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Grape (*Vitis Vinifera*) Leaf Disease Detection and Classification Using Deep Learning Techniques: A Study on Real-Time Grape Leaf Image Dataset in India

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A B S T R A C T

In modern horticulture, the grape industry across the globe has been coping with the issue of grape crop diseases. The detection of grape leaf diseases using automated methods can greatly assist farmers in mitigating yield losses and ensuring sustainability. However, existing systems face hurdles while handling grape leaf images at the farm level, and these models fail to generalize well on un-seen images. This study proposes the development of a well-curated real-time dataset of grape leaf images assimilated through field visits in the study area in India. This designed dataset is further used to train convolutional neural network models to accurately identify and classify grape leaves as either diseased or healthy. The potential of transfer learning using CNN models like VGG, ResNet, Inception, and Xception is assessed on the curated dataset. Our findings indicate that ResNet50V2 outperformed the other models in accurately identifying and classifying grape leaf diseases. Using transfer learning, existing weights (pre-trained) and learned features were utilized for further training and fine-tuning the CNN models on our curated dataset. The results of the proposed approach are compared with existing automated grape leaf disease identification techniques. It is observed that the proposed approach, which is on a real-time grape leaf image dataset, provides the highest accuracy among others. Further, this study provides a well-curated dataset of on-field grape leaf images in the Indian context, which can serve as a benchmark for future research. This study shows that deep learning techniques can aid farmers in identifying grape leaf diseases early.

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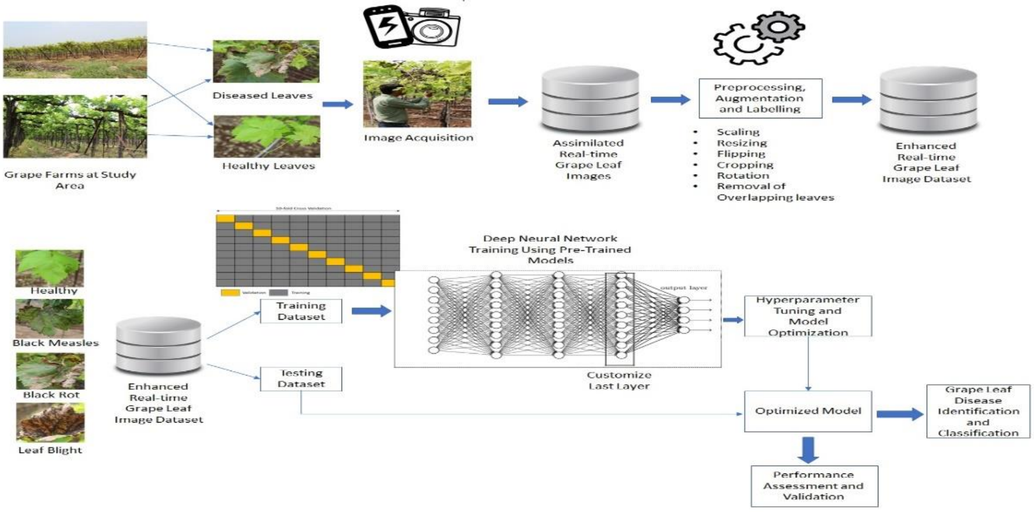
Graphical Abstract



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1. INTRODUCTION

The world population is continually rising, with an expectation of around 12.3 billion people by 2100 (1). Continual upsurge in population fosters attention on facilitating the basic needs of mankind. India stands 2nd in agricultural production in the world, and around 75% of the population is dependent on agricultural practices. About 51 major crops spanning types: Cash Crops, Food Crops, Plantation Crops, and Horticultural products are widely cultivated in India. It is further observed that India ranks 1st in Horticulture Cultivation, and returns from fruits are higher and monetary. Considering higher monetary benefits and the conducive atmospheric environment of tropical regions in the country, grapes are cultivated widely. Moreover, the contribution of grapes to the country's overall exports is around 98% (2). Factors like uncertain rainfall, unprecedented climatic conditions, pests and diseases, etc., account for heavy yield losses. Grape diseases occur on the leaves at the early stages of cultivation. These diseases, if remain unattended, can severely damage the entire grape farm under cultivation and degrade grapefruit quality, leading to monetary loss to the farmers. This drives attention towards techniques to identify and classify grape diseases followed by curing mechanisms.

The practices followed by the majority of the farmers for identifying grape leaf diseases are to use their experience to detect the grape leaf diseases by visualizing the symptoms. This approach may not be accurate every time as the disease symptoms/signs may vary. On the other hand, few farmers approach agricultural experts to know the whereabouts of disease presence. This involves the collection of grape leaves/soil samples etc., their laboratory testing, and advice by experts to know the health status of grapes. However, considering agricultural experts' availability and geographical limitations. It is practically impossible to detect grape leaf diseases using such approaches. Moreover, such visual recognition techniques by farmers or agricultural experts are time-consuming, and the recognition accuracy can be misleading (3). Such flawed diagnosis will lead to the misuse of pesticides, which can abolish the growth environment of the grapes and damage the quality of the fruit. To overcome these issues, grape leaf disease detection techniques can be automated using the latest cutting-edge technologies, which can identify diseases more precisely in a shorter time with less human intervention (4, 5). Current studies show the use of automated crop disease detection techniques based on image processing, machine learning, content-based image retrieval, genetic algorithms etc. (6-11). However, it is observed that in such techniques, disease features are selected based on human knowledge, which limits the generalizability of the models, and there exists a substantial scope to improve the accuracy of such models. In contrast, deep learning (DL) approaches using convolutional neural network (CNN) can help substantially reduce complex image pre-processing operations and automatically select disease features while training a model.

CNN is one of the pivotal techniques used widely for crop disease identification and classification. Alruwaili et al. (12) extensively studied and applied CNN models are to diagnosis of plant diseases, which highlights the potential of CNN to extract and learn features of diseases automatically from the input in contrast with handcrafted features of machine learning (ML). From the comparative study of existing approaches for grape leaf disease identification and classification, it is perceived that the majority of the approaches used publicly available grape leaf image datasets for system development and validation. However, if similar systems are exploited on real-time (on-field) grape leaf images, the challenge of precise discrimination of grape leaf disease is observed. This shows the inability of such models to generalize well on unseen datasets.

To overcome this challenge, this paper presents findings of research work undertaken in Pune district of Maharashtra state, India, for the recognition and classification of grape leaf diseases. In this study, we tackled the challenge of developing an accurate and efficient grape leaf disease detection model using real-time images captured from grape farms in Indian context. The main contributions of the presented study are as follows:

- Design of real-time grape leaf image dataset in the Indian context.
- Cutting-edge data augmentation techniques were employed to enhance the limited real-time image dataset size, enabling us to train our models more effectively.
- State-of-the-art CNN models, including VGG16, VGG19, InceptionV3, InceptionResNetV2, Xception, and ResNet50V2, were analyzed for checking their efficacy on designed dataset.
- Transfer learning technique is used for training the selected CNN models with pre-trained weights from ImageNet.

We fine-tuned our models' hyperparameters, such as batch size, number of epochs, and activation functions, through iterative experimentation to achieve optimal performance.

Our trained CNN models were rigorously evaluated against a comprehensive test dataset, and our results demonstrate comparable accuracy and validation loss metrics, demonstrating the capability to generalize well on a real-time grape leaf image dataset.

The remaining parts of this paper are organized as follows. Section 2 gives insights into the available knowledge of existing automated grape leaf disease identification and classification techniques. It follows the discussion on techniques used for dataset generation and its preprocessing. Methodology involving the step-by-step flow of the work undertaken is deliberated after the generation of the dataset. experimental results and discussion are presented in section 3. This section overviews the experiments used for evaluating the model's performance and analyses the experimental results. Finally, our observations are presented based on experimental evaluations during this work in the conclusion section along with a discussion on research avenues to focus on in this field.

2. RELATED WORK

In this section a survey of existing automated crop leaf disease identification techniques is discussed below: The classical automated identification and discrimination of grape leaf diseases involve five major stages: Image acquisition, Image pre-processing, Image segmentation, Feature extraction, and Classification (13-19). Figure 1 gives a schematic flow of an automated grape leaf disease recognition system.

Upon examining multiple research contributions in the field of crop disease identification, it is evident that there is a scarcity of studies focused on identifying grape leaf diseases compared to other crops (20-24). Therefore, we have also examined and scrutinized recent research articles on discovering various crop diseases. Every research item is analyzed by considering standard stages, as depicted in Figure 1.

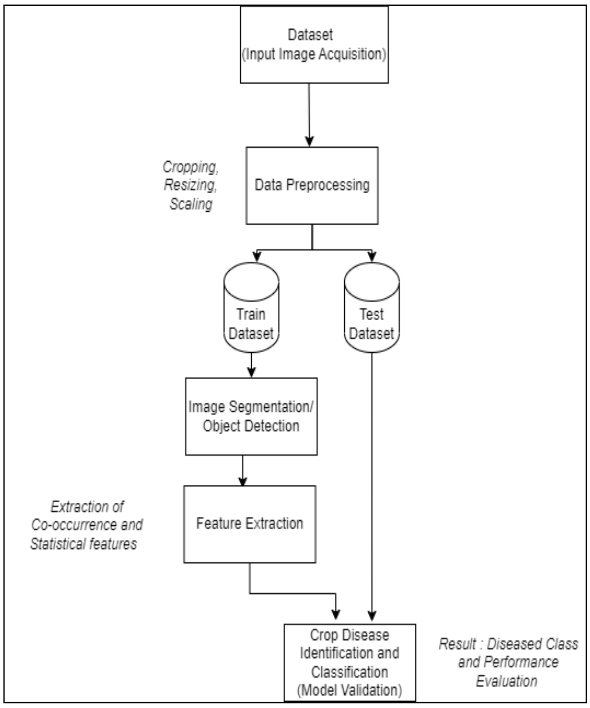


Figure 1. A Classical Automated Grape Leaf Disease Identification & Discrimination System (18)

The utilization of Convolutional Neural Networks (CNN) for identifying grape leaf diseases was examined in literature (13-19). The DR-IACNN model, which was introduced by Liu et al. (3), was designed to detect grape leaf diseases efficiently. This model improves illness detection accuracy by utilizing the Inception-v1 module, Inception-ResNet-v2 module, and SE-blocks to detect multiscale and minor diseased spots. Xie et al. (4) concentrated on utilizing an enhanced convolutional neural network (CNN) technique to identify illnesses in grape leaves. The classification accuracy is enhanced through the utilization of a unique method called Dense Inceptional CNN (DICNN). Data augmentation is employed on grape leaf photos as a mean to mitigate the issue of overfitting. The study conducted by Shantkumari and Uma (13) used machine learning techniques to identify grape leaf disease. They utilize diverse characteristics derived from leaf images and deploy multiple classifiers to attain high accuracy in categorization. Grape leaf diseases are forecasted using digital image analysis with FRCNN. Transfer learning approaches are employed to enhance the model's performance, resulting in comparable accuracy in classification (14). Ansari et al. (15) suggest an enhanced support vector machine (SVM) and image processing-based approach for identifying and categorizing grape leaf disease. Their study presents superior outcomes in comparison to alternative methodologies. Lin et al. (16) introduced GrapeNet, a compact convolutional neural network (CNN) model designed to detect grape leaf diseases. The model's accuracy is enhanced through the utilization of a transfer learning methodology. Phukhronghin et al. (17) provide a diagnostic system for grape leaf diseases utilizing Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). Contributions (18-24) comprehensively reviewed the latest techniques and methods used in automating agricultural processes. Every contribution specifies the techniques employed, their applications, and the encountered problems. The concept of employing deep learning to address complex problems in any field has been emphasized by Hinton et al (25). The contributions by Fuentes et al. (26) focused on developing an optimal CNN model for accurately detecting diseases in tomato plants. The proposed model incorporates the Faster R-CNN, Region-based Fully CN (R-FCN), and Single Shot Multibox Detector (SSD) algorithms. Moreover, the integration of these architectures with VGG net and ResNet feature extractors is performed. The results demonstrate an enhancement in performance, indicated by an increase in average precision. Joshi et al. (27) proposed a method for identifying virus-induced diseases in a specific crop species, Vigna Mungo. The suggested approach assesses the condition of plant leaves and categorizes them into three distinct groups: healthy, mildly diseased, and substantially sick. The CNN models in this approach were trained using real-time photos obtained from Vigna Mungo fields. Fenu and Malloci (28) presented a multioutput method for detecting plant diseases and assessing their severity in pear leaves. A multioutput (multitask) convolutional neural network (CNN) aims to provide predictions for multiple outputs using a single input. Given the input of a pear leaf, the suggested model aims to detect and assess the presence of stress (disease) and its level of severity. Applying Global Average Pooling (GAP) and Batch Normalization (BN) following feature extraction from pre-trained CNNs enhances the model's resilience, stability, and learning rates. Vashisht et al. (29) introduced a prognostic metric by employing a Gaussian filter in the pre-processing of data with pre-existing CNN models. Furthermore, a study was conducted to identify multiple disorders. Hybrid models that include different methodologies have been found to be more effective in enhancing the accuracy of identifying symptoms in damaged crops. Additionally, there is a significant decrease in the amount of time required for training. Ahmad et al. (30) explored the optimization of pre-trained models such as VGG16, VGG19, ResNet, and Inception V3 by fine-tuning hyperparameters. Most CNN models necessitate a substantial amount of time for training, and to categorize novel diseases, the models must undergo retraining. Furthermore, mobile devices lack the capability to do the complex computations required for Convolutional Neural Networks (CNN) (31-33). A technique utilizing the You Only Look Once (YOLO) algorithm was described by Morbekar (34) and Ponnusamy et al. (35) to address this challenge of crop disease identification. YOLO demonstrates superior processing speed as compared to current CNN models. A single convolutional neural network (CNN) is used to estimate both the bounding boxes and class probabilities in a single iteration. This approach effectively recognizes several diseases on a single leaf with a higher confidence level. Huayhongthong et al. (36) examined the application of Ensemble Modelling and Deep Transfer Learning for incremental object detection. Two models, YOLO and Transfer Learning, are employed for object class (disease class) detection. The class probability is then provided to the decision model, which utilizes the bagging approach to choose the class label with the highest probability score out of the two. The evaluation measures utilized in the researched studies predominantly include accuracy, precision, recall, F1-score, and mean average precision. Mean average precision provides valuable information into the overall performance of a crop disease diagnosis and classification model, surpassing the sole reliance on accuracy. The analyzed research publications provide classification accuracies ranging from 80% to 95% when the number of classes is restricted. Furthermore, it is widely recognized that as the number of illness categories grows, models need a significant amount of time for both training and evaluation (18-24).

According to these studies, it is inferred that CNN models can help to improve performance in crop disease recognition tasks. However, from our study, it is observed that most of the presented contributions used publicly available crop leaf image datasets for model training and evaluation. Such datasets reported in literature (24, 37-39) contained a collection of single plant leaf images taken in a controlled/simple background environment. If such models are used on real-time datasets, these will fail to identify and discriminate the disease accurately. These challenges limit the capability of generalizing well and giving accurate results on unforeseen images. Table 1 gives an overview of various datasets used by the researchers in their research. It can be perceived that around 60% of research contributions in plant leaf disease identification are using public datasets. This warrants a strong need for a technique that can accurately process real-time images using CNN and advanced state-of-the-art techniques. Focused on these challenges, a strong requirement arises to design a more generalized and accurate automated crop disease identification and classification system that can handle real-time data. This study presents a novel approach to use CNN models on a newly designed, well-curated grape leaf image dataset for improving the system generalizability. It further proposes customized and effective hyperparameter tuning for enhancing the overall performance of grape leaf disease recognition. Table 2 gives analysis of challenges faced by existing techniques and contributions of our work.

3. METHODOLOGY

3. 1. Data Acquisition For the data collection stage, grape fields in the Indapur (18.1187° N, 75.0234° E) and Baramati (18.1792° N, 74.6078° E) parts of the Pune district in Maharashtra, India were selected as the study area (Figure 2). A total of 300 high-resolution pictures of grape leaves were captured using a mobile camera. These images were categorized into two significant groups: Healthy and Diseased. The images were taken concerning various perspectives and at varying time intervals. During the process of capturing the image, much attention was given to ensuring optimal lighting

TABLE 1. Usage of datasets in crop leaf disease identification

Dataset Used	No. of Research Contributions
PlantVillage	30
PlantDoc	02
Expanded PlantVillage	13
APS	01
DigiPathos	01
Super Resolution Images	01
Local (Private)	12

TABLE 2. Existing Techniques vs. Proposed Approach

Technique	Dataset	Analysis	Ref.
SVM, KNN	Public	Poor validation accuracy &inability to generalize in real-time setting	[6,7, 10-12, 16]
CNN	Publicly Available/ Limited	Overfitting Inability to Genearlize	[19-26]
Faster R-CNN,YOLO	Publicly Available	Poor Performance on Unseen Crop Leaf Images gathered from fields	[28, 36-39]
Proposed Approach	Well-curated Grape Leaves Image Dataset gathered in real-time settings	Ability to generalize well on complex background and on-field data samples with higher performance	

conditions. The captured leaf images exhibited overlap with other leaves and complexity caused by the natural background, ground surface, or other organs of the crop. The photos underwent additional processing to eliminate the overlap and intricacy caused by the ground surface. The diseased leaf photos were classified into categories such as BlackRot, BlackMeasles, and LeafBlight according to the expertise of farmers and agricultural experts, using visual symptoms as a basis. Gathering this on-site data required visiting the vineyards from August 2021 to February 2023, specifically during favorable weather circumstances. Many criteria have been used throughout this period to improve the data being gathered. Table 3 presents statistical information regarding the dataset of acquired grape leaf images.

Representative grape leaf images from each of the four categories are represented in Figure 3. It can be clearly seen that discriminations in each disease category can be visualized through disease symptoms, i.e., the brown/black spots present on the surface of the leaf. These spots help farmers and experts to categorize grape leaves into diseased classes.

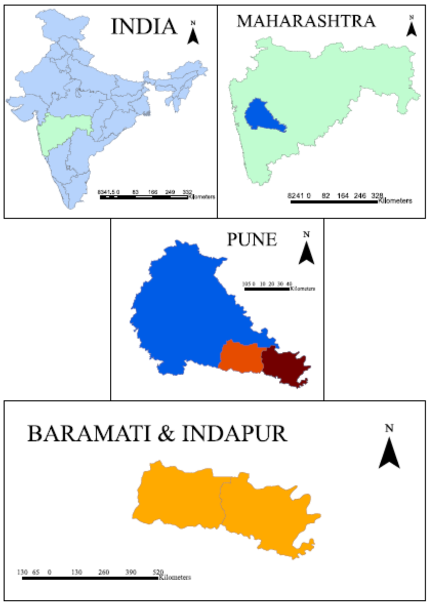


Figure 2. Study Area

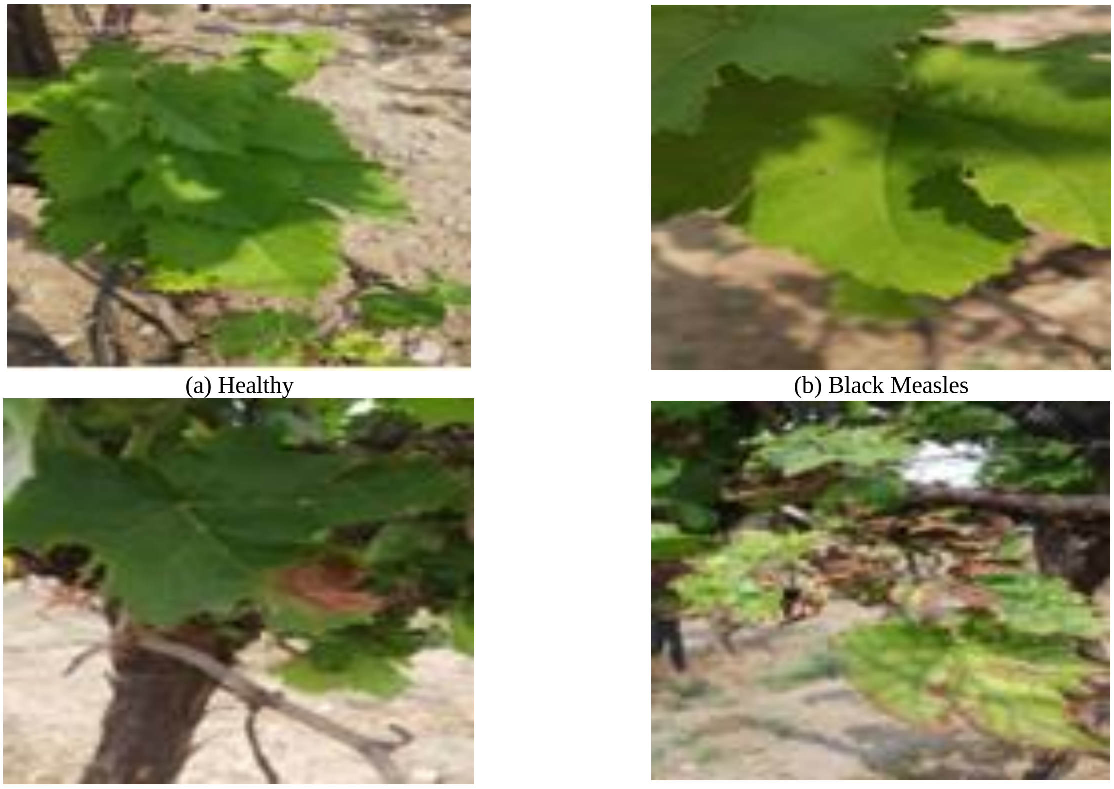
3. 2. Data Augmentation The size of the acquired image dataset is smaller considering the factors like: the practical limitations, larger geographical area of the farm, the man-hour efforts needed to capture the real-time images etc. CNN models can face challenges like poor accuracy if trained using smaller datasets. To avoid this problem, image augmentation techniques were applied. Image augmentation is a technique that involves the application of digital image processing operations on input images to upscale the existing number of images (24, 38-40). Typically, operations like cropping, rescaling, transformation, resizing, rotation, adjusting brightness, contrast, sharpness values, etc. are involved in image augmentation. Overlapping images were cropped in such a manner to have a single leaf without any complex background.

TABLE 3. Real-Time Grape Leaves Image Dataset

Class	Healthy	BlackRot	BlackMeasles	LeafBlight
No. of Images	145	43	49	63

Using such techniques, new images are derived from each image. After image augmentation, an augmented dataset of healthy and diseased grape leaf images has been curated, including an overall 1600 images, of which each class has around 400 images. All images are then resized to 224 × 224 for further experimentation. Finally, the image data set is divided into three parts at a ratio of 60:20:20, which are used as the training, validation, and test sets. Details of this augmented dataset are presented in Table 4.

3. 3. Proposed Approach Training a CNN model from scratch necessitates a substantial amount of time for the training process. These models depend greatly on datasets of larger sizes in order to achieve improved per for mance. In order to address this constraint, this work aims to employ the transfer learning technique to optimize hyperparameters by customizing the final layer of the CNN model. Transfer learning is a machine learning methodology that involves utilizing a pre-trained model as the initial foundation for a model designed to tackle a different but related job. Utilizing



(a) Healthy (b) Black Measles

(c) Black Rot (d) Leaf Blight

Figure 3. Categorization of Grape Leaf Images (Healthy & Diseased)

TABLE 4. Augmented Grape Leaves Image Dataset

Class	Training Images	Validation Images	Testing Images	Total
Healthy	240	80	80	400
BlackRot	240	80	80	400
BlackMeasles	240	80	80	400
LeafBlight	240	80	80	400
Total	960	320	320	1600

pre-trained models can result in time and resource savings compared to training a model from the start.

Additionally, it can enhance performance by leveraging the knowledge acquired from the initial work for the second task. A transfer learning technique often utilizes the pre-trained weights of a model that has been trained on a large-scale dataset from one domain (source) to address the problem of a smaller-scale dataset from another domain (target). Existing deep learning approaches may effectively leverage large-scale labeled data to acquire knowledge about a source domain. Hence, transfer learning can be employed to construct a model in a distinct target domain (32, 41-43). Figure 4 provides a schematic depiction of how pre-trained weights can be readily employed to decrease training time, handle fewer datasets, and thereby attain higher levels of accuracy. Within this particular framework, we have employed the weights acquired from ImageNet (44) to train the CNN models using our expanded image dataset.

A Convolutional Neural Network (CNN) model (25) comprises several layers that execute distinct operations on the input data, which, in this case, are images. The primary components of a Convolutional Neural Network (CNN) consist of a) the convolutional layer, b) the pooling layer, and c) the fully connected layer. Below, we will walk through the functioning of each of these layers. Readers are recommended to refer to literature (25) for a more in-depth understanding of mathematical concepts.

Convolutional layer: This is the first layer in CNN that applies filters to the input image. Each filter is a small matrix of weights convolved with a small portion of the input image, called a receptive field. The output of this operation is called a feature map, a filtered version of the input image. A convolutional layer can extract different features from the input image by applying multiple filters.

Pooling layer: CNN has one or more pooling layers after one or more convolutional layers. These are used to reduce the spatial size of the feature maps, which helps to reduce the network's computational complexity and make it more robust to small changes in the input image.

Fully connected layer: This layer is used to make predictions based on the features extracted by the

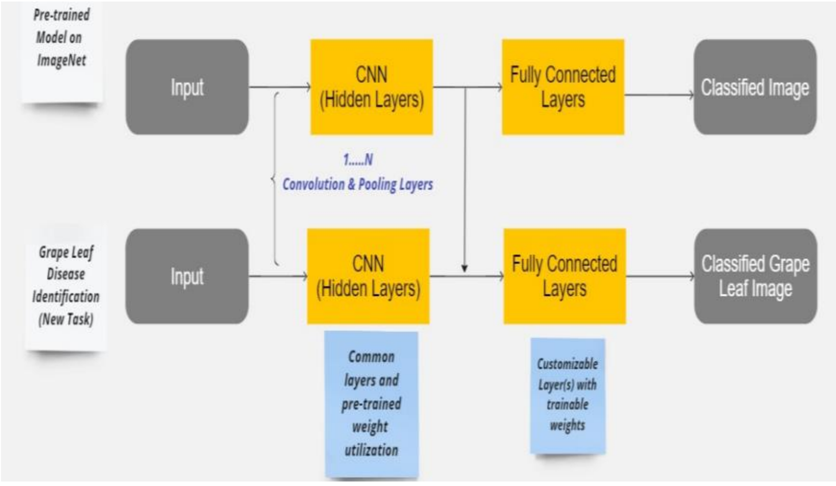


Figure 4. Conceptual Representation of Transfer Learning Technique

convolutional and pooling layers. The output of the final fully connected layer is typically a probability distribution over the possible classes of the input image.

A typical CNN model operates by employing filters on the input image to extract particular features. This is followed by down sampling the feature maps to reduce their spatial dimensions. Finally, fully linked layers are utilized to classify the image. Figure 5 illustrates the methods employed in this research for recognizing and differentiating grape leaf diseases. The grape leaf images collected in real-time are subjected to further preprocessing and augmentation techniques to increase the amount of the grape leaf dataset used as input.

The subsequent stage involved the training and compilation of several notable CNN models, including VGG16, VGG19, InceptionV3, InceptionResNetV2, Xception, and ResNet50V2 (20, 45, 46). These models have undergone training using ImageNet's image dataset. ImageNet comprises a collection of 1.2 million pictures categorized into 1000 different categories (44). This work uses the weights gained after training these models on ImageNet to fine-tune the weights and other parameters on the curated grape leaf image dataset. The proposed approach involved thorough validation using Google Colaboratory (47) and high-performance computing resources to fine-tune hyperparameters (48) and customize the final layer before classification. This was done through numerous iterations. Algorithm 1 provides a comprehensive account of the tasks performed during the experimental process.

Table 5 presents an overview of the features and parameters of the CNN models employed in this research. On the other hand, Table 6 focuses on the parameters utilized in the development of the CNN models.

Values below represent prediction scores obtained for the sample input test image:
Predicted Score:

Algorithm 1 Grape Leaf Disease Identification
Input: Augmented Real-time Grape Leaf Dataset(Training dataset T, Validation dataset V, Test dataset T_e)
1. Import necessary libraries and load the dataset
2. Define the hyperparameters for each model: HP = [hp_1, hp_2, ..., hp_n]
3. **foreach** hp_i ε HP do
   Train the model using the specified hyperparameters and the training dataset T
   Model = Train (T, hp_i)
   Validate the model using the validation dataset V
   Score = Evaluate (V, Model)
   End
4. Repeat step 3 till optimal performance is achieved by fine-tuning of HP
5. Save the score and the trained model
6. Select the best model based on the validation performance:
   best_model, best_score = SelectBestModel ()
7. Evaluate the saved best model using the test dataset T_e:
   test_score = Evaluate (T_e, best_model)
8. **foreach** img_p ε unseen_image_set do
   Predict the class probability using the saved best model:
   prob = Predict (img_p, best_model)
   end

Output: Identified Grape Leaf Image Category (Healthy or Diseased)

[[1.00000000e+00, 2.27766807e-12, 0.00000000e+00, 1.87562712e-25]
Max. Score: 1.00000000e+00
i.e., the Input Test image belongs to Class 0, which is BlackMeasles in our work. So, the image will be recognized as the image with the disease BlackMeasles.

4. RESULTS

4. 1. Experimental Settings

The experiments were conducted using Google Colaboratory which contained Tesla T4 GPU processors (32 GB memory) on

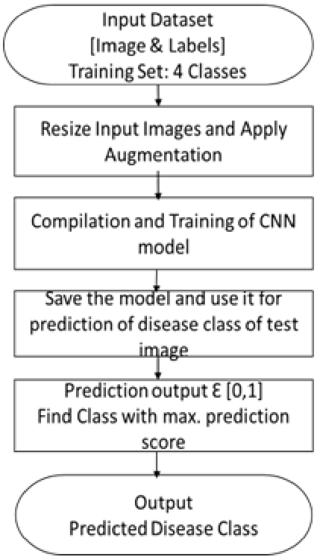


Figure 5. Methodology

TABLE 5. Comparative Analysis of CNN Models

CNN Model	Size (MB)	Parameters	Depth (No. of Layers)
VGG-16	528	138.4M	16
VGG-19	549	143.7M	19
InceptionV3	92	23.9M	189
InceptionRes-NetV2	215	55.9M	449
Xception	88	22.9M	81
ResNet50V2	98	25.6M	103

TABLE 6. Parameter Configuration of CNN Models

Parameter	Value
Activation Function	Softmax
Optimizer	Adam
Image Size	224 x 224
Batch Size	32
No. of Epochs	10
Learning Rate	0.01
Loss	Categorical Cross Entropy
Metrics	Accuracy

Windows 10 Operating System. The reason behind the usage of Google Colaboratory (47) is its on-the-fly use over the cloud without any requirement for high-end computing facilities at the host machine. TensorFlow and Keras deep learning libraries were used to implement and compare various CNN models (49, 50). These frameworks are flexible and appropriate for the development and validation of various CNN models due to their easy-to-use Python interfaces. Table 7 lists the configuration factors used while implementing different CNN models.

4. 2. Metrics Figure 6 shows performance of these models in terms of obtained accuracy (Equation 1) during validation while Figure 7 gives insights into how validation loss (Equation 2) is minimized when we increase the number of epochs for each model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where total number of images which are correctly classified is indicated as the sum of True Positives (TP) and True Negatives (TN). Value in the denominator indicates total number of images classified both correctly and incorrectly (FP: False Positives, FN: False Negative).

$$Validation\,Loss = -\sum (y_i * \mathrm{LOG}\,(p_i)) \quad (2)$$

where
y_i: true label (a one-hot encoded vector),
p_i : predicted probability for each class.

The sum is taken over all classes, and we are considering a validation loss at categorical cross-entropy.

Table 8 presents a comparative analysis of the results of recent studies in grape leaf disease identification and classification over our approach. The performance of ResNet50V2 in crop leaf disease identification and classification techniques is presented in Figure 8. It is observed that ResNet50V2 has been widely adopted in crop disease recognition, and results achieved in the presented study are comparable for grape leaf disease identification and classification.

5. DISCUSSION

We employed various deep-learning techniques to conduct a qualitative assessment and make comparisons. The results of the evaluation of the proposed approach are compared to those of existing methods in terms of accuracy and loss at various training epochs. The training and validation processes are performed to identify diseases in grape leaves until segmentation is completed,

TABLE 7. System Configuration used for Experimentation

Unit	Configuration
Central Processing Unit	Intel® Core i3-2330M Processor @ 2.20 GHz
Graphics Processor Unit	NVIDIA Tesla T4 processors (32 GB)
Operating System	Windows 10
Environment	Over the cloud through Google Colaboratory
Deep learning frameworks	TensorFlow, Keras

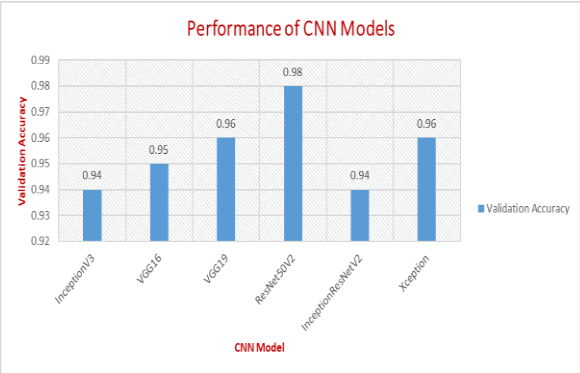


Figure 6. Performance Analysis of CNN Models

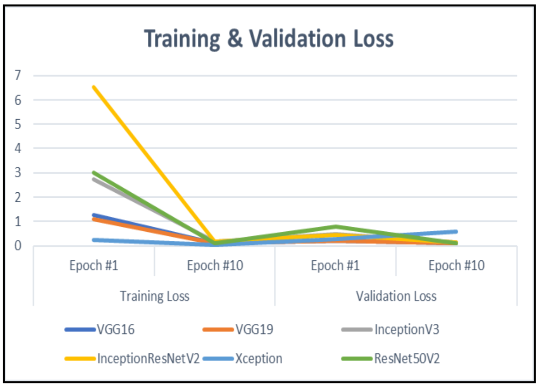


Figure 7. Comparative Analysis of Epochs Vs. Loss

TABLE 8. Comparative Analysis of CNN Models for Grape Leaf Disease Identification & Classification

Model	Dataset	Accuracy	Ref.
VGG16 & InceptionV1	PlantVillage and Grape Leaf Disease Image dataset generated using GANs	96.13	(51)
PSO SVM	450 Images	95	(15)
CNN& KNN	PlantVillage	94	(52-54)
Faster RCNN, YOLOx, SSD	2300 Images	93	(53)
GrapeNet	AI Challenger 2018	86.29	(16, 55, 56) [17,60, 61]
ResNet50V2	1600 Images	98	This Study

using epoch as the measurement unit to assess the accuracy and validation loss.

The accuracy and loss of the proposed approach is compared with literature (51-56). Our approach demonstrates superior accuracy compared to existing approaches, with a lower loss value. Figure 8 shows a comparative analysis of accuracies on various crops as discussed in existing studies and our approach.

The primary objective of the novel approach proposed in this study is to assist farmers in obtaining a definitive diagnosis of the specific type of grape leaf disease that has occurred in their land. During live testing, any farmer whose field is impacted by the grape leaf disease captures images of the crop. The image is fed to our technique for precise grape leaf disease identification and further categorization into healthy and diseased.

Firstly, the image undergoes pre-processing and segmentation.

Subsequently, the acquired features from the pre-existing model are utilized in the fine-tuned neural network. Deep learning is utilized to get knowledge about the disease that has affected the leaf by analyzing its multi-scale information. By utilizing pre-existing traits specific to various diseases inside the network, the prediction of disease type is enhanced with greater accuracy, and the resulting information is presented to the farmer. Utilizing a pre-trained model as a foundation and incorporating customization of the final layer approach enhances the prediction process with greater accuracy. As a result, the farmer can prevent misclassifications and implement targeted measures to maximize grape productivity. Therefore, the model is well-suited for real-time applications, particularly in the agricultural sector. Nevertheless, the training sets have exhibited some disparities between the projected and real labels due to unforeseen circumstances resulting from errors during annotation. Still, through rigorous experimentation, we achieved an impressive accuracy of around 98% and minimal validation loss compared with other CNN models (57-61).

As a part of model validation, we further deployed ResNet50v2 as a part of the application for utilization by grape farmers in the study area. It is inferred that our application gives more precise results faster than the existing models in the Indian context. This application can greatly benefit grape farmers by reducing overall yield losses.

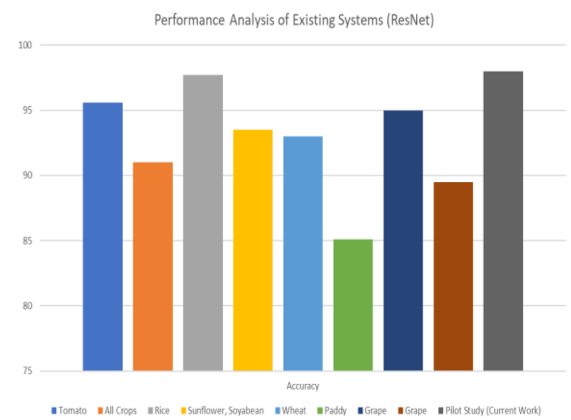


Figure 8. Performance Analysis of ResNet based Crop Disease Identification & Classification Techniques

6. CONCLUSION

The present research conducts a thorough and methodical examination of classical convolutional neural network (CNN) models in order to identify and categorize grape leaf diseases using a dataset of real-time grape leaf images. We tackled the issue of existing models' limited capacity to effectively generalize on real-time grape leaf images. Existing models encounter several challenges when dealing with the intricate nature of real-time leaf imagery. In order to tackle these problems, this study employs cutting-edge CNN models tailored for the real-time analysis of grape leaf images. This work involves the creation of a systematically curated dataset of grape leaf images in real-time, specifically in the Indian context. Furthermore, image augmentation techniques are utilized to substantially increase the size of the input dataset. In addition, a transfer learning technique is used to utilize pre-trained image weights from ImageNet. This approach decreases the dataset requirements by 40% and enhances computing speed by 60%. As a result, there is a substantial decrease in the duration required for training the model. The experimental findings demonstrate that Res-Net50V2 attains a validation accuracy of 98% for the identification and categorization of grape leaf diseases. This study has the potential to expand into a decision support system for larger datasets through mobile phones, considering the constraints of smaller datasets. The results of our study show that CNN models, which employ transfer learning on real-time grape leaf datasets, can be used as an effective solution and benchmark for deep learning applications in identifying and classifying crop diseases in real-time settings. Additionally, this work offers avenues for further exploration of the potential applications of deep learning techniques on real-time crop image datasets.

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Persian Abstract

چکیده

در باغبانی مدرن، صنعت انگور در سراسر جهان با موضوع بیماری های محصول انگور مقابله کرده است. تشخیص بیماری های برگ انگور با استفاده از روش های خودکار می تواند به کشاورزان در کاهش تلفات محصول و تضمین پایداری کمک زیادی کند. با این حال، سیستم‌های موجود هنگام مدیریت تصاویر برگ انگور در سطح مزرعه با موانعی روبرو هستند و این مدل‌ها نمی‌توانند به خوبی در تصاویر دیده نشده تعمیم دهند. این مطالعه توسعه یک مجموعه داده در زمان واقعی را به خوبی از تصاویر برگ انگور که از طریق بازدیدهای میدانی در منطقه مورد مطالعه در هند جمع آوری شده است، پیشنهاد می‌کند. این مجموعه داده طراحی‌شده بیشتر برای آموزش مدل‌های شبکه عصبی کانولوشنال برای شناسایی دقیق و طبقه‌بندی برگ‌های انگور به عنوان بیمار یا سالم استفاده می‌شود. پتانسیل یادگیری انتقال با استفاده از مدل‌های CNN مانند VGG، ResNet، Inception و Xception بر روی مجموعه داده‌های انتخاب‌شده ارزیابی می‌شود. یافته‌های ما نشان می‌دهد که ResNet50V2 در شناسایی دقیق و طبقه‌بندی بیماری‌های برگ انگور از مدل‌های دیگر بهتر عمل می‌کند. با استفاده از یادگیری انتقالی، وزن‌های موجود (از پیش آموزش داده شده) و ویژگی‌های آموخته‌شده برای آموزش بیشتر و تنظیم دقیق مدل‌های CNN در مجموعه داده‌های انتخاب‌شده ما مورد استفاده قرار گرفتند. نتایج روش پیشنهادی با تکنیک‌های شناسایی خودکار بیماری برگ انگور مقایسه می‌شود. مشاهده می‌شود که رویکرد پیشنهادی، که بر روی مجموعه داده‌های تصویر برگ انگور در زمان واقعی است، بالاترین دقت را در میان سایر موارد ارائه می‌دهد. علاوه بر این، این مطالعه مجموعه داده‌ای از تصاویر برگ انگور در مزرعه را در زمینه هند ارائه می‌کند که می‌تواند به عنوان معیاری برای تحقیقات آینده باشد. این مطالعه نشان می دهد که تکنیک های یادگیری عمیق می تواند به کشاورزان در شناسایی زودهنگام بیماری های برگ انگور کمک کند.