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Grapes Disease Detection

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Abstract

The Grapes Disease Detection system is an essential asset for farmers, presenting multiple possibilities that may aid in improved crop management. By utilizing a system that detects diseases early, farmers can respond immediately to mitigate spread, reducing crop loss and the economic impact that comes with despondent growers. By targeting specific diseases, farmers can also act quickly with treatment, avoid the unnecessary use of chemicals, and reduce damage to the environment when controlling disease outbreaks. Ultimately, farmers are able to increase crop yield, increase grape quality, and save money on a disease management system. In addition, there is added intelligence and information to be gained from the system on disease trends and making informed decisions in crop management, ultimately leading to labor savings and food safety. The two AI models X3ception and DenseNet from the project achieved 96% and 98% accuracy levels respectively in detecting diseases from the grape images. This technology is a potential solution to help farmers and professionals detect diseases early to help minimize loss and degradation while promising in enhancing the use of technology in agriculture.

INTRODUCTION

Grapes are a high-value cash crop with over 77 million metric tons produced globally and contribute a large part of the economy and food security around the world. Grapes can be susceptible to many diseases when they are cultivated that can result in significant yields, reduce fruit quality, and have huge economic impact. Early detection and accurate diagnosis of these diseases is necessary for effective disease management, reducing potential losses, and sustainability grape production. Current methods of diagnosing diseases, such as visual assessment of symptoms or laboratory testing, can be slow, labor intensive, and require special training. The impact of diseases on grape production can be devastating, with some diseases resulting in losses of up to 50%. For example, powdery mildew, a common fungal grape disease, can lead to a reduction in yield potential of up to 30%, while black rot can lead to losses as high as 20% of total yield potential. The economic consequences of these losses can be staggering, especially to grape growers and producers.

Recent advancements in computer vision and deep learning have allowed for image-based disease detection systems to become feasible, thus providing a possible replacement for grape disease diagnosis. These systems have the

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potential to analyze images of grape leaves, stems and fruits, and detect diseases in the early onset of the disease, allowing for intervention to occur at the correct time to limit spread. This study focuses on the application and evaluation of two deep models, Sequential and DenseNet121, for the diagnosis of seven prevalent grape diseases: Black Mild, Downy Mildew, Gray Mold, Mosaic Virus, Powdery Mildew, Sour Rot, and Ulcer Disease.
Each of the grape diseases had an image dataset made up of 125-175 images, with a combinedresearch institute, and web database. After the collection of the images, all of them were processed to improve clarity, reduce noise, and all to their size and format. The processed images were subsequently used for training and testing of the deep learning models..
Disease detection deep learning models offer a number of benefits over conventional approaches including accuracy, efficiency, and scalability. Deep learning models quickly learn complex patterns and relationships in data and can detect diseases with high accuracy. Additionally, because deep learning models can be trained using large datasets, they can be scaled to large applications in agriculture. Our results show that the Sequential model can predict an accuracy of 98% while the DenseNet121 model reaches an accuracy of 92%, which speaks to the models' capacity for accurate grape disease diagnostic and detection. The development of these models could provide grape growers/producers with practical tools for disease management which would allow them to act quickly and limit the economic impacts of the disease.

Fig (1): Grapes various diseases image

LITERATURE REVIEW

Grapes are a valuable crop that is susceptible to various diseases owing to climatic variations, bacteria, viruses, and fungi. Timely diagnosis of diseases to prevent loss of crop - productivity, and on crop management. This review presents new trends in disease detection in grapes and discusses the possibility of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) technologies in creating precise disease detection systems.The study aims to provide insight into current research gaps and future directions for development in improving grape disease detection and management. [1]. This study suggests an image-based grape leaf disease diagnosis system through thresholding, anisotropic diffusion, and K-means clustering, followed by classification with a Feed Forward Back Propagation Neural Network. The system ensures precise disease detection, minimizing misdiagnosis and pesticide abuse, and improving crop quality and yield. [2] Four deep learning models (altered MobileNet, AlexNet, and VGG16) are developed in this research for the detection and classification of four grape leaf diseases through transfer learning. The models show better accuracy and performance compared to pre-trained models, with an ensemble method further improving detection accuracy, reflecting great potential for real-world application in grapevine cultivation. [3] Artificial intelligence branch deep learning mimics the brain's capacity to identify patterns and therefore precisely process unstructured information. Applying deep learning in identifying diseases in grape leaves has several benefits, including early and precise detection, efficient disease management, and processing of complex image information to identify subtle patterns. Deep learning algorithms become wiser by experience, which improves predictability over time. Applying deep learning to vineyard management can lead to higher yields, reduced losses, and enhanced support for sustainable agriculture. [4] Grape leaf bacterial, fungal, and viral diseases have the potential to cause considerable loss in grape productivity, which will affect farmers. A precise diagnosis is necessary in order to effectively manage the illness. By using Keras libraries and Python programming, the model with CNN showed a learning rate of 91.37% when the learning rate was 0.0001.. This method proves the capability of CNN in achieving effective and precise grape leaf disease classification to support timely and specific control actions.[5] Plant diseases are a major contributor to agricultural loss, calling for precise detection approaches. The study maximizes pre-trained vision transformer and CNN models for the classification of grape leaves and disease diagnosis from digital images. High accuracy in the identification of leaves and diseases of grapes has been established in experiments with PlantVillage and Grapevine datasets. Surprisingly, four models are 100% accurate, with Swinv2-Base working very well. The process has some possible uses in enhancing crop yield through the early diagnosis of disease and grape variety characterization, providing valuable information on agriculture. [6] Leaf disease like black rot, black measles,

blight, and mites also affect heavily on the grape yield. This paper suggests a real-time disease detector for grape leaf diseases based on an enhanced deep convolutional neural network, Faster DR-IACNN. The model incorporates Inception-v1, Inception-ResNet-v2, and SE-blocks to enhance feature extraction. Grape Leaf Disease Dataset provide 81.1% mAP accuracy and 15.01 FPS detection speed. This study shows the possibility of deep learning for real-time grape leaf disease diagnosis, shedding light on other plant pathogen detection. [7] Precise identification of grape leaf diseases is essential for the long-term sustainability of grape production. This paper introduces Squeeze-and-Excitation Networks (SE), Efficient Channel Attention (ECA), and Convolutional Block Attention Module attention mechanisms to Faster R-CNN, YOLOx, and SSD models for enhancing feature extraction and real-time performance. Results show that such attention-based models improve detection speed and accuracy, with YOLOx+ECA having the best precision and SSD+SE having the best real-time performance. This paper provides a reference for the automatic analysis of grape disease and resolves the issue of accurate detection of grape leaf disease. [8] detection of grape leaf disease is very important in
the prevention of disease spread and healthy gra pe growth.. This research suggests a new method of using a better convolutional neural network (DICNN) in the diagnosis of grape leaf disease.An image database of 107,366 pictures was acquired by image improvement methods. The Inception structure-based DICNN model with dense connectivity provided an average accuracy of 97.22%. DICNN provides an improvement of 2.97% and 2.55% in recognition accuracy, respectively, over GoogLeNet and ResNet34. This study proves the effectiveness of deep learning for plant disease diagnosis, providing a theoretical foundation for agricultural information services. [9] Plant disease has a significant impact on agricultural production, and therefore must be detected effectively. This study fine-tunes pre-trained CNN and vision transformer networks to recognize grape leaves and plant disease diagnosis using digital images. Experiments performed on Grapevine and PlantVillage datasets exhibit excellent accuracy in distinguishing between grape diseases and leaf identification. Four models are 100% accurate, and Swinv2-Base gives excellent performance. This approach can be used to enhance crop yield by detecting disease at an early stage and grape variety characterization, providing valuable information to the field of agriculture. [10]Plant diseases significantly impact agricultural productivity, and hence their prevention and early detection are needed. Grapes are susceptible to a number of diseases like Black Measles, Black Rot, and Leaf Blight. This paper proposes an ensemble deep learning approach, employing pre-trained VGG16, VGG19, and Xception models, to accurately classify grape leaf diseases. The approach is experimented on the Plant Village dataset and achieves 99.82% accuracy, which is better than individual models and recent approaches. This ensemble method is promising for successful and accurate disease diagnosis, facilitating early intervention and reducing crop loss.[11] Protection of crops from diseases is critical to ensuring food security and economic stability. Grapes, a popular crop, are subject to a number of diseases that can cause major crop loss. This research applies image classification with deep learning to recognize three common diseases of grape: black measles, black rot, and isariopsis leaf spot, and healthy leaves. (>99.1%).This approach promises to develop efficient and accurate pilot and commercial packages for the diagnosis of grape diseases to assist farmers in combating plant diseases. [12]

DATASET

Data was collected from Tasgaon Taluka in Sangli district, covering more than ten farms with a total area of 25 acres. A Cannon Mark 3 camera device was used to capture images. The preprocessing of images was done using the Scikit-Image library, which helped reduce noise, detect edges, and correct colour. A dataset is enclude 8 differnet grapes disease, with 100 to 150 image for each disease. The diseases in the dataset are Black Mold, Downy Mildew,Gray Mold, Mosaic Virus Disease, Powdery Mildew, Sour Rot Disease, and Ulcer Disease

DATA PROCESSING

Data processing workflow for a project named "Graphs Disease Detection", where image processing and machine learning algorithms are employed in detecting and classifying disease or defect in graphical patterns, i.e., leaf of plants or textures. The process starts with the capture of an input image, followed by pre-processing to improve quality by eliminating noise and scaling features such as brightness, contrast, and size. After being pre-processed, the image is subjected to feature extraction, where key features like color, texture, shape, and edge patterns are detected to be used as input during the classification phase. At the same time, a

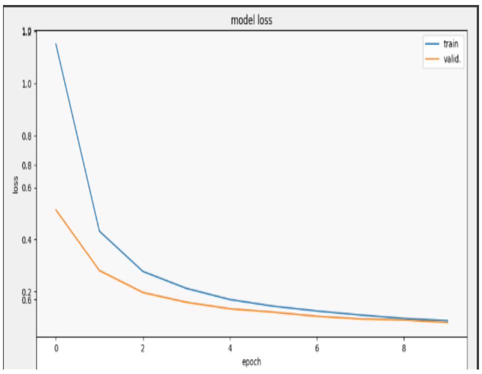
database set of images—that are tagged training images for healthy and diseased samples—are employed to train the model.
These training images are subjected to the same feature extraction process. Classification is done by comparing the features extracted from the input image with those in the training set to decide if the image is normal (healthy) or abnormal (diseased). If the image turns out to be normal, it is accepted as disease-free. But if it is labeled as abnormal, the system continues and tries to classify the defect area, indicating the affected area specifically and possibly determining the type or disease category involved. This ordered process guarantees a correct and systematic method of detecting disease in graph-based images.

MODELS Sequential

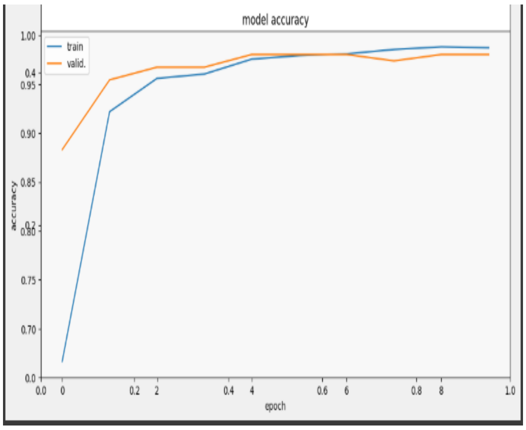
A sequential model in image processing works by breaking down an image into a series of features that can be analyzed and classified. Convolutional layers are the first step in the process, which extracts low-level information from the image, like edges and lines. These features are then passed through max pooling layers, which downsample the image to reduce spatial dimensions and retain only the most important features. The output from the convolutional and pooling layers is then flattened into a one-dimensional array, which is fed into dense layers that learn high-level features and make predictions. Throughout the process, the model learns to recognize patterns and relationships between pixels, allowing it to accurately classify images. In the context of grape disease detection, this means the model can learn to identify visual symptoms of disease and distinguish between healthy and diseased leaves.

Model Accuracy:

Sequential Model	
Training Accuracy	**0.9874**
Testing Accuracy	**0.9805**

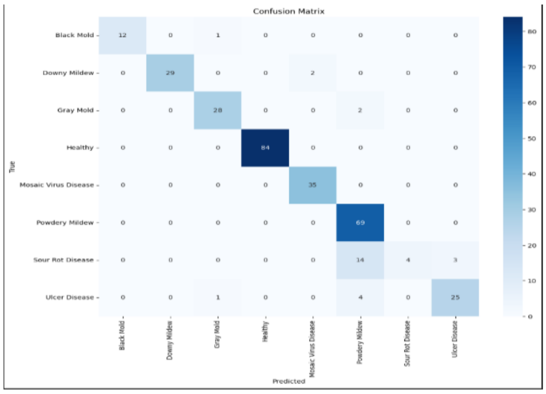


(a) Model Loss

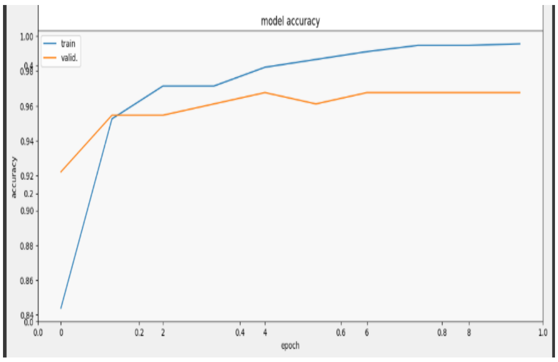


(b) Model Accuracy

Fig(2): Model accuracy and loss of Sequential Model confusion matrix- Sequential

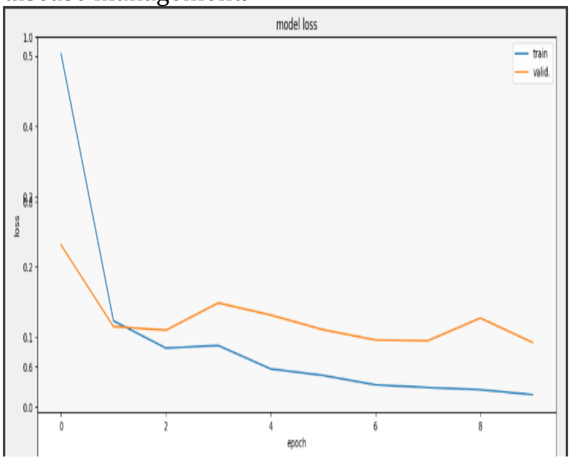


DenseNet121:



(a) Model Accuracy

The DenseNet121 model is a type of deep learning architecture that excels in image processing tasks. It works by using a dense connectivity pattern, where each layer receives inputs from all previous layers, allowing it to learn rich and complex features from images. Detection by analyzing images of grape leaves and identifying patterns and features that indicate disease presence. This architecture enables the model to effectively capture both low-level and high-level features, such as edges, textures, and shapes, and combine them to form a robust representation of the image. In image processing, DenseNet121 can be used for tasks like image classification, object detection, and segmentation, and has shown impressive performance in various applications, including medical image analysis, object recognition, and more. Its ability to learn detailed and nuanced features makes it a powerful tool for image-based tasks.DenseNet, a type of convolutional neural network (CNN), works with image processing by leveraging its unique architecture to extract features from images. The DenseNet121 model achieved an accuracy of 92% in grape disease detection, demonstrating its effectiveness in identifying diseases and providing a valuable tool for disease management.

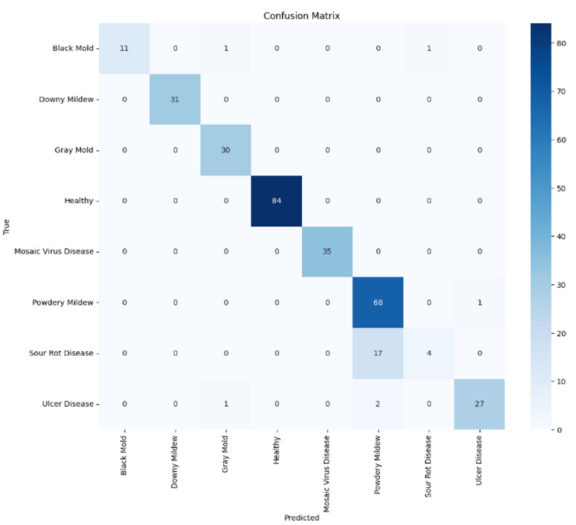


(b) Model Loss

Model Accuracy

Dense121 Model	
Training Accuracy	**0.9910**
Testing Accuracy	**0.9265**

Fig(3): Model accuracy and loss of Dense121
Model confusion matrix- DenseNet121



Comparison: Testing Accuracy

Model	Accuracy
Sequential	**0.9805**
DenseNet121	**0.9265**

Compared two deep learning models, Sequential and DenseNet121, for detection of grape diseases. The Sequential model produced the best accuracy of 98.05%, surpassing that of DenseNet121 at an accuracy of 92.65%. Hence, the Sequential model was chosen as the optimal model for this project based on better performance.

CONCLUSION

This review emphasizes the effectiveness of graph-based disease detection techniques in detecting and controlling Downy Mildew, Gray Mold, Ulcer Disease, Powdery Mildew, Mosaic Virus Disease, and Sour Rot Disease in grapes. The studies reviewed show considerable advancements in accuracy in disease diagnosis, detection time, and yield estimation. Nevertheless, there are gaps in multi-source data integration, investigating deep learning methods, and designing real-time monitoring systems. Future works should direct their focus to the aspects of gap filling in order to make graph-based disease detection systems scalable, transferable, and commercially viable. Standardization of evaluation metrics and comparative analyses of various approaches also need to be done in order to advance this field. Reviewing this content provides a basis for future works; the authors emphasize their potential to revolutionize grape disease management through graph-based methods.

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