International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(1s) 2026 pp. 1422-1431
https://doi.org/10.70917/ijcisim-2026-2470
Article

Advances in Machine Learning and Deep Learning Techniques for Grape Disease Classification: A Comprehensive Survey

Shwetha B V[1], Hemalatha K L[2]

[1]Dept. of Computer Science and Engineering, SKIT, Bangalore, SJCIT, Chickballapur,
Visvesvaraya Technological University, Belagavi, Karnataka, India. shwetharuku@gmail.com.
[2]Dept. of Computer Science and Engineering, SKIT, Bangalore
Visvesvaraya Technological University, Belagavi, Karnataka, India. hemalathaklise@skit.org.in

Abstract:

The health and productivity of a vineyard can be maintained through the early diagnosis of grape disease. Incorporating machine learning (ML) and deep learning (DL) methods has demonstrated to be a very effective strategy for this challenge. The recent developments in DL and traditional ML techniques for the recognition and categorization of the grapevine disease are discussed in this review. Alongside the traditional ML methods like fuzzy logic systems and Support Vector Machines (SVMs), a variety of methods have been recognized, which include Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), capsule networks, residual networks and hybrid methods. Hyperparameters have been adjusted through optimization algorithms which include Improved Salp Swarm Optimization (ISSA), while the improvement of model efficiency for real-time and mobile applications is finished by attention mechanisms and lightweight architectures. Furthermore, GAN-based data augmentation methods resolve the limitations of small datasets. Even with advancements in robustness and classification accuracy, problems regarding computational efficiency, generalizability, and real-time deployment in natural environments still exist. The strengths and weaknesses of these techniques are thoroughly analyzed. In this review, providing awareness into future research for grape disease detection.

Keywords: Crop disease detection, grape, machine learning, deep learning, literature survey

1. INTRODUCTION

Agriculture, as the leading contributor to the global economy, serves as a key supplier of food, livelihoods and employment. Similar to various low and middle-income countries with huge farmer populations, India's agriculture contributes 18% of the nation's income and boosts the employment to 53% [1]. Over the past 3 years, the Gross Value Added (GVA) by agriculture to the nation's overall economy has improved from 17.6% to 20.2% [2,3]. The greatest portion of the economic development is provided by this field. As a result, pest infections and plant diseases can significantly affect the global economy by compromising food production standards. With increasing population, the food requirement is also rising. Crop protection and increased agricultural production are necessary to meet this need. Because of the pathogens in their environment, crops are highly vulnerable to various diseases. While few of the disease pathogens being viral organisms, others include bacterial or fungal [1]. Crops can experience a productivity decrease of 10% to 95% due to diseases [2], resulting in a decline in both quantity and quality of agricultural production. Thus, timely disease detection is necessary to prevent major damages and minimizing the overuse of pesticides, which are detrimental for environment and human health. In emerging countries and small farms, crop diseases are identified by farmers using their naked eye based on symptoms. Knowledge in plant pathology and excess treatment time is compulsory for carrying out this mission [3]. Moreover, farmers look for expert assistance to acquire an accurate and efficient diagnosis when a rare disease attacks the crops, resulting in additional treatment costs [4]. Therefore, for large farms, visual observation is infeasible and impractical and may also result in inaccurate predictions due to potential biases [5]. To address growing consumer expectations and mitigate the effects of chemical inputs on human health and the environment, researchers are focused on creating innovative solutions for the rapid, accurate identification of cop diseases.

1.1Grape production and impact of diseases

Grape is a popular and widely consumed fruit, enjoyed both as food and in beverages. Being among the most consumed fruits globally, grapes are also a primary ingredient in wine production. As a result, grape output and quality are highly valuable economically [6]. Grapes also have medicinal properties and can treat a wide range of diseases. They are originated from Europe and Western Asia. The fruit can be eaten raw, processed into juice, fermented to make wines and brandy, or dried to produce raisins [7]. In 2019, the global production of fresh grapes, including both table grapes and wine grapes, totalled 77.13 million metric tons, with a market value of USD 189.19 billion. [8]. The global production of grapes was 7.8 million tons in 2016, with 39% from Europe, 34% from Asia, and 18% from America, making grapes an economically vital crop with worldwide mass production [9].

Generally, grapes need a hot and dry atmosphere for their growth and fruiting stages. They are cultivated effectively in areas with the temperature ranging from 15°C to 40°C. Warm temperatures above 40°C during fruit development and growth can result in reduced fruit set and smaller berries. Crop letdown can happen due to low temperature below 15°C and forward pruning, which hinders budbreak. Grapes can be grown in various types of soil such as red sandy soils, sandy loams, red loams, sandy clay loams and shallow to medium black soils.

Various diseases like black measles, black rot, and isariopsis leaf spot can affect grapes [10]. These diseases mainly affect the production of crops. Black rot, caused by the fungus Guignardia bidwellii, can occasionally result in 100% crop loss [11]. Fungi-caused black measles, also known as Esca, is a common disease in Europe which harms the crop significantly [12]. Isariposis leaf spot, which is triggered by the fungi Isariopsis clavispora, causes significant damage to the crop when climatic situations are favourable [13]. Based on the extent and severity of the disease, grape diseases result in crop losses ranging from 5-80% [14]. Therefore, they are at a significant production risk with serious financial implications. To limit the disease progression and reduce economic costs, early and accurate detection of these diseases are important.

- **Grape Black Measles (Esca):** Grape black measles (Esca) is one of the most primitive recognized plant diseases, caused by the fungi Phaeomoniella Aleophilum or Chlamydospore. The disease mainly impacts grapevines, appearing as irregular yellow and circular spots on the leaves. Being highly contagious, it spreads rapidly across grape fields, causing significant crop loss. Thus, early detection is necessary to mitigate its spread and reduce damage [15].
- **Grape Black Rot:** Grape black rot, caused by the Guignardia bidwellii fungus, is a serious disease that attacks on grape leaves. This condition poses a serious threat to grape production, leading to losses ranging from 5–80%. To prevent black rot, the application of fungicides is necessary, which increases the farming's financial costs [16].
- **Grape Isariopsis Leaf Spot:** Grape isariopsis leaf spot, caused by the Pseudocercospora vitis fungus, is a fast-spreading disease that appears as pale red to brown lesions on the leaves. Early detection is necessary since special fungicides are needed to control its spread [17].

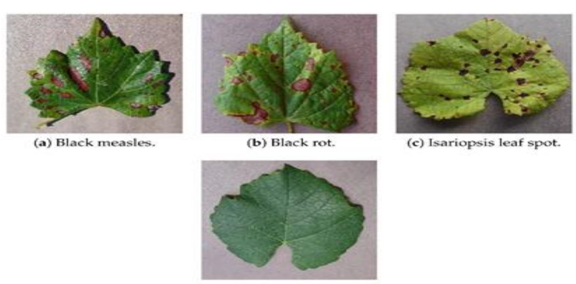

Fig. 1. Sample images of different plant leaf diseases

1.2 Crop disease detection: current progress

Numerous techniques [18, 19, 20, 21] have been suggested to automate disease detection. These approaches can be considered into two types: direct and indirect methods [22]. Direct methods, including molecular [23] and serological techniques [24,25] offer precise and direct pathogen detection. However, these approaches demand considerable time for the collection, processing, and analysis of samples. In difference, the indirect methods include optical imaging techniques [26,27] which detect diseases and assess crop health through various parameters like transpiration rate and morphological changes. Among the most often used indirect methods for early disease identification are fluorescence and hyperspectral imaging [28]. Although hyperspectral imaging provides detailed data and more insights than standard photographs, it is quite costly, cumbersome, and challenging for low-income farmers to access [29]. As an alternate, various digital cameras are available at affordable prices in electronics stores. Consequently, visible domain images have been the attention of the majority of automatic identification processes so far, enabling the usage of precise and efficient algorithms.

Assessing crop quality through visual inspection is challenging due to the cost, time and accuracy involved. Researchers have developed object detection and image processing technologies to address these issues. This paper highlights image processing technology for crop disease recognition and categorization, particularly in grapes. High-resolution images are important for precise identification and categorization of diseases using image processing techniques, but capturing these images can be difficult. As a result, making precise and efficient predictions about diseases remains a challenging task. Traditional crop disease detection techniques mainly rely on manual observation, which results in low efficiency and poor reliability. Farmers lack professional expertise and agricultural specialists cannot always serve the field, missing opportunities for preventive care. Image processing, pattern recognition, computer vision and other technologies have rapidly developed in the recent years to solve this issue. An efficient way of solving agricultural issues is over the habit of computerised automatic disease detection.

The traditional machine vision method for detecting crop leaf diseases involves three steps: image pre-processing, manual design of complex disease features by researchers for feature extraction, and categorizing of crop diseases using ML algorithms [18]. Various supervised ML techniques, such as Naive Bayes (NB), K-Nearest Neighbours (KNN) [18,19], Decision Trees (DT) [20], and Support Vector Machines (SVM) [21], are related for their power in disease detection and classification in plant leaves. This approach also evaluates different techniques to identify the most accurate methods. These techniques have been effectively applied in fields such as biomedical signal processing and healthcare.

In current years, deep learning (DL) technology has made remarkable strides in plant disease recognition. DL offers a transparent solution for users by automatically extracting image features and classifying plant disease spots. This is particularly beneficial for researchers in plant protection and statistics who lack advanced expertise. DL reduces the need for physical feature extraction and classifier design found in traditional image recognition methods, effectively capturing the original characteristics of images with an end-to-end approach. These characteristics have brought widespread attention for DL in plant disease recognition, creation it a prominent research area. This growing interest is driven by three key factors: the availability of larger datasets, the adaptability of multicore Graphics Processing Units (GPUs), and advancements in training deep neural networks alongside supporting software libraries like NVIDIA's Computing Unified Device Architecture (CUDA).

The complete article is planned as follows: section II presents a detailed literature review study about existing machine and deep learning based methods where their contributions are studies to identify the research direction, finally section III presents the concluding remarks for this work.

2. Literature Review

2.1 Machine Learning based methods for grape disease)

Javidan et al. [30] developed a method in which multi-class support vector machine (SVM) and unique image processing technique are used for the determination and grouping of illnesses affecting grape leaves, such as black measles, black rot, and leaf blight. They also used K-means clustering extracts features from RGB, HSV, and l*a*b colour models by separating illness symptoms from the healthy portions accordingly. In their study principal component analysis is employed to minimize the feature dimension and support SVM for effective categorised of diseases. In comparison to CNN and Google Net, the approach achieves a 98.71% accuracy and a 98.97% accuracy with far lower processing times according to the studies.

Jaisakthi et al. [31] Presented a technique for haphazardly indicating grapevine diseases using image processing and ML. This system employs grab cut segmentation to isolate the leaf (region of interest) from the background image.

The sick region is further segregated from the segmented leaf section utilizing two distinct techniques, such as global thresholding and semi-supervised methodology. Using an array of ML approaches, as well as Support Vector Machine (SVM), the Ada boost, and Random Forest tree, the features are retrieved from the segmented sick area and categorized as healthy, rot, esca, and leaf blight. They have achieved a higher correctness of 93% using SVM.

As per Shantkumari et al. [32], machine learning approach is used to precisely discriminate between dissimilar types of illness and to recognise grape leaf disease early. Additionally, in their research two novel models were presented for the categorisation of leaf diseases: the improvised K-Nearest Neighbour (IKNN) model and the Convolutional Neural Network based Classification (CNNC) model. According to them, information on structure, pattern, boundary, and discrimination is acquired by extracting high quality histogram and extended histogram characteristics. Next, using the high-quality gradient-based features that were assembled, the classification procedure is carried out. Their study also speaks that usage of CNNC and IKNN models significantly makes better classification exactness and precision.

Khan et al. [33] introduced a disease finding system that can notify farmers, offer decision-relevant information, and also to permit the permitted actions. The proposed model uses augmented and histogram-oriented gradient (HOG) preprocessing to classify datasets of powdery mildew, blotches, and healthy leaves. In their study the process is carried out by utilizing artificial intelligence algorithms like support vector machines (SVM), convolutional neural networks (CNN), decision trees (DT), Naive Bayes (NB), and random forest (RF). A stacking algorithm is utilized by them to determine which approach offers the best accuracy after the leaves that are impacted and those that are healthy have been classified. With accuracy of 96.1%, the CNN classifier exceeds the others, opinion to their analysis and results of trial. Applying fine tuning and transfer learning to the CNN-based model improves its accuracy by 3.1% and 1.4%. Additionally, SVM classification offers a sufficient 96.0% accuracy level for HOG enhanced data.

Chen et al. [34] described a three-phase deep learning architecture. This architecture employs a deterministic anarchic circuit (DCGAN) for information enhancement, a residual neural network (ResNet) is utilized for injury proof of identity, and a convolutional neural network (Faster R-CNN) for damage assessment. As per their study, grape leaf spots are first located using Faster R-CNN. Next, a tumors dataset is created for data augmentation. At last, ResNet is used for tumor detection. After that, DCGAN is applied to create artificial grape tumors using photographs of decaying leaves in order to diagnose tumors. In the end, hey used the majority voting approach for grape leaf tumor recognition, ResNet is taught on a dataset that includes real grape leaf tumors and artificial grape tumor depicts generated by DCGAN.

In a work by Mohammed et al. [35] a technique was introduced that consists of 4 different stages: augmentation, segmentation, textural feature extraction and classification. Also in their study, the stretch-based enhanced method has been refined for picture improvement and clarity. The k-means grouping algorithm was then used by the authors for the fragmentation of the acquired data. According to them Textural characteristics are derived from segmented grape leaf. In the end, they presented two classifiers, a multi Support Vector Machine and a Bayesian Classifier, are presented to determine type of grape leaf disease.

Ansari et al. [36] proposed an advanced method that makes use of support vector machines and image processing to figure out and classify grape leaf diseases. In this method, phases including image capture, noise reduction, image enhancement, segmentation of imagery, separating features, data categorization, and data discovery are included in Ansari and colleagues' suggested framework. Following completion of the mean function image denoising, CLAHE image enhancement, fuzzy C Means algorithm picture segmentation, PCA feature extraction, and PSO SVM, BPNN, and random forest methods image classification.

Zhu, et al. [37] addressed the use of backpropagation neural networks (BPNNs) and picture evaluation to create an automated diagnosis tool for grapevine leaf diseases. Currently, wavelet-based Wiener filtering is employed to eliminate noise from medical imaging data. They utilised Otsu technique to divide the grapevine leaf disease-affected areas, and morphological techniques were applied to enhance the lesions' appearance. They extracted the whole lesion neighborhood border by utilizing the Prewitt operator. According to their study, the factors like perimeter, area, circularity, rectangularity, and form complexity were found to be five helpful functions. The five grape leaf diseases that can be detected and identified using the proposed version of BPNN-based grape leaf disease detection are spot blight, Sphaceloma ampelinum de Bary, anthracnose, circular spot, and downy mildew.

Alajas et al. [38] utilized a combined approach of feature-based machine learning and computer vision to distinguish between healthy and diseased grape leaves and predict the extent of damage. This approach dataset consists of 943 images of healthier and diseased mature grape leaves, which were taken using a digital camera. They used

CIELab thresholding with slow snapping, to divide into healthy, diseased, and complete leaf regions. The classification tree (CTr/ee) was used to calculate the information gain and identify the most significant spectro-textural-morphological signatures of grape leaves (A, S, G, Y, H, B, Cr, entropy, correlation, contrast, and energy) for predicting the percentage of damaged surface. They demonstrated a superior performance in diagnosing grape leaf health issues, Linear discriminant analysis (LDA) with a correctness of 97.79% compared to CSVM, NB, and KNN. Additionally, in their research the regression tree (RTree) outperformed GPR, RSVM, and LDA in predicting the area of fungal damage, achieving an R2 value of 0.943.

According to Andrushia et al. [39], grape productivity and quality were adversely influenced by diseases of the grapevine. In their study, plant diseases were successfully identified and categorized using computer vision-based methods. This paper investigated the use of artificial bee colony (ABC)-based choice of features for identifying and categorizing of diseases in grape leaves. The input photographs were first subjected to pre-processing procedures in order to eliminate background and noise,Form, colour, and texture are obtained. The optimal feature set is found using the ABC-based attribute selection approach. To identify foliar disease in grapes, the selected attributes are fed into the support vector machine classifier.

Shantkumari et al. [40] suggested an adaptive snake approach (ASA) in this work. In their research, the background is first eliminated and then an Adaptive Snake method was suggested to locate the impacted region. Furthermore, this is accomplished by a dual technique, in which firstly quick segmentation is achieved and then absolute segmentation.

2.2 Deep Learning based methods for grape disease detection

Alsubai et al. [41] developed a Hybrid Deep Learning with Improved Salp Swarm Optimization-based Multi-class Grape Disease Classification (HDLISSA-MGDC) model, building on work of Alsubai and associates. The goal of proposed HDLISSA-MGDC model is to classify photos of grape skins into four different groups: healthy, Isariopsis leafy location, black rot, and black measles. To overcome the noise from the images, authors pre-processed the photos by applying the Median Filtering (MF) technique. Furthermore, the HDLISSA-MGDC model uses the Adam optimizer and Dilated Residual Network (DRN) to create a feature extractor. In their investigation, the Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU) model is implemented for grape disease categorization. Lastly, the CNN-GRU approach's hyperparameter values are modified by taking use of the ISSA.

Chen et al. [42] proposed a three stage deep learning-driven pipeline consisting of convolutional neural network faster (R-CNN) for lesions detection, a network of generative adversarial networks (DCGAN) for data augmentation, and a residual neural network (RESNET) for tumor verification. They used quicker R-CNN to mark the positions of grape leaf tumours and RESNET to identify tumours, a tumours dataset for data augmentation was first created. Secondly, leaf tumor photographs were synthesized and used for tumour diagnosis. Finally, the resulting images were loaded into the DCGAN and the overwhelming polling criteria was used to identify the grape leaf tumours. Using RESNET that was created by the researchers from the original collection, which contained photos of real grape leaf lesions and false grape lesion photos taken with a DCMANA.

Xie et al. [43] created grape leaf disease dataset GLDD by enlarging photos of grape leaves sickness using techniques for digital image processing. They presented a deep learning-based rapid DI-IACNN framework that improves feature mining capabilities for grape foliage disease identification utilizing GLDD and the quicker R-CNN discovery approach. This model includes the inception-v1 module inception-RESNET-v2 module and SE-blocks.

As per Math et al. [44], machine learning (ML) algorithms, as well as deep learning (DL) algorithms, are especially helpful in accurately identifying crop diseases in the early stages. The goal of project is to create a Deep Convolutional Neural Network (DCNN) system that employs RGB leaf photos to identify and classify grape diseases. The Plant Village dataset, which is openly accessible to scientists and engineers, contains an image dataset of grape crops that is used in the proposed model. In their study, the unique feature of the produced model is its CNN classification model, which is constructed from the ground up and offers accuracy that is on par with or even higher than that of certain pre-trained models that were trained by transfer learning.

Liu et al. [45] suggested a unique detection approach centered on enhanced convolutional neural networks to detect grape leaf sickness. First, by employing image enhancement techniques, researchers created an inventory of 107,366 grape leaf photos, consisting of 4,023 photographs taken in the field and 3,646 images taken from public data sets. To further enhance the effectiveness of multifaceted feature discovery, the conception framework was applied. Moreover, to improve the dissemination of features and promote reuse of attributes, an extensive connection technique was presented in the end. DICNNA, a unique CNN-based model, was created and trained entirely from scratch. It achieved 97.22% of total precision using the hold-out test set. Consequently, the ability to identify objects accurately improved by 2.55% and 2.97% respectively above GoogleNet and ResNet-34.

In a research by Diana Andrushia et al. [46], neural capsule-based networks were used to recognize ailments in grape leaves. One neural network design with promise for advanced learning is the capsule-like circuit. The above system efficiently reflects the geographic data of attributes by using a collection of neurons as capsules. According to the study, the added layering of convolutions before the core caps layer thus obliquely reduces the number of capsules and accelerates the continually changing process, which is what makes the suggested work innovative. Both enhanced and non-augmented datasets have been used in experiments using the suggested approach. Its 99.12% accuracy rate allows it to locate grape leaf infections with effectiveness.

Ji et al. [47] proposed a deep learning and fuzzy reasoning-based automated approach for grape black measles disease identification and severity analysis. In this approach, in the first phase pixel-level predictions are trained for the state-of-the-art ResNet50-based DeepLabv3 semantic segmentation model using pictures of individual leaves with fungal-caused pathological lesions. The extracted characteristics, such as ROI and POI, are thus acquired. Second, a fuzzy rule-based system is constructed for every characteristic to estimate the level of illness damage. In the suggested fuzzy reasoning system, suitable relationships for the input and output are also taken into consideration for the purposes of fuzzification and defuzzification.

Tang et al. [48] suggested an inexpensive convolutional neural network approach for evaluating black rot, black measles, and leaf blight in grapes. A novel approach is proposed centered around inexpensive convolutional neural networks employing the channel-wise attention (CA) mechanism with a focus on small and low-latency models operated on mobile devices. Squeeze-and-excitation (SE) blocks are measured as a CA method to boost the ShuffleNet architecture, with ShuffleNet v1 and v2 selected as the backbones.

Yuan et al. [49] offered an enhanced DeepLabv3+ artificial neural network for grape leaf black rot spot separation. The ResNet101 system makes up DeepLabv3's base system, and the remaining component includes an additional lane awareness module. The DeepLabv3+ encoder also incorporates an attribute unification stream that is built on a characteristic pyramid network. The two test sets, TS1 from crop village and TS2 from a vineyard area, were used to evaluate the categorization efficacy of this approach. In the test data set TS1, the newer DeepLabv3+ outperformed the initial version of DeepLabv3 by 3.0, 2.3, and 1.7, with assessment metrics of 0.848, 0.881, and 0.918 for recall, F1-score, and mean intersection over union (MIoU). In the test set TS2, the newly released DeepLabv3+ improved its rating criteria, MIoU, recall, and F1-score, by 3.3, 2.5, and 1.9.

Adeel et al. [50] emphasized grape diseases and suggested a unique paradigm for early illness identification and classification. For best results, a deep learning-based solution is integrated into a traditional architecture. This process consists of three main steps: (a) obtaining features using transfer learning on pre-trained deep models such as AlexNet and ResNet101; (b) best feature selection using the suggested Yager entropy along with kurtosis-Yeak strategy; and (c) the union of strong features employing the suggested parallel approach, which is then followed by the categorizing step through the least squared support vector machine (LS-SVM).

Zhang et al. [51] introduced YOLOv5-CA, a deep learning based methodology, to attain the optimum compromise amongst the GDM sensing speed and precision in real scenarios. In order to progress effectiveness, of detection, the downy mold disease-related visual traits are highlighted by the integration of the coordinate attention (CA) strategy into YOLOv5. To test the suggested method, a difficult GDM dataset with a variety of illuminations, shadows, and backgrounds was collected in a vineyard setting. According to the experimental findings, the suggested YOLOv5-CA outperformed popular approaches involving a faster R-CNN, YOLOv3, and YOLOv5 by having a recognition precision of 85.59%, recall of 83.70%, and mAP@0.5 of 89.55%.

Lin et al. [52] suggested an inexpensive CNN model named GrapeNet to discriminate between the various phases of symptoms linked to certain grape illnesses. Remaining barriers, convolution unit focus elements, and residual feature fusion blocks (RFFBs) are the basic elements of GrapeNet. The suggested network is deepened and rich properties are extracted from the remaining blocks. To mitigate the negative impact of a high number of concealed layers on CNN effectiveness, we created an RFFB component built around the residual block. This model achieves feature fusion at different depths by concatenating the extremely dimensional characteristic maps that come after the residual block's output and the median aggregated feature map that comes prior the block's input. Furthermore, each RFFB module is followed by the convolutional block attention module (CBAM).

According to Liu et al. [53], due to insufficiency of instructional pictures for grape leaf illnesses, this study presents a leaf GAN innovative system constructed using generative adversarial networks (GANs). This system produces visuals of four distinct grape leaf ailments with the purpose of establishing detection algorithms. The brittle interaction tactics and case-in-point adjustment combined into an effective marker for distinguishing between both genuine and bogus sickness visuals through applying their outstanding feature acquisition power on grape foliage tumors. A generator model with degressive channels was initially created for producing visuals of grape leaf diseases. Lastly, the deep regret gradient penalty approach is used to stabilize the models training process.

Nagi et al. [54] presented a Convolutional Neural Network (CNN) based technique for grapevine disease diagnosis. In this technique an accessible library containing three disease segments and one dataset of healthy leaf imagery was used to train a lightweight, six-layer CNN model was created from scratch. There were 3423 photos of grapevine leaves in the collection. A 70–30 train–test ratio was used to train model. To prevent the model from being overfit, early halting strategies and image augmentation were applied by the authors. On the test dataset, the suggested model's classification accuracy was 98.4%.

As per Jin et al. [55], generative adversarial networks (GANs) are a prominent device for creating grape leaf graphics. Sadly, the structural integrity and clarity of the leaf disease pictures produced by traditional GANs are inadequate. In this research, a novel architecture called GrapeGAN is developed to tackle this issue. In order to prevent the loss of texture detail information during the creation of images, convolutions are integrated with residual blocks and reorganizing (reorg) techniques to create a generator that resembles a U-Net. In order to preserve additional size texture knowledge, the engine also uses the concatenation (concat) approach simultaneously. Next, a discriminator with a convolution block and capsule structure is constructed to make the produced grape pictures physically complete and prevent misalignment of the petiole and leaf structure. General traits are derived via convergence whereas the spatial information and likelihood of spot occurrence are encoded by the capsule structure.

Wang et al. [56] presented a cross-channel interactive attention mechanism-based lightweight model ECA-SNET to address the a fore mentioned issues. First instruction confirmation and test sets are built using imagery augmentation techniques using 6867 gathered photos containing five major leaf illnesses measles, black rot, downy mildew, leaf blight, powdery mildew and healthy leaves, then an effective channel attention technique is provided using shufflenet-v2 as the foundation to enhance the model's capacity. To extract smooth lesion characteristics; ultimately, the network is further simplified to provide the effective ultralight architecture ECA-SNET.

Yeswanth et al. [57] suggested a new technique called Residual Skip Network-based Super-Resolution for Leaf Disease Detection (RSNSR-LDD) that detects leaf disease in grape plants. In this technique two parts are extracted from the original LR snapshot through aided sifting. To extract attributes for the two separate smaller sections, four distinct stages of the 2-channel remnant dropout circuit and one neuronal base layer are used. Combining is necessary in order to merge the qualities of two paths. The super-resolution (SR) image is then produced by a convolutional layer and a decryption step. A fresh cooperative approach to loss is offered for schooling. Sending the results of the SR image to the Disease Detection Network (DDN) allows for confirmation of grape leaf disease.

3. Conclusion

This review highlights the significant advancements in grapevine disease detection that have been accomplished by both traditional machine learning and deep learning models, each having their own set of advantages and disadvantages. While traditional machine learning techniques like support vector machines and fuzzy logic systems offer interpretability and simplicity but may struggle with huge datasets and complex feature extraction. On the other hand, deep learning models such as CNN-based architectures have demonstrated greater accuracy and feature extraction capabilities. These models benefit from advancements such as GAN-based data augmentation, attention mechanisms, and optimization techniques like ISSA for hyperparameter tuning. Promising outcomes can be obtained from hybrid models that combine both machine learning and deep learning approaches, particularly for real-time applications and mobile deployment.

However, despite these advances, several difficulties still exist. Under diverse environmental conditions, data scarcity limits model generalizability. Although GANs can produce synthetic data, this raises concerns of overfitting and possible bias. Moreover, deep learning models require substantial computational resources, which makes it difficult to use them in low-latency or mobile applications. Some of these challenges are mitigated by lightweight architectures like ShuffleNet and effective channel attention strategies, but more research is required to balance accuracy with efficiency, particularly for real-time applications in uncontrolled environments. Future research should concentrate on lowering computational requirements, increasing model interpretability and improving model robustness across various environmental conditions and disease phases. Combining traditional machine learning with deep learning, optimization strategies, and feature fusion techniques offers a way to create more flexible and efficient solution for grape disease detection, making a significant impact in the field of precision agriculture.

REFERENCES

1. Ramesh, S., Hebbar, R., Niveditha, M., Pooja, R., Shashank, N., & Vinod, P. V. Plant disease detection using machine learning. In 2018 International conference on design innovations for 3Cs compute communicate control (ICDI3C),2018, pp. 41-45. IEEE.
2. Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. Plant leaf disease detection using computer vision and machine learning algorithms. Global Transitions Proceedings, 3(1), 305-310.
3. Chug, A., Bhatia, A., Singh, A. P., & Singh, D. (2022). A novel framework for image-based plant disease detection using hybrid deep learning approach. Soft Computing, 2022, 1-26.
4. Saleem, M. H., Potgieter, J., & Arif, K. M. A performance-optimized deep learning-based plant disease detection approach for horticultural crops of new zealand. IEEE Access, 10, 2022, 89798-89822.
5. Nandhini, M., Kala, K. U., Thangadarshini, M., & Verma, S. M. Deep Learning model of sequential image classifier for crop disease detection in plantain tree cultivation. Computers and Electronics in Agriculture, 197, 106915,2022.
6. Peng Y, Zhao S, Liu J Fused deep features-based grape varieties identification using support vector machine. Agriculture 11(9):869,2021
7. Kulshreshtha, S. K., & Kumar, A. Consumption Culture of Indigenous Beverages: An Explorative Study of Fruit Wines of Meghalaya (India). Territoires du vin, (13), 2021.
8. Fraiwan, M., Faouri, E., & Khasawneh, N. . Multiclass classification of grape diseases using deep artificial intelligence. Agriculture, 12(10), 1542, 2022
9. Aravind, K. R., Raja, P., Aniirudh, R., Mukesh, K. V., Ashiwin, R., & Vikas, G. Grape crop disease classification using transfer learning approach. In Proceedings of the International conference on ISMAC in Computational Vision and Bio-Engineering 2018 (ISMAC-CVB) (pp. 1623-1633). Springer International Publishing.2019.
10. Kaushik, P. Machine learning algorithms aided disease diagnosis and prediction of Grape Leaf. In International Conference on Machine Learning, IoT and Big Data (pp. 11-21). Singapore: Springer Nature Singapore.2023.
11. Szabó, M., Csikász-Krizsics, A., Dula, T., Farkas, E., Roznik, D., Kozma, P., & Deák, T. Black rot of grapes (Guignardia bidwellii)—A comprehensive overview. Horticulturae, 9(2), 2023, 130.
12. Ji, M., & Wu, Z. Automatic detection and severity analysis of grape black measles disease based on deep learning and fuzzy logic. Computers and Electronics in Agriculture, 193, 2022, 106718.
13. Ferreira, G. M., Moreira, R. R., Jarek, T. M., Nesi, C. N., Biasi, L. A., & May De Mio, L. L. Alternative control of downy mildew and grapevine leaf spot on Vitis labrusca. Australasian Plant Pathology, 51(2), 2022, 193-201.
14. Crandall, S. G., Spychalla, J., Crouch, U. T., Acevedo, F. E., Naegele, R. P., & Miles, T. D. Rotting grapes don't improve with age: Cluster rot disease complexes, management, and future prospects. Plant disease, 106(8),2022, 2013-2025.
15. Ji, M.; Wu, Z. Automatic detection and severity analysis of grape black measles disease based on deep learning and fuzzy logic. Comput. Electron. Agric. 2022, 193, 106718.
16. Esteban, M.A.; Villanueva, M.J.; Lissarrague, J. Effect of irrigation on changes in berry composition of Tempranillo during maturation. Sugars, organic acids, and mineral elements. Am. J. Enol. Vitic. 1999, 50, 418–434.
17. Maia, A.; Oliveira, J.; Schwan-Estrada, K.; Faria, C.; Batista, A.; Costa, W.; Batista, B. The control of isariopsis leaf spot and downy mildew in grapevine cv. Isabel with the essential oil of lemon grass and the activity of defensive enzymes in response to the essential oil. Crop Prot. 2014, 63, 57–67.
18. Arun, R. A., & Umamaheswari, S. Effective multi-crop disease detection using pruned complete concatenated deep learning model. Expert Systems with Applications, 213, 2023,118905.
19. Naduvinamani, A. (2026). Hybrid Vision and Sequence Learning for Crop Disease Detection: A Multi-Stage Deep Learning Approach. International Journal of Computational Intelligence in Engineering (IJCIE), 1(3), 31-41.
20. Hassan, S. M., & Maji, A. K. Plant disease identification using a novel convolutional neural network. IEEE Access, 10, 2022, 5390-5401.
21. Thakur, P. S., Sheorey, T., & Ojha, A. VGG-ICNN: A Lightweight CNN model for crop disease identification. Multimedia Tools and Applications, 82(1), 2023, 497-520.
22. Abd Algani, Y. M., Caro, O. J. M., Bravo, L. M. R., Kaur, C., Al Ansari, M. S., & Bala, B. K. Leaf disease identification and classification using optimized deep learning. Measurement: Sensors, 25, 2023, 100643.
23. Pandian, J. A., Kumar, V. D., Geman, O., Hnatiuc, M., Arif, M., & Kanchanadevi, K. Plant disease detection using deep convolutional neural network. Applied Sciences, 12(14), 2022, 6982.
24. Mahum, R., Munir, H., Mughal, Z. U. N., Awais, M., Sher Khan, F., Saqlain, M., ... & Tlili, I. A novel framework for potato leaf disease detection using an efficient deep learning model. Human and Ecological Risk Assessment: An International Journal, 29(2),2023, 303-326.
25. Chen, Z., Wu, R., Lin, Y., Li, C., Chen, S., Yuan, Z., ... & Zou, X. , Plant disease recognition model based on improved YOLOv5. Agronomy, 12(2), 2022, 365.
26. Y. Kawasaki, H. Uga, S. Kagiwada, H. Iyatomi, Basic study of automated diagnosis of viral plant diseases using convolutional neural networks, in: International symposium on visual computing, Springer, 2015, pp. 638–645.

27. H. Durmus¸, E. O. Gunes¸, M. Kırcı, Disease detection on the leaves ¨ of the tomato plants by using deep learning, in: 2017 6th International Conference on Agro-Geoinformatics, IEEE, 2017, pp. 1–5.
28. P. Jiang, Y. Chen, B. Liu, D. He, C. Liang, Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks, IEEE Access 2019 59069–59080.
29. J. G. A. Barbedo, Plant disease identification from individual lesions and spots using deep learning, Biosystems Engineering 180 , 2019 96–107.
30. Javidan, S. M., Banakar, A., Vakilian, K. A., & Ampatzidis, Y. , Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning. Smart Agricultural Technology, 3, 2023, 100081.
31. Jaisakthi, S. M., Mirunalini, P., & Thenmozhi, D. . Grape leaf disease identification using machine learning techniques. In 2019 International conference on computational intelligence in data science (ICCIDS) , 2019, pp. 1-6 . IEEE.
32. Shantkumari, M., & Uma, S. V.. Grape leaf image classification based on machine learning technique for accurate leaf disease detection. Multimedia tools and applications, 82(1), 2023, 1477-1487.
33. Khan, K. H., Aljaedi, A., Ishtiaq, M. S., Imam, H., Bassfar, Z., & Jamal, S. S. Disease Detection in Grape Cultivation Using Strategically Placed Cameras and Machine Learning Algorithms with a Focus on Powdery Mildew and Blotches.2024, IEEE Access.
34. Chen, M., Brun, F., Raynal, M., & Makowski, D.. Forecasting severe grape downy mildew attacks using machine learning. PLoS One, 15(3), 2020, e0230254.
35. Mohammed, K. K., Darwish, A., & Hassenian, A. E. Artificial intelligent system for grape leaf diseases classification. Artificial intelligence for sustainable development: theory, practice and future applications, 2021, 19-29.
36. Ansari, A. S., Jawarneh, M., Ritonga, M., Jamwal, P., Mohammadi, M. S., Veluri, R. K., ... & Shah, M. A. (2022). [Retracted] Improved Support Vector Machine and Image Processing Enabled Methodology for Detection and Classification of Grape Leaf Disease. Journal of Food Quality, 2022(1), 9502475.
37. Zhu, J., Wu, A., Wang, X., & Zhang, H. Identification of grape diseases using image analysis and BP neural networks. Multimedia tools and applications, 79(21), 2020, 14539-14551.
38. Alajas, O. J., Concepcion, R., Dadios, E., Sybingco, E., Mendigoria, C. H., & Aquino, H. Prediction of grape leaf black rot damaged surface percentage using hybrid linear discriminant analysis and decision tree. In 2021 International Conference on Intelligent Technologies (CONIT) (pp. 1-6).2021, IEEE.
39. Andrushia, A. D., & Patricia, A. T. Artificial bee colony optimization (ABC) for grape leaves disease detection. Evolving Systems, 11(1), 2020, 105-117.
40. Shantkumari, M., & Uma, S. V. Adaptive machine learning approach for grape leaf segmentation. In 2019 International conference on smart systems and inventive technology (ICSSIT) (pp. 482-487).2019, IEEE.
41. Alsubai, S., Dutta, A. K., Alkhayyat, A. H., Jaber, M. M., Abbas, A. H., & Kumar, A. Hybrid deep learning with improved Salp swarm optimization based multi-class grape disease classification model. Computers and Electrical Engineering, 108,2023, 108733.
42. Chen, Y., & Wu, Q. Grape leaf disease identification with sparse data via generative adversarial networks and convolutional neural networks. Precision Agriculture, 24(1),2023, 235-253.
43. Xie, X., Ma, Y., Liu, B., He, J., Li, S., & Wang, H. . A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks. Frontiers in plant science, 11, 2020, 751.
44. Math, R. M., & Dharwadkar, N. V. Early detection and identification of grape diseases using convolutional neural networks. Journal of Plant Diseases and Protection, 129(3), 2022, 521-532.
45. Liu, B., Ding, Z., Tian, L., He, D., Li, S., & Wang, H. Grape leaf disease identification using improved deep convolutional neural networks. Frontiers in Plant Science, 11,2020, 1082.
46. Diana Andrushia, A., Mary Neebha, T., Trephena Patricia, A., Umadevi, S., Anand, N., & Varshney, A. Image-based disease classification in grape leaves using convolutional capsule network. Soft Computing, 27(3), 2023, 1457-1470.
47. Ji, M., & Wu, Z.. Automatic detection and severity analysis of grape black measles disease based on deep learning and fuzzy logic. Computers and Electronics in Agriculture, 193,2022, 106718.
48. Tang, Z., Yang, J., Li, Z., & Qi, F. Grape disease image classification based on lightweight convolution neural networks and channel wise attention. Computers and Electronics in Agriculture, 178, 2020, 105735.
49. Yuan, H., Zhu, J., Wang, Q., Cheng, M., & Cai, Z. An improved DeepLab v3+ deep learning network applied to the segmentation of grape leaf black rot spots. Frontiers in plant science, 13,2022, 795410.
50. Adeel, A., Khan, M. A., Akram, T., Sharif, A., Yasmin, M., Saba, T., & Javed, K. Entropy-controlled deep features selection framework for grape leaf diseases recognition. Expert Systems, 39(7),2022, e12569.
51. Zhang, Z., Qiao, Y., Guo, Y., & He, D. Deep learning based automatic grape downy mildew detection. Frontiers in Plant Science, 2022, 13, 872107.
52. Lin, J., Chen, X., Pan, R., Cao, T., Cai, J., Chen, Y.& Zhang, X. Grapenet: A lightweight convolutional neural network model for identification of grape leaf diseases. Agriculture, 12(6), 2022, 887.
53. Liu, B., Tan, C., Li, S., He, J., & Wang, H. A data augmentation method based on generative adversarial networks for grape leaf disease identification. IEEE Access, 8, 2020, 102188-102198.
54. Nagi, R., & Tripathy, S. S. Deep convolutional neural network based disease identification in grapevine leaf images. Multimedia Tools and Applications, 81(18),2022, 24995-25006.
55. Jin, H., Li, Y., Qi, J., Feng, J., Tian, D., & Mu, W. GrapeGAN: Unsupervised image enhancement for improved grape leaf disease recognition. Computers and Electronics in Agriculture, 198,2022, 107055.

56. Wang, P., Niu, T., Mao, Y., Liu, B., Yang, S., He, D., & Gao, Q. Fine-grained grape leaf diseases recognition method based on improved lightweight attention network. Frontiers in Plant Science, 12, 2021, 738042.
57. Yeswanth, P. V., Deivalakshmi, S., George, S., & Ko, S. B. Residual skip network-based super-resolution for leaf disease detection of grape plant. Circuits, Systems, and Signal Processing, 42(11),2023, 6871-6899.