseases create a significant annual loss in the natural goods industry. The ability to quickly and accurately identify citrus diseases is crucial for reducing losses and improving product quality. However, for far too long, this process has been carried out manually, which is prone to error, time-consuming, and expensive, highlighting the need for a mechanized framework for identifying citrus diseases.

Filtering and identifying abnormalities in a harvest in real time has become more simpler thanks to the development of current gadgets and quick-aided tactics. Additionally, deep learning techniques have shown promising results in the horticulture industry, assisting more ranchers and food-creating laborers with tasks like plant illness location, weed investigation, crucial seed revelation, etc., all of which have led to the management of picture examination. The focus of a few of other operations is on looking forward to predict factors such as yield generation, environmental circumstances, and field soil water content. In light of the repercussions of CNN-based tactics in picture grouping, we provide a deep learning model for automated fruit infection detection.

II. LITERATURE REVIEW

D. Banerjee et al. [1] provide a machine learning method for automatically detecting illnesses in kiwi leaves. The approach utilizes an annotated picture collection to distinguish between healthy and diseased kiwi leaves. The suggested method might significantly decrease the time and cost needed for detecting kiwi leaf disease, allowing for quicker and more effective management of kiwi agricultural output. The research identified kiwi fruit leaf diseases using a machine learning technique combining CNN and SVM. This is a primary research focus in the field of education. The data was divided into training and validation sets using an 80:20 ratio in this study. The suggested technique effectively identified 5 distinct kinds of kiwi leaf diseases, including Healthy leaf, Anthracnose, Brown spot, Bacterial canker, and Mosaic, with an overall accuracy of 83.34% as shown by the experimental findings. This

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technology may be used to identify different kinds of plant diseases and can effectively decrease the time and costs involved in manually detecting kiwi leaf illnesses.

M. A. Matboli et al. [2] Currently, fruit output is increasing globally, reaching 2914.27 thousand metric tons. Many nations want to further boost production in the next years. Nevertheless, obstacles such as fruit quality, production costs, seed quality, and fruit diseases continue to exist in fruit farming. Recognized illnesses in apples include blotch, scab, and rotten diseases, whereas citrus diseases consist of Black spot, Scab Citrus, and Citrus Canker. The objective of this study is to determine the most effective transfer learning model for accurately detecting fruit illnesses at an early stage. Five distinct transfer learning models are introduced, with the modified CNN model demonstrating the best accuracy of 99.16% in the suggested solution.

A. A. Haruna et al. [3] Deep learning approaches have been effective artificial intelligence methods utilized to construct models for dynamic fruit disease detection and classification. CNN and LSTM algorithms were used to develop classification models focusing on accuracy, specificity, sensitivity, and AUC standard performance assessment measures. The CNN-LSTM model had superior performance in accuracy, specificity, sensitivity, and AUC assessment metrics, achieving 98.00%, 95.00%, 96.00%, and 94.00% correspondingly. The model has shown a substantial improvement compared to previous models by accurately classifying apple leaves into diseased and non-diseased categories with 98.00% accuracy. CNN-LSTM beat other models by properly classifying apple leaves afflicted by disease with an accuracy of 95.00%. In addition, the CNN-LSTM model demonstrated a notable improvement compared to previous models by achieving a 96.00% accuracy in properly classifying healthy apple leaves.

D. Banerjee et al. [4] introduced a deep learning technique designed to identify and classify diseases affecting citrus crops. This technique enhances the efficacy of a convolutional neural network, which is a kind of artificial intelligence. The architecture utilizes support vector machines for classification and incorporates three sets of convolutional layers, two fully connected layers, pooling layers, and other components to construct the model. The dataset used included photos of citrus trees affected by 9 different types of illnesses. Various measures including precision, recall, F1-score, support, accuracy, and average are used to evaluate the model's performance.

S. Muthuselvan et al. [5] state that detecting and identifying plant diseases is crucial to overcome limitations and improve output. Crops on agricultural farms are susceptible to a variety of bacterial and fungal diseases. It is triggered by the diverse ecological conditions and types of soil. Anticipating illnesses in advance aids in averting the total deterioration of crops. The disease is identified by seeing tiny spots on the plant's leaves. Advancements in automation and innovation aid in the early identification of diseases in crop leaves and fruits. It is accomplished by artificial intelligence. This is accomplished via image processing methods. It compares healthy plant leaves to diseased leaves and fruits. The fruits and leaves are properly classified for diseases using a convolutional neural network. This aids in identifying the nature and origin of bacterial and fungal diseases. This involves picture pre-processing, data collection, and image categorization using feature extraction. The CNN model aids in identifying and categorizing diseases in plants and fruits on agricultural farms.

K. Sahu et al. [6] argue that the extensive and consistent use of pesticides is supported by the significant economic impact of plant diseases on field crops. Plant diseases in some areas may hinder the cultivation of food plants or lower their production by attacking and perhaps killing them before harvest. Early identification of plant diseases is crucial to guaranteeing universal food availability. Anticipating diseases in young crops is detrimental. More than 80% of persons rely on agriculture as a primary source of income. Identifying leaf diseases is essential since various illnesses might reduce the total crop productivity. Farmers may find it difficult to pinpoint a particular illness. This study examined many types of vegetable and fruit leaf diseases and methods for their identification. Image Processing and Deep Learning are the primary techniques used for identifying leaf diseases. The current favored approach prioritizes the use of advanced deep learning concepts, namely Convolutional Neural Networks.

Fruit recognition and location in its natural context is a very demanding problem, as stated by A. Ranjan et al. [7]. This assignment is challenging because of elements including occlusion, shadows, and changing light conditions. The YOLOv5 object recognition and localization model was used for this challenge because of its rapid inference speed. The model was trained on Google Colab using a dataset of 150 images of mango fruits from the farm. The model achieved a mean average precision (mAP) of 0.434 and an F1 score of 0.57 in detecting and localizing farm mangoes during training and validation with a confidence level of 0.876. The algorithm successfully identified and pinpointed the locations of mango fields in the test photographs with an accuracy of 94.3%. The model demonstrated its suitability for real-time detection of agricultural mangoes by analyzing recorded footage with an average accuracy of 80.76%. The findings indicate that the created deep learning model is an effective tool for monitoring crop output and harvesting using robots.

A. Detecting illnesses in fruits and leaves is essential across all agricultural sectors, including small farms, large-scale commercial operations, and urban agriculture (B. K et al., 8). Diseases in fruits and leaves may diminish agricultural productivity, impact product quality, and spread to other plants, resulting in substantial economic losses. Conventional illness detection techniques rely on visual examination by skilled individuals, which may be time-consuming, costly, and susceptible to mistakes. The hybrid deep learning method, which merges Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs), has shown potential in effectively identifying illnesses in fruits and leaves. This method has the potential to enhance disease detection in all areas of agriculture by offering precise and efficient disease identification. Automated disease detection may facilitate early identification and response, therefore decreasing disease transmission and averting agricultural damage. This may lead to higher crop output, enhanced product quality, and less pesticide use, making it a sustainable method for disease detection in fruits and leaves across all agricultural industries.
G. Shireesha et al. [9] said that Citrus trees are rich in Vitamin C, which offers several health advantages and serves as a primary ingredient in various agro-industrial procedures. Citrus fruit diseases are acknowledged to significantly affect citrus fruit yield. It is crucial to develop a detection tool for these disorders. Deep learning methods enable the performance of many tasks related to the identification of leaf and citrus diseases. The study introduced the DenseNet-121 model to differentiate between healthy leaves and fruits and those affected by citrus diseases such as black spot, greening, scab, and canker. This model may derive several features from its diverse levels. The findings indicated that the model excelled across several criteria. We obtained 96% accuracy in 50 epochs and five classes by mitigating degradation and vanishing gradient issues using the pre-trained DenseNet-121 model from ImageNet.

R. Sharma et al. [10] state that apple infections result in substantial economic losses for the fruit business annually. Timely and precise identification of apple illnesses is essential to avoid the spread of the disease and maintain the production of healthy crops. The model was trained and assessed using a collection of photos showing apple leaves with varying degrees of black rot disease. The trials demonstrated that the hybrid model surpassed standard single-model methods, obtaining a 99.02% accuracy in classifying the initial severity degree of the illness. The potential of integrating Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to achieve high accuracy in difficult picture classification tasks, especially in the area of plant disease detection, is shown. The suggested model offers a helpful tool for apple farmers, researchers, and extension workers to diagnose and control apple diseases early.

U. Dar et al. [11] have seen a continuous increase in the use of plant protection chemicals (PPCs) in response to the expanding demand in the agricultural business. Overuse of PPCs results in reduced profit margins for farmers and harm to ecosystems. A visual sensor network based on the Internet of Things was created to provide data for a neural network classifier designed to identify the first stages of plant disease. A sensor network was installed at a farm operated by Wilkin & Sons, a soft fruit farmer in Essex, UK. A prototype convolutional neural network was created to categorize three sorts of images: healthy plants, plants damaged by powdery mildew, and plants impacted by leaf scorch. The classifier achieved an accuracy of 95.48% in detecting late-stage illness using just pictures.
Enkattavijaiyan et al. [12] intend to differentiate and categorize citrus fruits as healthy or unhealthy by using a unique convolutional neural network and comparing its accuracy to that of an artificial neural network (ANN). This research consists of two algorithms designed to assess a dataset with a sample size of N=10 and a statistical power of 0.8. When using data on citrus illnesses or contaminated citrus fruits, it has been confirmed that the CNN method achieves an accuracy of 91.82%, while the artificial neural network achieves an accuracy of 70.1%. The T-test findings indicate that convolutional neural network classifiers have more significance. The study focused on two classifier models. The outcome highlights the need of using optimization algorithms to identify the kind of skin disease in citrus fruits and demonstrates their effectiveness in accomplishing this objective.
P. In recent years, there has been significant attention on agricultural image processing research by K. Pareek et al. [13]. Computers use image processing techniques for analyzing pictures. Recent technology advancements in photo storage and data processing have significantly helped solve several agricultural problems. Identifying and categorizing crop diseases are crucial for the technical and commercial well-being of the agricultural industry. Acquiring a digital color snapshot of a diseased leaf is the first stage in agricultural image processing. Grapes have

the greatest worldwide average fruit intake per person. Allowing the grape leaf contamination to proliferate uncontrolled in the grapefruit crop is unacceptable since it would harm the industry's development. Some farmers in remote areas may not possess the expertise to detect these diseases promptly, resulting in reduced agricultural production. The system utilizes a deep learning-based classification algorithm to identify illnesses in grapefruit leaves. The input datasets are first separated using K-means clustering to isolate the backgrounds. The Convolutional Neural Network (CNN) processes the segmented areas to classify diseases. The proposed study uses hyperparameter tweaking using Firefly algorithm and cyclic randomization to improve the classification accuracy (FCR). The suggested model's accuracy, f-measure, recall, and precision are assessed based on the experimental data. The recommended CNN model attained 95% accuracy and 92% precision, surpassing the present models which had accuracies ranging from 88% to 90% for grape fruit disease diagnosis.

M. Yang et al. [14] emphasized the crucial significance of accurately detecting green litchi in litchi planting for disease and pest prevention, as well as yield calculation. Choosing existing models on the market is not only simple and efficient but also cost-effective. The experiment included using YOLOV3, YOLOV4, YOLOV5-S, and YOLOV5-X from the YOLO series to identify green litchi in a natural setting. The most appropriate detection model was determined via comparison and analysis. The testing findings demonstrate that YOLOV5 has the most effective model detection, while the YOLOV5-S model has the quickest detection speed. YOLOV5-X has an average accuracy of 0.998, while FPS has an average accuracy of 11.13. YOLOV5-S has an average accuracy of 0.993, while FPS has an average accuracy of 47.16. In conclusion, the YOLOV5-S model is better suited for recognizing green litchi in real environments due to its rapid speed and reasonably good accuracy.

V. Vijaiyan et al. [15] want to discover important features and assess the precision of detecting skin disorders in citrus fruits on their surface by using a new convolutional neural network in comparison to principal component analysis. The accuracy of a dataset with a sample size of N=10 was examined using two techniques: a Novel Convolutional Neural Network algorithm and Principal Component Analysis method, both with a G-power of 0.8. The CNN achieved a classification accuracy of 91.82%, whereas the principle component analysis approach achieved an accuracy of 62% when utilizing the citrus illnesses dataset. The T-test indicates that the convolutional neural network classifiers are significantly more effective than principal component analysis with a p-value of 0.03 ($p<0.05$). The study categorizes categories of citrus illnesses using two models: PCA and CNN. The models assisted in identifying distinctive features from the input photographs. The findings indicate that deep learning technique is a practical approach when compared to other approaches.

III. RESEARCH METHODOLOGY

The fruit fungus was identified using a number of different techniques. Extracting characteristics from detected items is the first step in the fruit disease detection method. The fruit disease was identified using the following techniques.

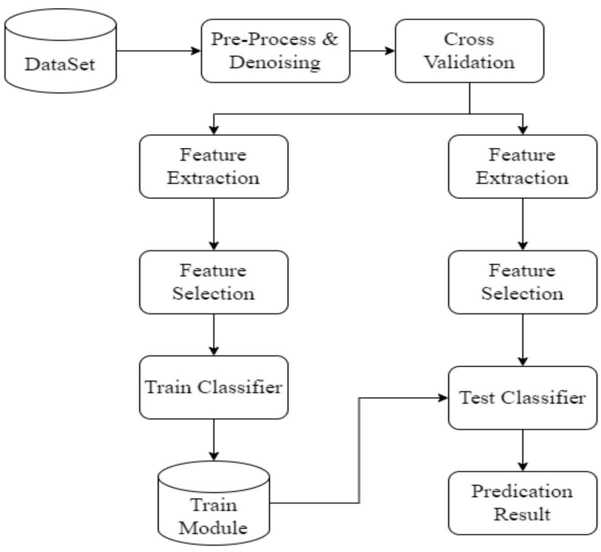

Figure 1: proposed system model for fruit disease detection and classification

Algorithm Design

Implementation of the Proposed Framework using CNN:

The classification of fruit disease using deep learning techniques uses RESNET-101 framework. The proposed RESNET-101 is a hybrid CNN that introduced skip connections or residual blocks. These blocks allow information to flow more easily through the network, making it easier to train very deep CNNs.

The above Figure 1 depicts the flowchart implementation of the suggested system. It illustrates the proposed system's performance in detecting various image abnormalities using CNN. The complete framework demonstrates how the system works with test image identification and detection, and we discuss the execution method as follows. This study aims to integrate feature selection methodologies with DL to detect potential illnesses. This system utilizes image processing and DL algorithms for the early detection of disorders in MRI, CT scans, and X-ray images. The dataset included defective images from various areas and was pre-processed and segregated to enable efficient feature extraction.

Image Acquisition: Image acquisition involves gathering heterogeneous pictures of clinical datasets containing aberrant and healthy samples from a range of individuals and converting them into digital form using a camera or other artificial dataset.

Pre-processing: Because the input data specimens were obtained from a variety of persons, there may be issues such as distortion, picture blurring, as well as other challenges. As a result, pre-processing methods are applied to photos to minimize noise and improve image quality utilizing an innovative approach. Because the picture was initially in RGB color format, transforming it is difficult. To decrease the complexities of a 3-dimensional pixel value to a 1-dimensional value, the RGB to greyscale transformation is needed. The usage of 3-dimensional pixels is not advantageous in many cases, like edge detection.

Extraction of Features: There are six distinct sets of photographs gathered from diverse datasets. The collected images are then submitted to image processing techniques to obtain relevant data for future research. Because the accepted photos are of varying sizes, they must be converted to a consistent size for efficient preprocessing. The RGB images are resized and converted to Hue Saturation Intensity type first. The adoption of Hue Saturation Intensity space representation dramatically improves color perception. The pixels are then removed using masking. Masking is changing a photograph's pixel value to 0 or the other surrounding deal. The purpose of segmentation is to convert the depiction of a picture into a relevant image that is easier to analyses. Using feature selection, the best qualities from this database are then chosen for efficient classification. The three feature selection methods used in this research are binary, autoencoder and GLCM based features.

Feature Selection: Feature selection is crucial in image processing as well as data mining. It derives the optimal subset of expected features from the source data. A subset of the original features is selected that preserves sufficient data to effectively discriminate between categories.

Detection and Classification: The procedure of identifying a test sample and assigning it the proper class label is known as disease categorization. The extraction of the features module's output is fed into the classification model as an input. Depending on the gathered features, the classifier will determine the appropriate class label for the source images. There are numerous categorizing techniques. The study that is being presented comprises an evaluation of the performance of autonomous fruit disease identification from MR image processing methodologies that depend on numerous hard and soft computing methods. The proposed deep CNN model was used to identify fruit disease in the images. The performance of Deep CNN models is assessed, and it is discovered that VGG19 outperforms all other Deep learning models. The best performing pre-trained system was discovered amongst 10 different pre-trained Deep Learning models by layering these pre-trained models on top of the suggested CNN framework. VGG-19 is found to be the best pre-trained classifier for identifying fruit disease pictures in the proposed research.

Proposed deep learning algorithm

The goal is to have the trained CNN model identify damaged fruits from healthy ones. We have utilized the CNN model to classify images of diseased fruit and recommend an appropriate insecticide. Acquisition of Datasets Preparing the Data The Third Use of the CNN Model In order to increase agricultural output and contribute to the global economy, plants being farmed in India should be free of disease and pests. Using a CNN, we can not only identify but also categorize a variety of fruit-related disorders. The primary goal is to improve the identification of diseases in fruit.

Input: Input values for all parameters HashMap <Double Value, String class> which contains the extracted features

Output: predicted class label using proposed classification algorithms

Step 1 : *for each all training data*

$$Extracted\_Attribute[i][j] \sum_{i=0,j=0}^{n} \left(a_{[i]}, a_{[j]} \ldots\ldots\ldots a_{[n]}, a_{[n].}\right)$$

Step 2*:* *Generate instance for CNN as objCNN*

Master_Training_List[] ← *objCNN.compile(*$Extracted_{Attribute[m][n]}$*)*

End for

Step 3 : *for each all testing data*

$$Extracted\_Test\_Data[i][j] \sum_{i=0,j=0}^{n} \left(a_{[i]}, a_{[j]} \ldots\ldots\ldots a_{[n]}, a_{[n].}\right)$$

Step 4 : *Apply all classifiers on test data using above training rules*

Pred1[] ← *objCNN.Buildclassifier(*$Extracted_{Test_{Data[m][n]}}$*, Master_Training_List[])*

Step 5 : *C_Matrix[]* ← *Calc_Accuracy(Pred1[])*

Step 6 : *Review C_Matrix[]*

IV. RESULTS AND DISCUSSIONS

The two major different machine learning frameworks are utilized called as VGGNET16 and VGGNET19 for detection of fruit disease detection and classification. Two different datasets are utilized for entire analysis. The Below Table 1 demonstrates comparative analysis various deep learning models including proposed two deep learning techniques.

Table 1: Evaluation of proposed model with various deep learning algorithms

Model	Accuracy	Precision	Recall	F-Score
RESNET50-V2	0.82	0.94	0.78	0.85
INCEPTION-V3	0.83	0.92	0.79	0.86
MOBILENET-V2	0.94	0.96	0.94	0.95
INCEPTION-RESNET-V2	0.91	0.90	0.92	0.91
XCEPTION	0.92	0.93	0.92	0.92
MOBILENET	0.92	0.93	0.94	0.93
VGG-16	0.96	0.96	0.97	0.98
VGG-19	0.98	0.96	0.97	0.98

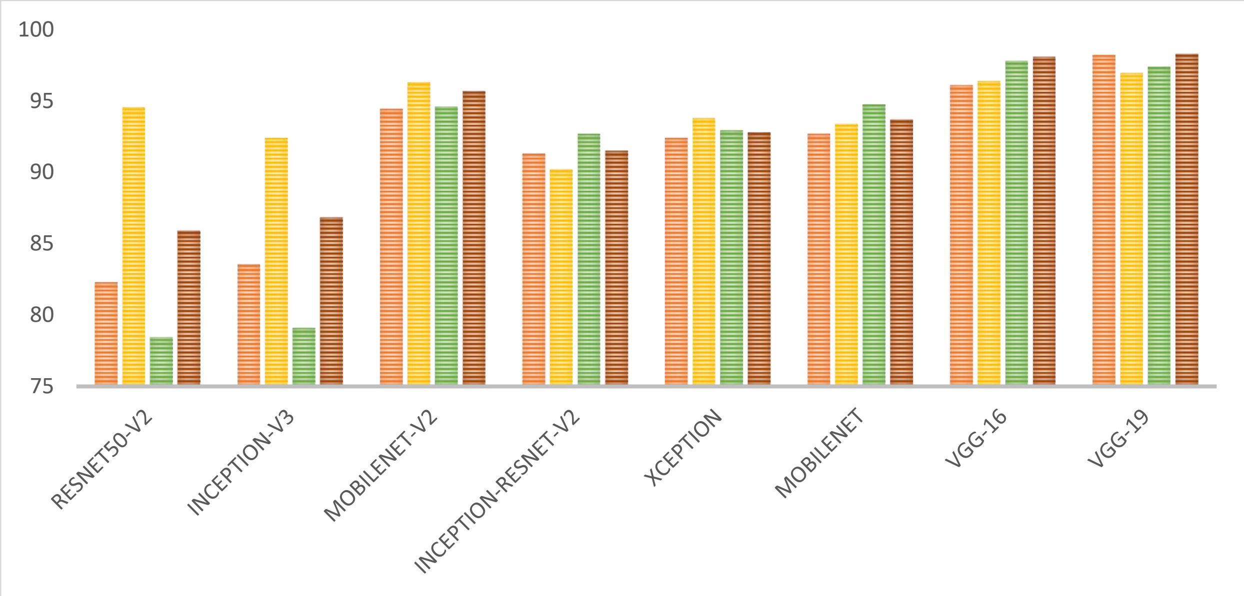

Figure 2: performance evaluation of proposed VGG-19 models with various deep learning algorithms

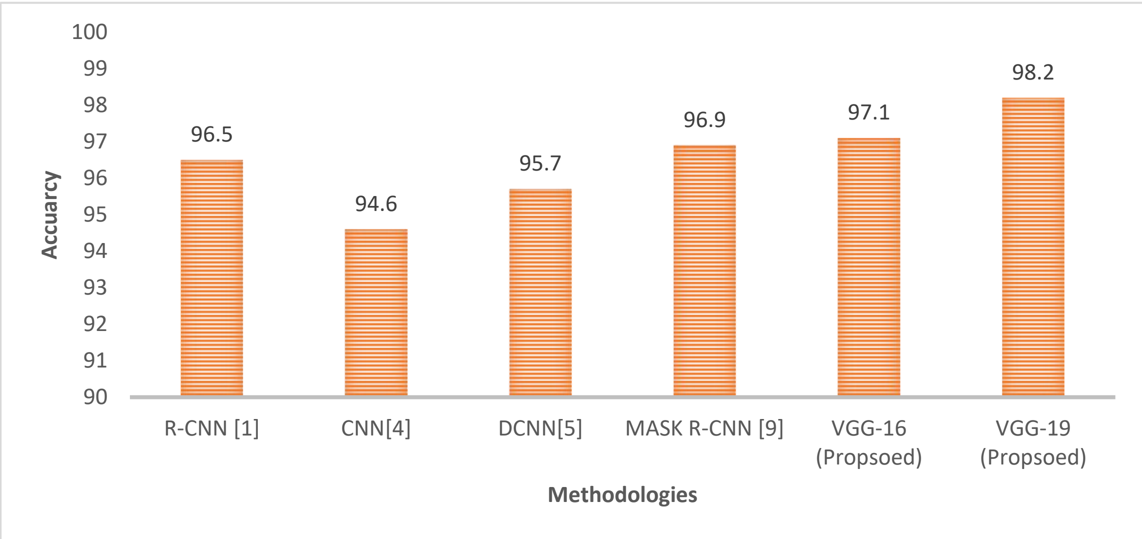

Figure 3 : The comparative analysis for fruit disease detection and classification using various deep learning techniques

The above Figure 2 describes an frit disease detection and classification using various deep learning algorithms. The VGG19 obtains higher accuracy than other deep learning algorithms. The VGG19 provides around 1.8% average higher accuracy than other deep learning models.

V. CONCLUSION AND FUTURE WORK

The VGG-19 model, if used in conjunction with suitable datasets, pretrained weights, and appropriate training methodologies, has considerable potential for the diagnosis of fruit diseases. Nevertheless, it is important to assess the efficacy and appropriateness of the model in accordance with the distinct goals and objectives of the project. This evaluation should take into account several elements, including the quality of the dataset, the availability of resources, and any limitations pertaining to the deployment process. The present study outlines a system that focuses on the identification and classification of fruit diseases via the use of diverse deep learning methods. Different feature extraction approaches are used on both the training and testing datasets. The VGG-19 deep learning model has been presented as an effective method for classifying real-time fruit photos. The techniques provide superior levels of detection accuracy compared to conventional deep learning classification algorithms. The next work for this project is the use of hybrid deep learning classification and hybrid feature selection approaches for the real-time detection of fruit diseases on images.

REFERENCES

[1] D. Banerjee, V. Kukreja, S. Hariharan and V. Sharma, "Fast and Accurate Multi-Classification of Kiwi Fruit Disease in Leaves using deep learning Approach," 2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India, 2023, pp. 131-137, doi: 10.1109/ICIDCA56705.2023.10099755.

[2] M. A. Matboli and A. Atia, "Fruit Disease's Identification and Classification Using Deep Learning Model," 2022 2nd International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), Cairo, Egypt, 2022, pp. 432-437, doi: 10.1109/MIUCC55081.2022.9781688.

[3] A. Haruna, I. A. Badi, L. J. Muhammad, A. Abuobieda and A. Altamimi, "CNN-LSTM Learning Approach for Classification of Foliar Disease of Apple," 2023 1st International Conference on Advanced Innovations in Smart Cities (ICAISC), Jeddah, Saudi Arabia, 2023, pp. 1-6, doi: 10.1109/ICAISC56366.2023.10085039.

[4] D. Banerjee, V. Kukreja, N. Jain, S. Vats and S. Tanwar, "A Regularized CNN-SVM Framework for Improved Diagnosis of Citrus Fruit Diseases, both Common and Exotic," 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 407-411, doi: 10.1109/ICSCSS57650.2023.10169629.

[5] S. Muthuselvan, V. Rajasekhar, B. Shankar, P. Mohana, D. N and B. Suresh, "Classification of Automatic Detection of Plant Disease in Leaves and Fruits using Image Processing with Convolutional Neural Network," 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2023, pp. 1408-1414, doi: 10.1109/ICOSEC58147.2023.10275843.

[6] K. Sahu, T. Saraswat, A. Singhal and G. Langer, "CNN Based Disease Detection in Apple Leaf via Transfer Learning," 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN), Ghaziabad, India, 2023, pp. 447-451, doi: 10.1109/CICTN57981.2023.10141259.

[7] Ranjan and R. Machavaram, "Detection and Localisation of Farm Mangoes using YOLOv5 Deep Learning Technique," 2022 IEEE 7th International conference for Convergence in Technology (I2CT), Mumbai, India, 2022, pp. 1-5, doi: 10.1109/I2CT54291.2022.9825078.

[8] B. K, M. Mohammed, V. Shaik, S. Unisa, S. Khan and R. Noorullah, "Enhancing Disease Detection in Fruits and Leaves Through a Hybrid Deep Learning Approach," 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2023, pp. 898-906, doi: 10.1109/ICOSEC58147.2023.10276218.

[9] G. Shireesha and B. E. Reddy, "Citrus Fruit and Leaf Disease Detection Using DenseNet," 2022 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, 2022, pp. 1-5, doi: 10.1109/SMARTGENCON56628.2022.10083852.

[10] R. Sharma, V. Kukreja, P. Sood and A. Bhattacharjee, "Classifying the Severity of Apple Black Rot Disease with Deep Learning: A Dual CNN and LSTM Approach," 2023 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS), Kalady, Ernakulam, India, 2023, pp. 173-177, doi: 10.1109/ACCESS57397.2023.10199549.

[11] U. Dar, M. H. Anisi, V. Abolghasemi, C. Newenham and A. Ivanov, "Visual sensor network based early onset disease detection for strawberry plants," 2023 IEEE Applied Sensing Conference (APSCON), Bengaluru, India, 2023, pp. 1-3, doi: 10.1109/APSCON56343.2023.10101121.

[12] enkattavijaiyan and K. V. Kanimozhi, "A Novel Method of Detection of Skin Defects in Citrus Fruit using Convolutional Neural Network Compared with ANN Method," 2023 9th International Conference on Smart Structures and Systems (ICSSS), CHENNAI, India, 2023, pp. 1-5, doi: 10.1109/ICSSS58085.2023.10407079.

[13] P. K. Pareek, R. I M, J. B. N and L. H. M, "Clustering Based Segmentation with 1D-CNN Model for Grape Fruit Disease Detection," 2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS), Raichur, India, 2023, pp. 1-7, doi: 10.1109/ICICACS57338.2023.10099916.

[14] M. Yang and C. Wang, "Automatic detection of green litchi based on YOLOV3, YOLOV4, YOLOV5-S and YOLOV5-X deep learning algorithm," 2023 4th International Conference on Computer Engineering and Application (ICCEA), Hangzhou, China, 2023, pp. 865-868, doi: 10.1109/ICCEA58433.2023.10135322.

[15] V. Vijaiyan and K. V. Kanimozhi, "Enhanced Method of Detection of Skin Defects in Citrus Fruits Using Convolutional Neural Network Algorithm in Comparison with Principal Component Analysis Method to Improve Accuracy," 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), Gautam Buddha Nagar, India, 2023, pp. 1539-1542, doi: 10.1109/IC3I59117.2023.10398090.