Deep learning for grape leaf disease detection

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ABSTRACT

Agriculture is crucial to India's economy. Agriculture supports almost 75% of the world's population and much of its gross domestic product (GDP). Climate and environmental changes pose a threat to agriculture. India is recognized for its grapes, a commercially important fruit. Diseases reduce grape yields by 10-30%. If not recognized and treated early, grape diseases can cost farmers a lot. The main grape diseases include downy and powdery mildew, leaf blight, esca, and black rot. This work creates an Android grape disease detection app which uses machine learning. When a farmer submits a snapshot of a diseased grape leaf, the smartphone app identifies the ailment and offers grape plant disease prevention tips. In this research, an android app that detects grape plant illnesses use convolutional neural network (CNN) and AlexNet machine learning architectures. We investigated and compared CNN and AlexNet architecture's efficacy for grape disease detection using accuracy and other metrics. The dataset used comes from Kaggle. CNN and AlexNet architectures yielded 98.04% and 99.03% accuracy. AlexNet was more accurate than CNN in the final result.

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1. INTRODUCTION

In India, grapes are among the most economically feasible crops for the production of wine and raisins. Grape production in India is at its peak and has the potential for further growth. Grapes are a prominent crop in India and hold significant commercial value due to their export potential to many nations. Nevertheless, there is approx. 30% loss in production in grapes owing to ailments. Agronomy is India's primary source of sustenance. Agriculture is currently affected by alterations in climate and several environmental issues. Erratic climate fluctuations, such as erratic rainfall, elevated temperatures, and humidity, adversely affect grapevines, rendering them susceptible to various illnesses. Conducting pertinent research for sustainable agricultural development is now essential due to developments in farming equipment and applications of artificial intelligence in identifying plant illnesses [1]. The current modern irrigation system, devoid of technological assistance, fails to precisely determine the requisite water quantity for viticulture. This can result in either under-irrigation or over-irrigation. This impacts soil moisture, potentially leading to crop destruction. Over-irrigation also results in agricultural illnesses. It will impact grape output.

Grape diseases compromise quality and substantially impact production rates, resulting in considerable losses for farmers and negatively influencing the economy and public health. The most effective method for safeguarding crops, enhancing production, and reducing losses is accurate identification [2].

The effective management of disease proliferation and the promotion of healthy growth within the grape industry relies significantly on timely judgment and accurate detection of diseases present on the leaves of the grape plants [3], [4]. Black rot, powdery mildew, esca, leaf blight, and downy mildew represent significant threats to grape cultivation, leading to considerable losses for agronomists and diminishing yield of grapes. Diseases on grape plant leaves can be identified by the shape and pigmentation of the impacted region. Nonetheless, certain diseases may exhibit comparable colors and shapes in the affected regions, which complicates the classification of various grape diseases significantly. A significant number of farmers rely on manual techniques for disease detection, yet these methods often yield unreliable results. The inability of the farmer to detect the disease at an early stage can lead to significant losses. A farmer typically requires specialists to identify diseases, which can be quite time-consuming for extensive agricultural operations. Identifying diseases at an early stage is crucial to implementing effective solutions, thereby minimizing issues and enhancing profitability.

Recent research has shown the effectiveness of deep learning (DL) models in identifying a wide range of plant diseases using image data, showcasing their immense efficiency for real-time applications [5]. The convolutional neural network (CNN) is the most widely utilized DL algorithm for the detection of plant diseases [6], [7]. Digital image processing technologies have multiple applications across various sectors, including industry, agriculture, and medicine. The detection of plant diseases represents a prominent application of digital image processing within the agricultural sector [8], [9]. Numerous pre-trained CNN models are commonly utilized in image classification tasks, such as VGGNet, AlexNet, ResNet, and GoogleNet. They are also have been effectively employed to address computer vision challenges, including image analysis, image classification, and segmentation [10], [11].

Ishengoma and Lyimo [12] propose an ensemble model that integrates CNN-based feature extractors with an random forest (RF) classifier to improve overall performance. The suggested ensemble model is constructed using CNN architectures including ResNet50, InceptionV3, visual geometry group-16 (VGG16), and Xception. The models employ the grape leaf dataset, which is categorized into two subsets: original and modified. Results demonstrate that ensemble models trained on altered images surpass those trained on the original dataset. The model trained on altered photos attained a peak accuracy of 95.34%, thereby substantiating the efficacy of the method in improving grape leaf disease identification.

Rangeetha *et al.* [13] performed a review on the financial and production harm to crops caused by leaf diseases. The wrong detection can cause use of wrong pesticides which in turn create losses. This research utilized Multi support vector machine (SVM), gray level co-occurrence matrix (GLCM), and K-means clustering techniques to detect different diseases impacting grape leaves. The impacted region is assessed to enable the implementation of preventive strategies. The motor connected with pesticide sprinkler turns itself on after the detection of a disease.

Sannakki *et al.* [14] employed neural networks for the detection and classification of grape leaf illness. They used thresholding to hide the green pixels and anisotropic diffusion is used to remove the noise. Grape leaf disease is classified into specific groups using K-means clustering. The split images enable the identification of the impacted region. The training of a feed-forward back-propagation neural network for classification produced ideal outcomes in this investigation. The research investigated two varieties of grapevine diseases impacting grape foliage: powdery mildew and downy mildew. Algorithms employing feature extraction, classification, and image processing approaches are utilized. Feature removal methods utilized to leverage the texture of a picture for producing distinctive features that characterize the image.

Xie *et al.* [15] introduced a real-time application for the identification of grape leaf diseases with deep CNNs. The authors have developed a dataset of grape leaf photos for their research via digital image processing. They selected the faster region-based CNN (R-CNN) and deformable region-based interleaved attention CNN (DR-IACNN) algorithms for feature extraction based on the dataset. Inception-ResNet-v2, Inception-v1, and squeeze-and-excitation (SE)-blocks have been employed for the detection of grape leaf diseases. The results indicate that the faster DR-IACNN attains a precision rate of 81.1%, the highest among the evaluated models.

Ji *et al.* [16] created a comprehensive model to establish an automatic way for the detection of grape diseases employing various CNNs. This model exhibits a cohesive CNN architecture founded on a comprehensive approach. The diseases detected from healthy leaves with the proposed CNN design, referred to as the united model. Experimental results show that the model exhibits robust performance across multiple evaluation metrics. The model demonstrates optimal efficacy for farmers in detecting grape illnesses, attaining accuracy of 99.17% (validation) and 98.57% (test).

Picon *et al.* [17] and Wang *et al.* [18] utilized the AlexNet architecture to create a system for the detection of illnesses in plants. This work entailed taking example photos using a digital camera, extracting their features, and subsequently integrating those attributes into the ImageNet collection. This research utilized DL methodologies to create an intelligent system for diagnosing plant concerns. The main goal of this endeavor is to classify various plant pests, illnesses, and weeds. This study employs a dataset consisting of 16 distinct categories of pests, weeds, and illnesses affecting agricultural production. The advanced intelligence system exhibits a remarkable accuracy of 96.50% in detecting and categorizing plant illnesses. A mobile application has been developed enabling farmers to use their smartphones for identifying infections in crop fields and providing advice on mitigating disease risk, resulting from this work. This signifies the most recent progress for agricultural experts utilizing cutting-edge technology. Rayhan and Setyohadi [19] developed a method that combines image fusion with graph-structured text to improve plant disease recognition by integrating visual information with relational patterns, leading to enhanced accuracy and robustness in classification [19].

This project entails the development of an Android application intended for the detection of grape diseases. The tool allows farmers to capture or submit a photograph instantly from their device. A farmer can capture or submit an image of a diseased grape leaf using the smartphone application, which subsequently forecasts the disease and offers options to mitigate the related risks. A method has been established employing DL algorithms for the identification and classification of illnesses in grape leaves. The system's innovative feature is its capacity to aid farmers in maximizing grape yield. The architectures of CNN and AlexNet are utilized for disease detection in grape plants. A comparison is conducted regarding the accuracy and efficiency of both architectures. The image dataset included in this research was obtained from the Kaggle platform. A number of photographs were acquired from Google via the Internet. The collection consists of 10,216 photos.

2. METHODS

The methodology of this study consists of several steps and is presented in this section. The steps include data description and collection, data preparation, and the proposed method. Each of these steps is described in detail.

A conceptual model that describes the system's behavior, structure, and other features is the system architecture shown in Figure 1. First, we collected a grape disease dataset and then trained our model using the AlexNet CNN architecture. After training, we checked the accuracy and fine-tuned some hyper parameters to achieve the highest accuracy. After getting optimized accuracy, we create a disease detection model that is imported into the mobile application.

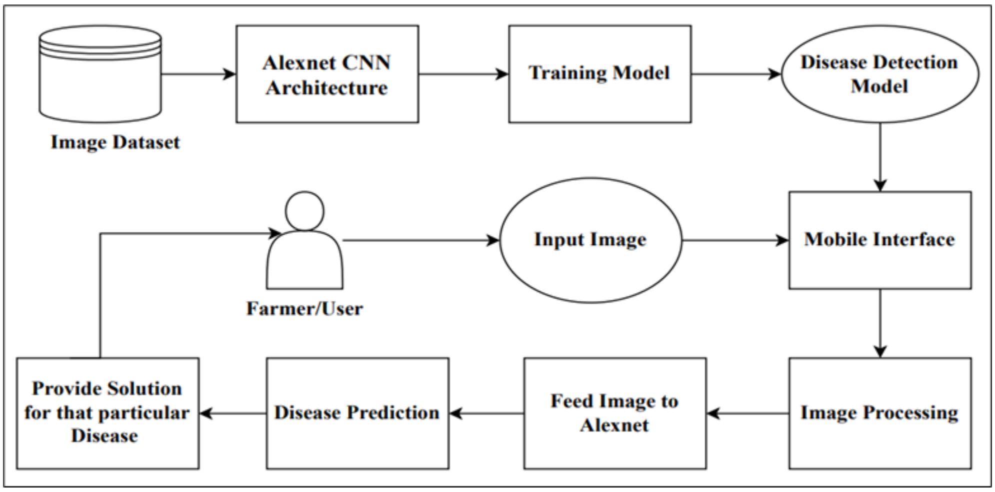

Figure 1. System architecture

This study presents the design of an Android application aimed at detecting grape disease. We converted the DL model into a TensorFlow lite file for integration into the Android application. The mobile application allows farmers to capture or upload a photograph immediately from their device. A farmer captures an image of a diseased grape leaf, which is subsequently analyzed by a smartphone application that identifies the ailment and offers tips to reduce the risk of future infection. This section delineates the sequential stages necessary for formulating a model to identify illnesses in grape leaves.

2.1. Image acquisition

We created a tailored dataset by mixing photos extracted from Kaggle and google. The dataset consists of 8,072 pictures. Six classes are delineated: powdery mildew, leaf blight, downy mildew, black rot, and a healthy. We implemented augmentation to equilibrate the dataset and enhance the image count. Post-augmentation, the total number of photos is 10,216. Table 1 displays the number of photos in each class, prior to and subsequent to augmentation. Some representative images depicted in Figure 2. The dataset was partitioned in an 80:20 ratio for training and testing objectives. Each class label consists of approximately 1,700 to 1,710 photos. By default, all images are in JPG format with RGB color space.

Table 1. Dataset details

Sr.No.	Class name	Sample size
1.	Black rot	1,701
2.	Downy mildew	1,706
3.	Esca	1,705
4.	Healthy	1,692
5.	Leaf blight	1,702
6.	Powdery mildew	1,710
7.	Total	10,216

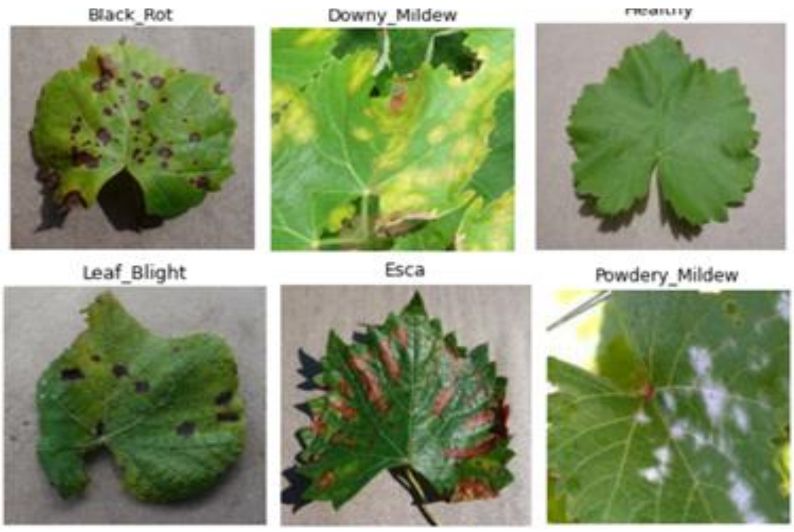

Figure 2. Different images from dataset

2.1.1. Image preprocessing and data augmentation

Image pre-processing is an essential phase for converting raw data into a suitable format for training and creating DL models. This activity improves the model's performance at a great extent. It boosts data quality and produces significant insights. Every image in used dataset possesses an red, green, and blue (RGB) value that spans from 0 to 255. We modified the measurements and proportions of the photos. The dataset encompasses multiple formats with differing resolutions and quality, since some pictures were sourced from Google while others were obtained from Kaggle. Consequently, to optimize feature extraction, reduce training duration, and ensure uniformity, we resize the images to 224×224 for the CNN and 227×227 for the AlexNet. The pre-processing phase adjusts all images to meet the model's specifications and normalizes each pixel's values to a range of 0 to 1. This study employs multiple augmentation techniques, such as rotation, vertical and horizontal flipping, shearing, and random zooming. Vertical and horizontal image flipping have yielded optimal outcomes here.

2.2. Model building

During the model development phase, we employed two DL architectures for the detection of grape leaf diseases: AlexNet architecture and CNN.

2.2.1. Convolutional neural network

The CNN is a distinguished DL technique that proficiently trains numerous layers. Our CNN design consists of nine unique layers: three max-pooling layers, one dropout layer, three convolutional layers, and one output layer. The image has been scaled to dimensions of 224×224×3. The predominant computations take place in the convolutional layer, which functions as the primary layer of the CNN architecture.

The first convolution layer uses rectified linear unit (ReLU) activation function, thirty-two filters, a 3×3 size kernel, and a 224×224 input image. The pulling layer reduces the feature map using a 2×2 filter. The second convolution layer uses ReLU activation function, 64 filters with size 3×3 and take the input from first layer. Again here, a pulling layer is applied using 2×2 filter layer to further reduce the feature map. The third convolution layer compromises of 3×3 kernel, 64 filters, and a ReLU function. This layer receives the input from the second layer. The multi-dimensional array input is converted into a single dimensional array using a flattening layer before passing it to the fully connected layer. Two fully connected layers were implemented, comprising 64 and 6 neurons, respectively. The dropout layer functions to eliminate neurons that are randomly chosen with a probability of 0.2, thereby addressing the problem of overfitting. The SoftMax activation function in the output layer categorizes the image into six distinct classes, providing the candidate that aligns most closely with the target class. The architecture of the CNN is illustrated in Figure 3.

2.2.2. AlexNet architecture

AlexNet stands out as one of the most commonly employed CNN architectures. The AlexNet architecture was created by Alex Krizhevsky. The architecture consists of five convolutional layers along with three fully connected layers. In AlexNet, every convolutional layer is succeeded by a ReLU activation, max pooling, and normalization processes. A feature map is generated by convolving an image with a set of filters in a convolution layer. Convolutional layers are integrated with the ReLU layer to perform non-linear operations, effectively setting all negative values to zero. The pooling layer is essential for reducing the feature map obtained from the preceding layer.

The initial convolution layer uses 96 filters, a 11×11 kernel, a 4 pixels stride which applied to a 227×227 image with ReLU activation function. By using a 2×2 filters, the pulling layers decreases the feature map dimension. The output of the first convolution layer is processed by second layer using 256 filters operating with 5×5 size stride of 1 pixel. A 3×3 kernel and 384 filters are used by convolution layers 3 and 4 while fifth layer uses 256 filters. There are three fully connected layers, which encompasses a configuration of 1024, 1024, and 6 neurons in its first, second and third layer respectively. To alleviate the overfitting, a drop layer is integrated with each fully connected layer. The SoftMax function is used by the output layer to achieved the results based on the categorization of the classes to the target class. The architecture of the CNN is illustrated in Figure 4.

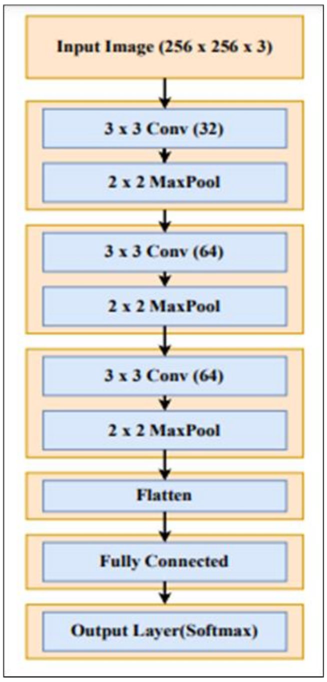

Figure 3. CNN architecture

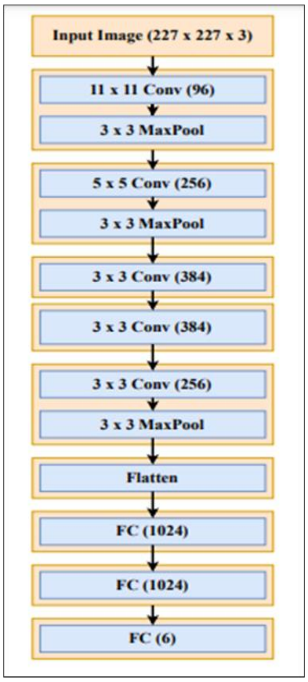

Figure 4. AlexNet architecture

3. RESULTS AND DISCUSSION

A total of 2,043 images were utilized for validation and training, whereas 8,172 images were employed for testing. As illustrated in Figures 5 and 6, the training accuracy for the CNN model stands at 98.04%, whereas AlexNet achieves a training accuracy of 99.03%. The classification efficiency of the model is assessed through the use of a confusion matrix (see Figures 7 and 8). The confusion matrix contains values for false negatives (FN), false positives (FP), true negatives (TN), and true positives (TP). Higher diagonal values of the confusion matrix signify improved accuracy in the model's predictions. Figures 7 and 8 shows the values achieved for various evaluation metrics using CNN and AlexNet. The results indicate that the AlexNet architecture surpasses CNN's accuracy of 95.84%, achieving a notable 98.03% accuracy instead.

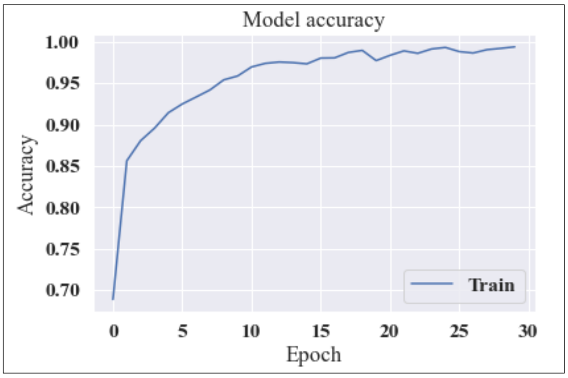

Figure 5. CNN graph

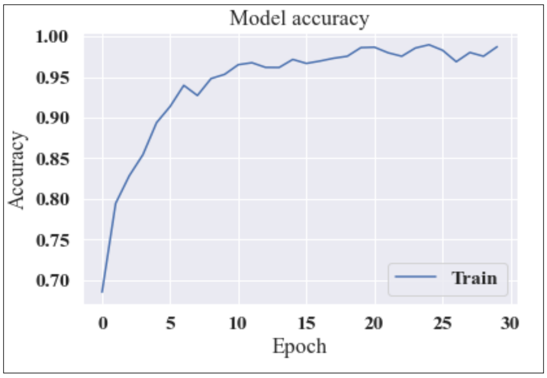

Figure 6. AlexNet graph

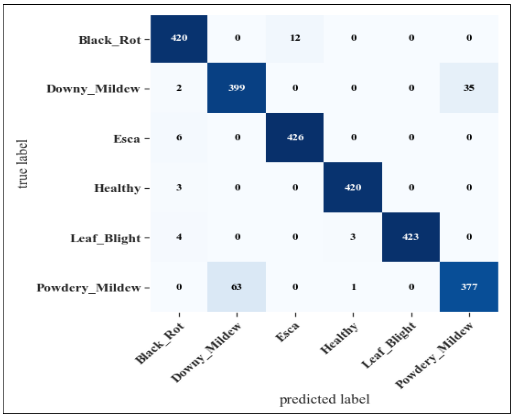

Figure 7. Confusion matrix of CNN

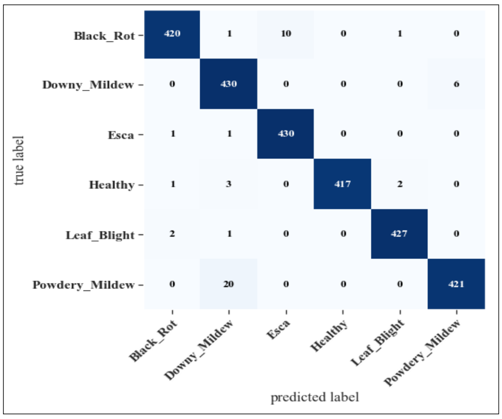

Figure 8. Confusion matrix of AlexNet

Following the categorization and comparison of the DL-based studies, Figures 5 and 6 illustrate that employing the AlexNet architecture can enhance accuracy. It has been also observed that AlexNet requires more computation time due to its increased number of layers. Both architectures are capable of detecting and categorizing the illness after the training process. The study demonstrated that the proposed model is capable of running on the CPU without requiring any supplementary hardware. This occurs due to the employment of the small size filters in CNN and AlexNet architectures, along with a reduced number of training parameters. Consequently, the model provides an efficient approach for identifying grape diseases.

Classification report in Table 2 shows that the CNN model shows accuracy results, with a weighted average of 0.95 in precision, 0.95 in recall, F1-score of 0.95 and an accuracy of 0.95. Classification report in Table 3 shows that the AlexNet model shows accuracy results, with a weighted average of 0.98 in precision, 0.98 in recall, F1-score of 0.98 and an accuracy of 0.98. A few screenshots of the application are shown in Figure 9. In the suggested system, the farmers click and upload the images of the leaves. They can upload the existing pictures also. The app will store and perform preprocessing on the image. And then this preprocessed image is feed to the AlexNet for classify and detect the disease. Based on the result achieved the farmers are advised for the preventive cures.

Table 2. Classification report of CNN

	Precision	Recall	F1-score	Support
0	0.97	0.97	0.97	432
1	0.86	0.92	0.89	436
2	0.97	0.99	0.98	432
3	0.99	0.99	0.99	423
4	1.00	0.98	0.99	430
5	0.92	0.85	0.88	441
Accuracy			0.98	2594
Macro avg	0.95	0.95	0.95	2594
Weighted avg	0.95	0.95	0.95	2594

Table 3. Classification report of AlexNet

	Precision	Recall	F1-score	Support
0	0.99	0.97	0.98	432
1	0.94	0.99	0.96	436
2	0.98	1.00	0.99	432
3	1.00	0.99	0.99	423
4	0.99	0.99	0.99	430
5	0.99	0.95	0.97	441
Accuracy			0.99	2594
Macro avg	0.98	0.98	0.98	2594
Weighted avg	0.98	0.98	0.98	2594

Multiple studies, including [20], have investigated the effectiveness of machine learning algorithms such as CNN and the pre-trained VGG16 in predicting grape leaf disease, achieving accuracies of 93.35% and 97.9%, respectively. Furthermore, Hasan *et al.* [21] demonstrated that the CNN achieved an impressive accuracy of 97% in predicting grape leaf disease using the faster RCNN. Liu *et al.* [22] and Huang *et al.* [23] attained accuracies of 91.37% and 97.22%, respectively, using CNN. The study conducted by Lauguico *et al.* [24] introduced a method for detecting grape leaf disease using AlexNet, resulting in an accuracy of 77%. In a similar vein, Peng *et al.* [25] and Li *et al.* [26] proposed methods for predicting grape leaf disease using AlexNet and attained accuracy rates of 95.65%, 97.29%, and 92.30%, respectively. This proposed investigation demonstrated that model training with CNN reached an impressive accuracy of 98.5%. The evaluation outcomes utilizing the AlexNet model indicated an accuracy of 99.0%. The enhancement in accuracy was linked to the implementation of vertical and horizontal image flipping, which facilitated augmentation and contributed to the training process, thereby enhancing accuracy and minimizing overfitting. Additional areas that can be explored in future studies includes feature selection, and hyper parameter tuning. A variety of feature selection and hyper parameter tuning methods may be employed to achieve improvement. When evaluating the balance of each class, it is essential to consider the number of datasets, as an increase in this number may also influence performance.

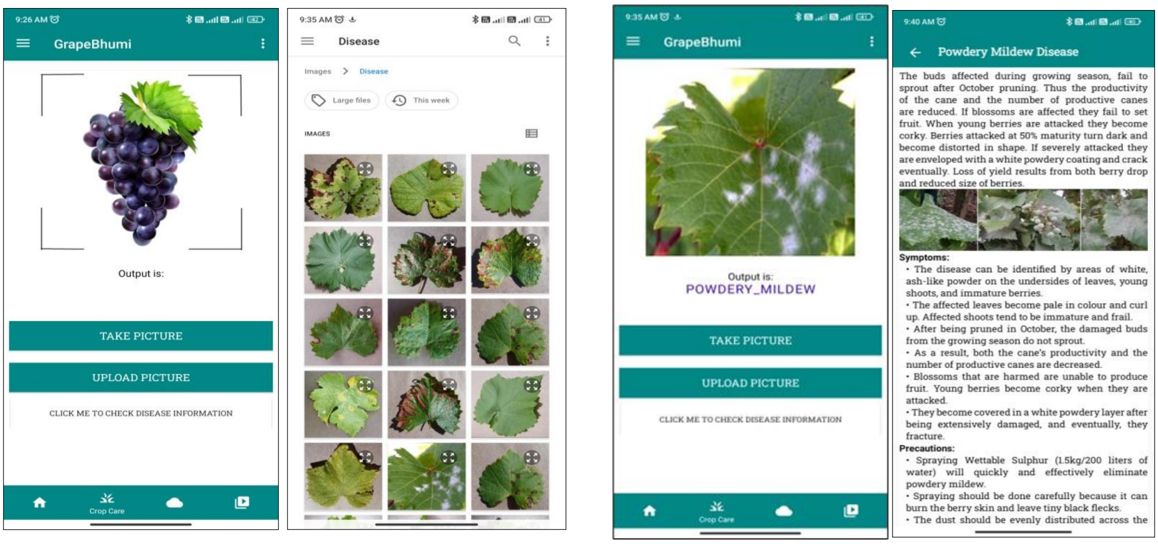

Figure 9. Screenshots mobile app for detecting grape disease

4. CONCLUSION

In the core strategy of this study is to predict grape diseases and offer preventative measures. Additionally, this system will assist the farmers in maximizing production and earning a good profit. Using DL algorithms, appropriate datasets were gathered, studied, and trained, and the model is successfully implemented in an android application. This study presents a comparison of CNN and AlexNet structures for the detection of grape leaves diseases. The study focuses on five primary grape diseases: powdery mildew, downy mildew, black rot, powdery mildew, leaf blight, and esca, along with a healthy class for comparison. The design of AlexNet demonstrates superior performance compared to traditional CNN architecture, particularly in precision and accuracy. It is also observed that AlexNet requires more training time then CNN due to more umber of layers. This study demonstrates that DL architectures are capable of differentiating between the most and less important attributes in images. Following 50 iterations (epochs) of with hyperparameter tuning, CNN and AlexNet reached an accuracy of 95.84% and 98.03% respectively. In summary, the document provides a thorough examination of the model and its results. The findings indicate that the presented method effectively detect and classify grape diseases.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Priyanka Jadhav	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓		
Nandini Chaudhari	✓				✓				✓					
Nitesh Sureja	✓	✓		✓	✓	✓	✓			✓	✓	✓	✓	
Umesh Pawar		✓	✓				✓		✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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