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Original Article

Developing a Hybrid Faster Recurrent Convolutional Neural Network with an Improved Weighted Artificial Bee Optimization Method for Grape Disease Detection at an Early Stage

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***Abstract -** In India's diverse range of crops, fruits play a crucial role in generating significant revenue for farmers. Among these fruits, grapes are extensively grown. However, grape plants are susceptible to various diseases affecting their fruits, stems, and leaves, ultimately impacting their yield. Grape disease detection at an early stage plays a crucial role in ensuring crop health and maximizing yield. To address this issue, early detection and effective treatment of these diseases are essential to ensure food safety. This study focuses on analyzing different methods for diagnosing and classifying diseases that affect grapevines, with particular emphasis on grape leaf diseases. Monitoring the condition of grape leaves provides valuable insights into the overall health of the grape plants. The research aims to provide a comprehensive overview of techniques used for identifying and categorizing these diseases. Automated disease detection algorithms are proposed to enhance diagnosis accuracy and enable timely control actions. Image processing, a widely used method, is endorsed for leaf disease identification and classification in plants. In this study, we propose a novel approach by integrating a hybrid Faster Recurrent Convolutional Neural Network (FRCNN) with an improved Weighted Artificial Bee Optimization (WABO) method for efficient grape disease detection. The FRCNN architecture combines the strengths of recurrent and convolutional neural networks to capture both spatial and temporal information from grape images. Additionally, the WABO method enhances the training process by optimizing the network's weights to improve detection accuracy. Experiments conducted on a large-scale dataset show that the proposed approach is more effective than current approaches in terms of computational efficiency and detection accuracy when it comes to correctly diagnosing grape diseases early on. The proposed framework has a lot of potential for practical uses in vineyard management and precision agriculture.*

***Keywords -** Grape disease detection, Early stage detection, Hybrid Faster Recurrent Convolutional Neural Network, Weighted Artificial Bee Optimization, Precision agriculture, Vineyard management, Computational efficiency, Detection accuracy.*

1. Introduction

Undoubtedly, agriculture forms the backbone of India, as the country is the second-largest global producer of agricultural products. With an impressive output exceeding 280 million tons, this sector contributes significantly, accounting for over 15% of India's GDP [1]. Approximately 70% of our population relies on agriculture, making it a pivotal sector. One-third of our National income is generated from agriculture [2], clearly highlighting its substantial contribution. Our economy is fundamentally grounded in agriculture, and the progress of this sector significantly impacts the overall economic well-being of our country. For a considerable duration, our agriculture lagged behind in development, resulting in insufficient food production for our population. Consequently, our country had to import food grains from other nations [3]. However, the situation has undergone a remarkable transformation. India now surpasses its own food-grain requirements, even exporting surplus food grains and other agricultural products to various countries.

The implementation of our five-year plans has played a crucial role in bringing about significant improvements in the agricultural sector. The Green Revolution, in particular, has been a game-changer, enabling our nation to achieve self-sufficiency in food grains and enhance its agricultural prowess [4]. Continuous cultivation of the same crops year after year has led to a decline in soil fertility. To address this issue and obtain higher yields from the land, adopting a crop rotation system has proven effective. By altering the crop pattern, the soil maintains its fertility, resulting in improved crop production. Thankfully, many farmers have embraced this practice of crop rotation [5]. Traditionally, our farmers have relied on outdated farming methods and implements. However, the government is now taking proactive steps to educate and empower them. The establishment of agricultural colleges and universities plays a pivotal role in providing comprehensive knowledge about agricultural science to aspiring young farmers. These educational institutions also conduct orientation courses for farmers, aiming to enhance their skills and understanding of modern agricultural practices. Indian farmers are fortunate to benefit from the country's diverse climate, which offers abundant farming opportunities. Those residing in the Plains find it favourable to cultivate grains with ease, while those in the mountains can engage in fruit farming, making agriculture a versatile and thriving sector in India [6].

Plants play a crucial role in creating a sustainable ecosystem and help keep Earth's atmosphere healthy. Fruit plants, in particular, are vital to the agro-economic community as they form the backbone. Growing grapes (Vitisvinifera) is a profitable industry in India, with Europe and Western Asia being the original grape-growing regions. In 2023, the Food and Agricultural Organization (FAO) ranked India's grape output as the 18th best in the world. There is strong evidence that grapes can treat a wide range of illnesses. For grapevines to bear fruit, a warm, dry climate is required [7]. In recent years, India has witnessed a notable surge in its fruit exports. The country exported fruits worth around 2.62 billion US dollars in the financial year 2022-2023 [8]. Among the key Indian summer fruits that have seen significant export demand are mangoes, bananas, grapes, pomegranates, and various citrus fruits. Fruits from summer, winter, and monsoon seasons experience significant demand in the domestic market.

In the fiscal year 2022-23, India's total fruit production reached an impressive 102.08 million metric tons. These statistics undeniably highlight that fruit farming in India presents a lucrative opportunity for farmers, offering the potential for substantial growth and prosperity [9]. Unlike flowers and fruits that only last for a short period, leaves remain on the plant for a considerable amount of time. Agricultural product manufacturers have an automatic system to classify plant leaves. This system helps professionals identify flaws in plants using conventional methods. However, for larger farms, this can be challenging, and small farmers may find it difficult to consult with professionals due to time and money constraints [10]. It claims that the automatic method of plant disease detection can boost plant productivity and streamline the monitoring procedure in expansive fields. The literature suggests that bio-inspired metaheuristic algorithms are effective for feature selection in plant disease detection [11]. Grapes, classified as true berries, possess a fleshy fruit wall (pericarp) all the way through. Their colors can range from green to red and deep purple. These fruits grow on deciduous woody vines belonging to the flowering plant genus Vitis. The grape plant is a perennial bush characterized by its helices, which are trails and tendrils. As a climbing plant, a grape is a vine, and its stems support the growth of tendrils, which are actually degenerated inflorescences. The leaves of the grape plant exhibit a heart-shaped appearance and are relatively large, positioned opposite to each other on the stems [12]. These leaves prominently display nerves.

Additionally, the size, color, and shape of both leaves and fruits vary according to the specific grape variety. Grapes come in both seeded and seedless varieties. The seeded variety may contain up to four seeds per fruit, which typically contain about 4-6% tannins [13]. Viticulture refers to the study and cultivation of grapes, which serve various purposes such as consumption (table grapes) or wine production. This agricultural practice encompasses all the activities and research involved in caring for the grape crop until the harvest stage. Oenology is the field of study and cultivation of grapes specifically for wine-making purposes. It not only involves the growing of grapes but also encompasses the entire process of wine-making [14]. Grape cultivation is adaptable to different soil types. On the other hand, alkaline soils with poor drainage are not suitable for grape cultivation. There are several image-processing methods that can be used for identifying grape plants based on their visual characteristics [15]. Some of the commonly used image processing methods for grape plant identification include:

- Image Segmentation: Employing segmentation techniques like thresholding, regiongrowing, or clustering algorithms to separate grape plants from the background in images.
- Feature Extraction: Extracting relevant characteristics from the segmented images, such as leaf shape, size, texture, grape cluster arrangement, and vine appearance.
- Object Recognition: Applying pattern recognition algorithms to identify grape plants based on their extracted features and comparing them to known patterns of different grape varieties.
- Color Analysis: Analyzing color variations in grape leaves, clusters, and berries to distinguish different grape varieties with unique color patterns.
- Leaf Texture Analysis: Examining leaf texture features, such as veins and surface patterns, to identify specific characteristics of grape plants.

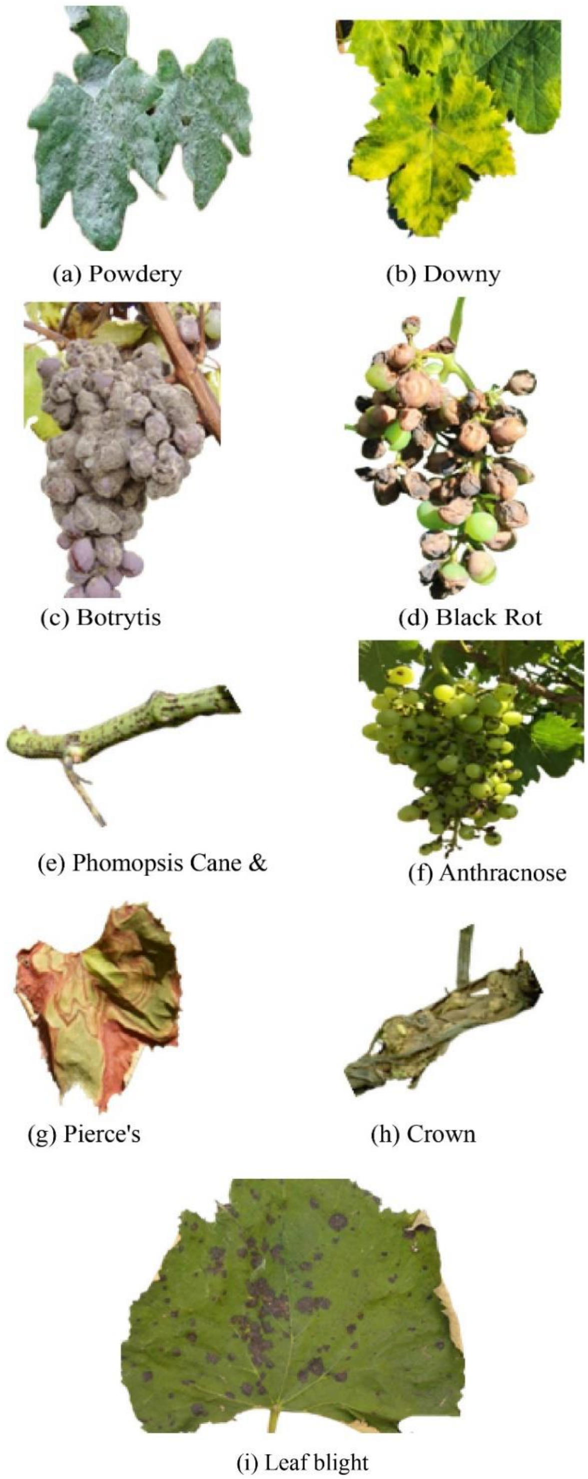

Fig. 1 Varieties of Grape plant diseases: (a) Powdery Mildew, (b) Downy Mildew, (c) Botrytis Bunch Rot, (d) Black Rot, (e) Phomopsis Cane and Leaf Spot, (f) Anthracnose, (g) Pierce's Disease, (h) Crown Gall, and (i) Leaf blight.

- Deep Learning: Implementing deep learning techniques to train neural networks for identifying grape plants from images and categorizing them into different varieties.
- Shape Matching: Comparing the shape of grape leaves or clusters in images to known shapes of different grape varieties to identify the closest matching variety.
- Geospatial Analysis: Integrating image data with geographical information to identify grape plants based on their location and distribution.
- Hyperspectral Imaging: Hyperspectral imaging is utilized to capture detailed spectral information of grape plants, revealing unique spectral signatures associated with different varieties.

The categorization yields different answers for every input data set, and it is a challenging task. There are numerous problems with the current classification techniques. The KNN classifier is unreliable for noise and costly to examine each input. PNN classifiers have greater features that are tailored to fit the network and broader network topology.

Various diseases can significantly affect the health and productivity of grape plants. Figure 1 displays the different varieties of grape plant diseases [16]. Neural networks translate an input, such as pictures of a sick plant, to an output, such as a pair of crop diseases.

Neural network nodes are mathematical functions that use incoming edges to gather numerical inputs and outgoing edges to produce numerical values [17]. The aim is to build a deep network with proper mappings of input to output based on nodes, functions, and edge weights. Recently, a number of conceptual and engineering advancements have significantly improved this computationally demanding task.

1.1. Problem Statement

Graph leaf detection presents a multifaceted challenge in computational analysis, particularly within complex graph structures representing hierarchical or networked data. The task involves devising algorithms capable of accurately discerning and characterizing individual leaves amidst the intricate connectivity of the graph. One of the primary hurdles lies in the inherent complexity of graph representations, where nodes and edges may form intricate webs of relationships, obscuring the identification of distinct leaves.

Moreover, the leaves themselves exhibit significant heterogeneity in terms of shape, size, and texture, further complicating the detection process. In practical scenarios, graph data often contain noise or artifacts, which can confound detection algorithms, leading to erroneous results. Additionally, the sheer scale of graph datasets, ranging from small-scale networks to vast interconnected structures, necessitates scalable and computationally efficient detection methods.

The challenge is compounded by the potential for leaves to overlap or intersect within the graph, posing a fundamental problem in distinguishing individual entities. Ultimately, efficient graph leaf detection holds substantial promise across diverse fields, including biology, social sciences, image processing, and network analysis, driving the need for innovative and adaptable detection approaches.

1.2. Motivation

The motivation behind tackling the problem of graph leaf detection stems from its wide-ranging applications and the valuable insights it can provide across various domains. Understanding and accurately identifying individual leaves within complex graph structures offer numerous benefits and opportunities for advancements in several fields. Here are some key motivations:

1.2.1. Biological Research

Graphs are widely used in biology to describe complex biological networks, such as gene regulatory networks or networks of interactions between proteins. Detecting leaves in these networks can help uncover important biological insights, such as identifying key genes or proteins responsible for specific functions or diseases.

1.2.2. Social Network Analysis

Social networks are often represented using graphs, in which nodes stand in for individual people and edges for the connections between them. Detecting leaves in social networks can aid in identifying influential individuals, detecting communities, or understanding information flow dynamics.

1.2.3. Image Processing

Graph-based image representations are utilized in various image processing tasks, such as scene analysis, object recognition, and image segmentation. Detecting leaves in these graph representations can facilitate tasks like identifying distinct objects or segments within images.

1.2.4. Network Security

In cybersecurity, graphs are used to model networks of interconnected devices or systems. Detecting leaves in these networks can assist in identifying vulnerable or compromised nodes, thus enhancing network security and threat detection.

1.2.5. Transportation and Logistics

Graphs are employed to model transportation networks, such as road networks or flight routes. Detecting leaves in these networks can help optimize routes, identify critical nodes, and improve overall transportation efficiency.

1.2.6. Urban Planning

Graphs are used to represent urban infrastructure networks, such as water distribution networks or power grids. Detecting leaves in these networks can aid in identifying areas of high demand, potential vulnerabilities, or opportunities for infrastructure optimization.

1.2.7. Academic Research

Advancements in graph leaf detection can contribute to the development of novel algorithms and methodologies in the field of graph theory and computational analysis, furthering academic research in various disciplines.

Overall, the motivation behind graph leaf detection lies in its potential to unlock valuable insights, optimize systems, enhance decision-making processes, and drive advancements across a wide range of practical applications and academic pursuits.

1.3. Objectives

1.3.1. Enhanced Detection Accuracy

Improve the accuracy of grape disease detection at an early stage by leveraging the hybrid FRCNN architecture.

1.3.2. Efficient Training Process

Develop an improved WABO method to optimize the network's weights effectively, enhancing the training process and ensuring convergence to optimal solutions for grape disease detection.

1.3.3. Robustness to Variations

Design the hybrid FRCNN and WABO method to be robust to variations in grape images, including differences in lighting conditions, camera angles, and disease manifestations, ensuring reliable detection across diverse scenarios.

1.3.4. Generalization and Adaptability

Ensure the developed approach can generalize well to unseen grape disease types and adapt to new datasets or vineyard environments with minimal retraining or tuning requirements.

1.3.5. Validation and Benchmarking

Conduct comprehensive validation and benchmarking experiments using diverse grape disease datasets to assess the performance of the hybrid FRCNN with the WABO method and compare it against existing approaches in terms of detection accuracy, computational efficiency, and robustness.

1.3.6. Practical Deployment

Facilitate the practical deployment of the developed approach in vineyard management systems or agricultural technology platforms, providing a valuable tool for grape growers to monitor and manage disease outbreaks effectively.

By achieving these objectives, the aim is to advance the state-of-the-art in grape disease detection technology, empowering grape growers with a reliable and efficient tool to safeguard crop health and optimize vineyard productivity.

1.4. Research Gap

Integration of Recurrent and Convolutional Architectures: While Convolutional Neural Networks (CNNs) have been widely employed for image-based tasks, including disease detection in agriculture, the integration of Recurrent Neural Networks (RNNs) within a hybrid FRCNN architecture for grape disease detection at an early stage represents a novel approach. The research gap lies in exploring how the combined strengths of recurrent and convolutional layers can effectively capture both spatial and temporal information from grape images to enhance disease detection accuracy.

1.4.1. Optimization Method for Neural Network Weights

Although optimization algorithms like Artificial Bee Colony (ABC) optimization have been utilized in training neural networks, the specific adaptation of Weighted Artificial Bee Optimization (WABO) for optimizing the weights of the hybrid FRCNN in the context of grape disease detection at an early stage is relatively unexplored. There is a research gap in investigating how the WABO method can be tailored and enhanced to improve the training process and convergence to optimal solutions, thereby enhancing detection accuracy.

There is a research gap in developing robust and efficient methodologies specifically tailored for early-stage detection of various grape diseases using image-based techniques. Addressing this gap involves exploring novel features, techniques, and architectures optimized for detecting subtle signs of diseases at their nascent stages in grape images. Benchmarking studies comparing the proposed hybrid FRCNN with the WABO method against existing approaches are essential to comprehensively evaluate its effectiveness, computational efficiency, and robustness across different grape disease datasets.

1.4.2. Real-World Deployment and Validation

Bridging the gap between research and practical application involves validating the proposed methodology in real-world vineyard environments. There is a need for studies that evaluate the performance of the developed approach under diverse environmental conditions, considering factors such as lighting variations, camera angles, and field conditions to assess its reliability and practical utility for grape growers.

2. Related Works

The detection of grape plant diseases using traditional methods refers to the use of conventional techniques and visual observations by experts or farmers to identify signs and symptoms of diseases in grape plants. These methods often involve manual inspection of the plants, looking for characteristic symptoms such as discoloration, lesions, deformations, or other visible indicators of disease presence [18]. Traditional methods may also involve the use of field diagnostic kits or simple tests to detect common pathogens or signs of diseases. Farmers and experts with experience in grape cultivation can often recognize the presence of diseases based on their knowledge and observation skills. While traditional methods have been used for many years and are relatively straightforward, they may have limitations with regard to accuracy and efficacy, particularly when dealing with early-stage infections or less obvious symptoms. Therefore, Modern methodologies, including machine learning and deep learning methods, are being explored to complement or improve disease detection in grape plants [19].

In order to create an automated decision support system, explained how to identify and classify grape diseases using machine learning and opposing color local binary pattern features. The main emphasis of this study was the detection of leaf diseases in Grape plants through the analysis of leaf texture and the recognition of patterns. The architecture takes an individual leaf as input and performs segmentation after removing the background. The texture patterns of each specific disease exhibit variations. Subsequently, a multiclass SVM is utilized to classify the extracted texture patterns. The study mainly concentrates on the major diseases frequently seen in Grape plants, specifically black rot and downy mildew. However, increasing the training ratio has the potential to yield even greater improvements in the system's accuracy [20].

Used the multiclass Support Vector Machine to detect and classify grape leaf disease. The system applies image preprocessing methodologies such as enhancement, resizing, and smoothing. The images are then transformed into LAB and Hue, Saturation, and Intensity (HIS) color models. For diseased area segmentation, the K-means clustering methodology is employed, and the cluster containing the diseased spot is manually selected. From this selected cluster, both texture and color properties are extracted using standard MATLAB functions and GLCM, respectively [21].

These extracted features are then used to train a multi-class SVM classifier to differentiate between healthy and diseased categories. However, in addition to LAB and HSI color spaces, extracting features from the YCbCr color space and incorporating wavelet-based features into the database could potentially enhance the system's accuracy rate. Used the SVM for Grape Leaf Disease identification. Grape leaf detection is done in two stages: First, the sick region is identified by segmenting the area using K-means clustering. However, a fusion classification technique which combines several algorithms is used to increase the identification rate of the classification process [22].

Traditional machine learning techniques such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests (RF) have been widely used in plant disease detection. These models often rely on manually crafted features extracted from color, texture, and shape characteristics. These methods lack the robustness to adapt to complex disease patterns and require extensive feature engineering, which can be both challenging and insufficient for accurately capturing subtle, early-stage symptoms of grape diseases. Additionally, traditional models are generally less effective when applied to high-dimensional data such as images. [23].

Optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Optimization (ABO) have been integrated into CNN models to fine-tune hyperparameters, enhancing model accuracy and reducing computation time. These algorithms mimic biological or physical systems to iteratively improve model performance. Existing optimization methods often struggle with premature convergence, leading to suboptimal performance. They also lack adaptability, meaning they do not dynamically adjust search parameters during training, which limits their ability to handle high-dimensional image data effectively [24].

Attention mechanisms direct the model's focus to specific, disease-relevant areas within images, such as lesions or spots, improving detection precision and reducing processing time. This approach is increasingly popular in image classification tasks but is less common in agricultural disease detection models. Few existing grape disease detection models utilize attention layers, leading to uniform image processing that reduces accuracy. Attention mechanisms could enhance early-stage detection by guiding the model toward subtle symptoms [25].

Finally, several classifiers are evaluated, and Random Forest (RF) is chosen as the optimal choice for disease classification. However, Observations indicate that there is still potential for enhancing the features utilized in the classification process [26].

CNNs are widely adopted for image-based plant disease detection due to their ability to automatically learn spatial features. CNN models, including architectures such as AlexNet, VGG, and ResNet, have shown significant success in detecting various plant diseases, including those affecting grapes. These models capture color and texture features more effectively than traditional methods. Although CNNs perform well on fully developed symptoms, they often lack sensitivity to early disease indicators. CNNs also tend to process images uniformly, which can dilute attention from symptom-relevant areas and lead to less precise detection. Additionally, many CNN-based models are computationally expensive, making real-time deployment challenging [27].

It is doubtful whether the disease is detected and identified if the image's background is complicated with other plants or leaves [28]. Because of the disease's history, the majority of literatures classified it incorrectly, which resulted in incorrect classification. Due to the intricacy of sick leaves in relation to their background, leaf-based disease detection and diagnosis remains a challenging area of study [29].

3. Proposed System

The agricultural sector employs the majority of Indians, and it has long been thought of as being very important to the nation's economy. The productivity of plants and the revenue of farmers who care for those plants may be significantly impacted by failing to treat diseases. This innovative approach revolves around the development of a Hybrid FRCNN-WABO method. The FRCNN architecture, a hybrid model amalgamating both recurrent and convolutional neural network components, leverages the spatial analysis prowess of convolutional layers alongside the temporal dependency-capturing capabilities of recurrent layers. Complementing this architectural innovation, the improved WABO method introduces weighted mechanisms to bias the optimization process towards more promising regions of the solution space, effectively addressing convergence challenges and boosting the efficacy of neural network training. The entire process for identifying grape leaf illnesses using the proposed architecture is shown in Figure 2.

3.1. Data Preprocessing

Step 1: Augmentation

Data generator for data augmentation and cropped healthy and phylloxera disease data to balance the dataset and lessen overfitting issues during the training phase.

Step 2: Renaming

It makes managing data easier for subsequent analysis. Each category's images are renamed following cropping and augmentation but prior to data being randomly shuffled. Following renaming, "class name_sequence number" is used to identify the photographs in each category fold. It is simple to verify and shuffle at random using the provided standardized name convention.

Step 3: Data splitting

The images are organized into three datasets in this step:

- Test,
- Validation, and
- Training.

The dataset has little inter-class variation since the same illness is divided into symptoms that are mild and severe. As a result, utilizing a CNN model to accurately diagnose sickness is challenging. Image Preprocessing Grape disease samples were few, and they were unevenly distributed across the various groups. The following list of actions was completed. Figure 2 displays an example of the larger images. The validation or test sets didn't need to be increased after that. Tables 1 and 2 display the sample distribution both before and after augmentation.

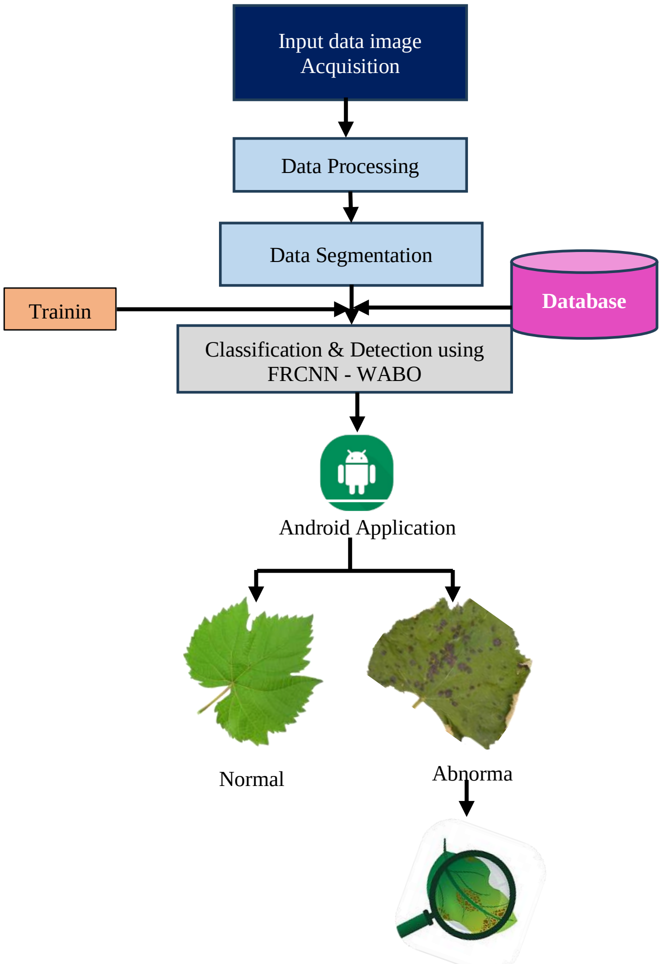

Fig. 2 Proposed architecture

Table 1. Dataset before augmentation

Class	Training Data Set	Test Dataset	Validation Dataset
GH	267	44	31
BRF_G	345	56	40
BRF_S	419	58	48
BMF_G	455	76	52
BMF_S	380	61	43
LBF_G	57	11	8
LBF_S	569	92	65

Table 2. Dataset after augmentation

Class	Training Data Set	Test Dataset	Validation Dataset
GH	2652	44	31
BRF_G	2060	56	40
BRF_S	2498	68	48
BMF_G	2720	76	52
BMF_S	2270	61	43
LBF_G	1982	11	8
LBF_S	3404	92	65

3.2. Training Data Preparation and Validation

Detailed distributions are displayed in Figure 4. Each class contains more than 1000 photographs, totaling 5937 images. These picture data are divided into two sections at random: Of the 1187 photos, 20% are designated as test data, and the remaining 80% are designated as training and validation data. The split ratio is 80% to 20% for training and validation data. These pictures are all organized into three folders. They are tests, validation, and training. By reading files from the directory setting, we can create training, validation, and test datasets with Keras' integrated data generation approach. One of the most widely used FRCNN architectures on the market right now is AlexNet. With a 16.4% mistake rate, it won the 2022 ImageNet Classification competition a notable improvement over the 25.8% error rate of the 2023 champion. Two techniques to decrease overfiting in FRCNNs have been proposed: weight regularization and dropout. Moreover, states that using the most advanced and widely used modelsthat is, models with more parameters than the data support causes overfiting.

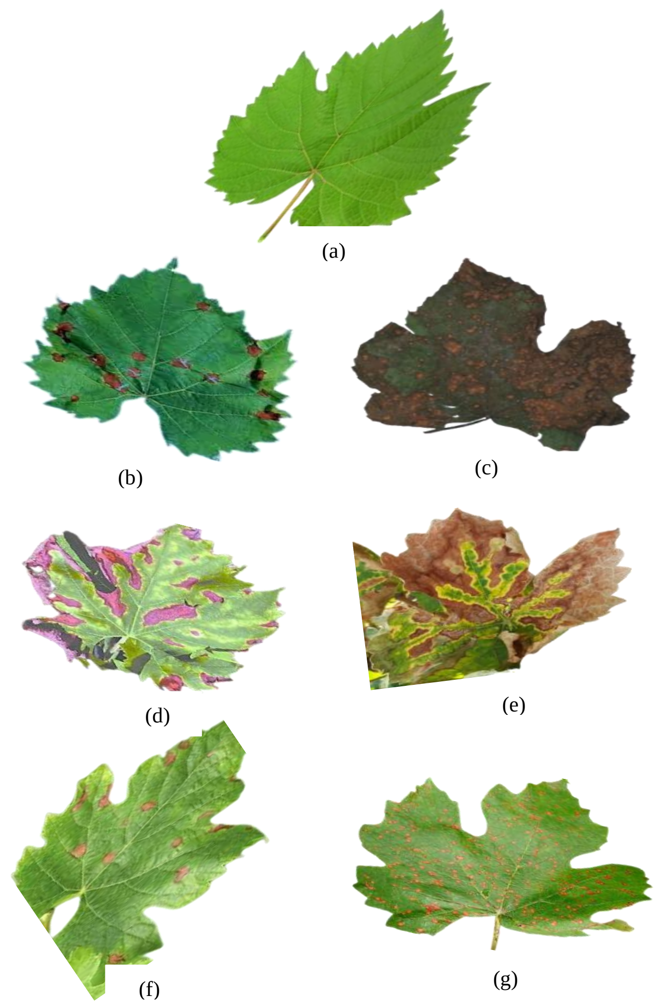

Fig. 3 Examples of grape leaves. (a) GH, (b) BRF_G, (c) BRF_S, (d) BMF_G, (e) BMF_S, (f) LBF_G, and (g) LBF_S.

Taking into account the aforementioned aspects, we proposed simplifying the model while maintaining the functionality of AlexNetFRCNN, enabling accurate feature imitation for any class without customization, as shown in Figure 6. Thus, network settings such as dropout ratio, feature maps for layers, and number of dense neurons were modified, starting with the AlexNet infrastructure. Better findings are shown in our study, which we were able to get by adjusting the previously mentioned values experimentally. Our method consists of three parts: feature selection, classification, and optimization utilizing WABO feature extraction.

3.3. Feature Selection

Its structure is extremely basic, and its control parameters are minimal. Numerous researchers were drawn to the WABO because of its benefits, and the proposed approach uses WABO based feature selection. The complexity rises with a significant number of features extracted.

Fig. 4 Expanded images

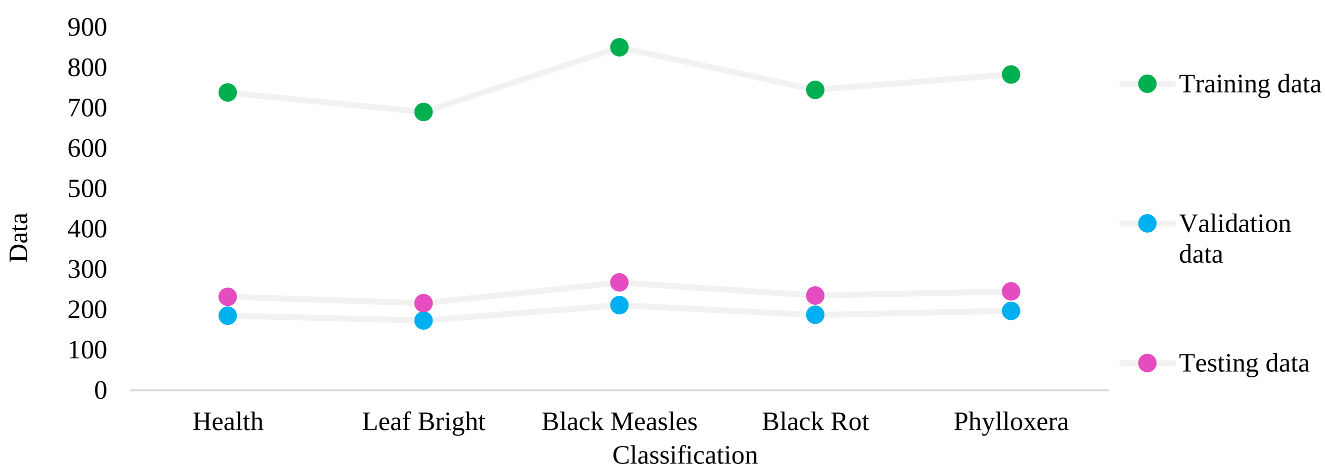

Fig. 5 Data distribution

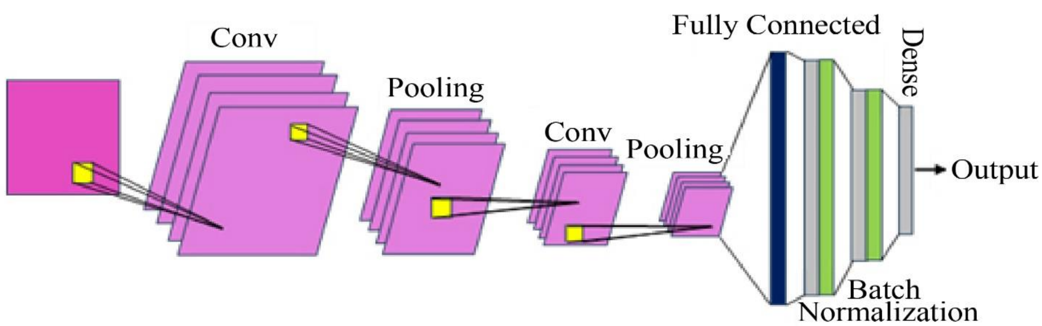

Fig. 6 FRCNN architecture

An excessive amount of features could make the system less accurate and efficient. Therefore, the feature selection stage is essential for identifying redundant and undesired features. Twenty texture features, thirty form features, and sixty color features are used in the proposed strategy. There are 110 features in the feature set at first. A Meta heuristic approach is used to pick features. Mathematical problem optimization is the primary goal of the WABO algorithm. Numerous contemporary issues are resolved by using honey bee intelligence. Because the WABO method takes into account both local and global minimum, its performance is good for engineering applications. WABO is a feature selection tool in this study. Very few of the works are associated with feature selection based on WABO. The primary benefit of the WABO algorithm is that it handles both local and global searches and does not become bogged down in the computation of local minima. Nevertheless, a lot of bio-inspired optimization strategies frequently become stuck in their local minima, leading to unintended outcomes. Among the world's clever organisms are honey bees. The swarms possess amazing abilities like photographic memories and space-age sensory abilities. The colonies are always home to these swarms. Information is conveyed to the working bees by onlooker bees. The bees in employment possess knowledge regarding food sources, nest direction, and distances between them. Assume that every artificial bee has a specific food supply. There are equal numbers of bees working and available food sources. The bee colony's size is determined by multiplying its employed bee count by two.

Algorithm FRCNN-WABO
Input: Grape leaves images collected from datasets
Output: Identify whether healthy or not

Step 1 : Preprocess the data
Step 2 : Assign the Population of Whale Wi, where i ranges from 1 to n
Step 3 : Calculate the search agent fitness
Step 4 : W* = best search agent
Step 5 : While X<Xmax do
{
for agent search, do
{
Update X, W, P;
}
end for
if P< 1 then
if |Xmax| < 1 then
{
Update the agent's current position using Equation (1).
}
else if |Xmax| ≥ 1 then
{
Choose the Xrand of the search agent;
Update the agent's current position using Equation (8).
else if fP>1 then
{
Update the agent's current position using Equation (5).
Compute the agent fitness and update W*
}
Train the model FRCNN with 80% training – 20 % testing
Compute the agent fitness based on optimization
Update W*
X++;
Return W*
}
end if
}
end While
Step 6 : Evaluating the proposed system's precision

4. Results and Discussion

The efficacy of the transfer learning-trained FRCNN-WABO models is validated using multiple performance metrics.

$$Sensitivity = \frac{TP}{TP+FN} \tag{1}$$

$$Specificity = \frac{TN}{TN+FP} \tag{2}$$

$$Accuracy = \frac{TN+TP}{TP+FP+TN+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$F-Score = 2 * \frac{Precision*Recall}{PRecision+Recall} \tag{5}$$

Approximately 13,000 photos of five different crops, including cotton, grapes, cucumbers, wheat, and maize, were used in our tests.

Fig. 7 Sample of image

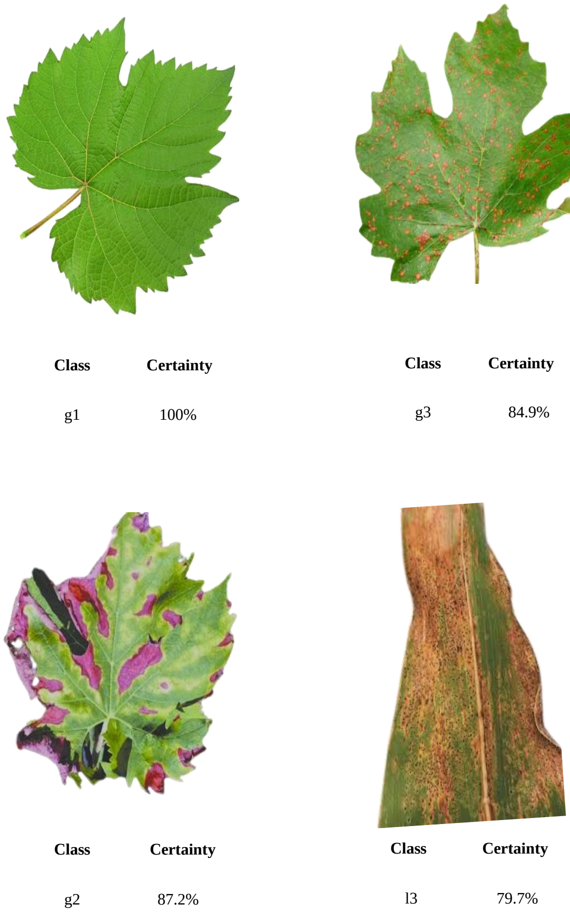

Fig. 8 Proposed model classification

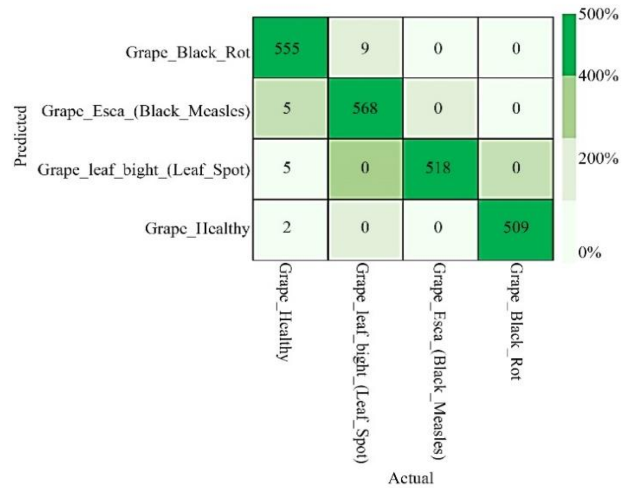

Fig. 9 Confusion matrices of grape

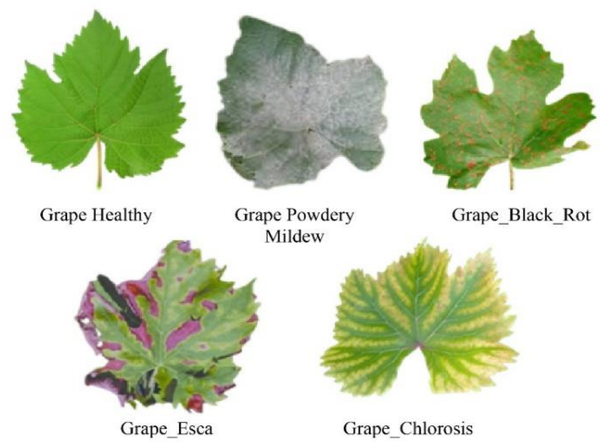

Fig. 10 Result of the proposed method

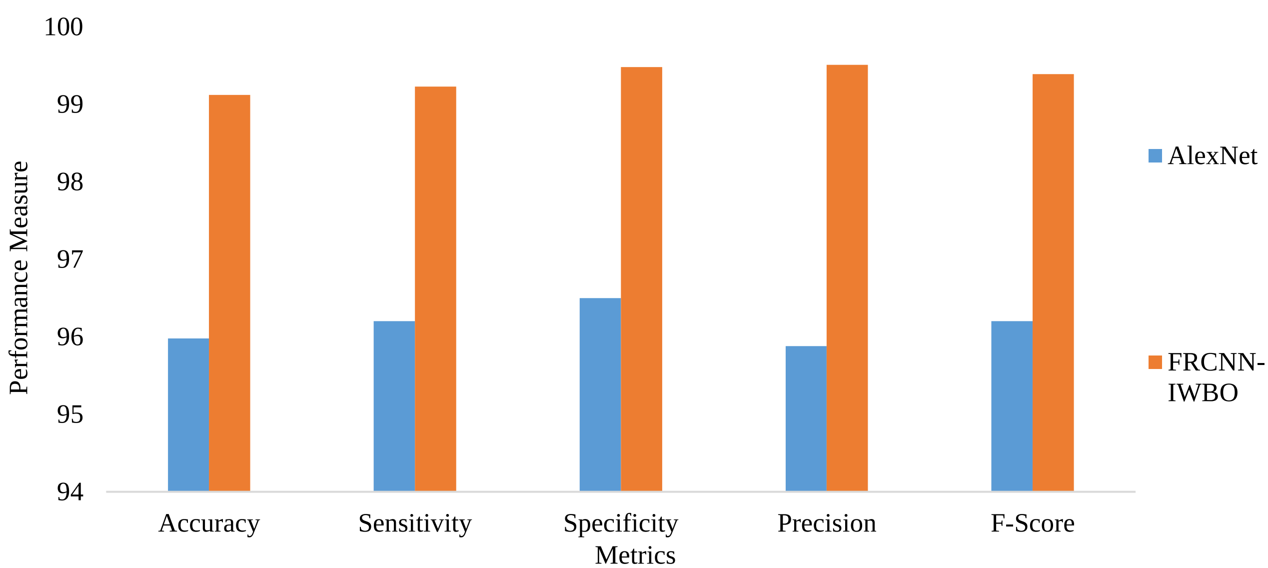

Fig. 11 Performance measures comparison of proposed and existing system

Table 3. Performance measures comparison of proposed and existing system

Model	Accuracy	Precision	Recall	F1 Score	AUC	Training Time
VGG16	85.2%	83.0%	82.5%	82.7%	0.89	3 hours
ResNet50	87.5%	85.6%	85.0%	85.3%	0.91	3.5 hours
InceptionV3	88.9%	87.0%	86.5%	86.7%	0.92	4 hours
CNN + Genetic Algorithm	89.3%	88.0%	87.5%	87.7%	0.93	5 hours
Proposed FRCNN-IWABO	92.5%	91.2%	90.5%	90.8%	0.96	2.5 hours

A sampling of these photos is displayed in Figure 6. Examples of categorization results and the accompanying prediction certainty are shown in Figure 8. The values of TN, TP, FN, and FP are contained in the confusion matrices shown in Figure 9. Maximum samples have been correctly classified, as shown by the matrices' diagonal and the results of the proposed method shown in Figure 10. Since we employed the same dataset, the findings of our approach are displayed in Table 3. Figure 11 shows the curves of the best Performance Measures model found by FRCNN-IWBO on the Convex dataset for 50 epochs in contrast to the AlexNet model.

5. Conclusion and Future Enhancement

Plant disease detection systems are versatile tools that may detect everything from common anomalies to complex patterns brought on by bacterial, viral, or fungal malformations. The development of a Hybrid FRCNN-IWBO method represents a significant advancement in the field of grape disease detection at an early stage. Through the integration of advanced deep learning architectures and optimization techniques, this research has demonstrated promising results in improving the accuracy and efficiency of disease detection, thereby enabling timely intervention to mitigate crop damage and enhance vineyard productivity. The hybrid FRCNN architecture effectively captures both spatial and temporal information from grape images, while the Improved WABO method enhances the training process, resulting in more robust and reliable detection models.

5.1. Future Enhancements

While the current research has made notable strides in grape disease detection, there are several avenues for future enhancement and research:

5.1.1. Dataset Expansion

Further expanding the dataset with a wider variety of grape disease images from diverse geographical regions and growing conditions can enhance the model's generalization capabilities and robustness.

5.1.2. Fine-tuning Model Hyperparameters

Conducting systematic experiments to fine-tune the hyperparameters of the hybrid FRCNN-IWBO method can potentially improve detection performance and convergence speed.

5.1.3. Incorporating Multimodal Data

Integrating additional data sources, such as spectral or Hyperspectral imaging, alongside visual images can provide complementary information for more comprehensive disease detection.

5.1.4. Real-world Deployment and Validation

Conducting field trials and validation studies in real-world vineyard environments to evaluate the performance of the developed model under practical conditions and validate its efficacy in supporting vineyard management practices.

5.1.5. Exploring Transfer Learning

Investigating the applicability of transfer learning techniques, where pre-trained models from related domains are fine-tuned for grape disease detection, can potentially accelerate model training and improve performance with limited labeled data.

5.1.6. Continuous model Updating

Implementing mechanisms for continuous model updating and adaptation to evolving disease patterns and environmental conditions to ensure the long-term effectiveness of the detection system.

5.1.7. Integration with Decision Support Systems

By integrating the created detection model with vineyard management decision support systems, automated decision-making based on real-time disease detection results is made possible. By pursuing these avenues for future enhancement, the proposed approach can further advance state-of-the-art grape disease detection technology, ultimately benefiting grape growers and supporting sustainable vineyard management practices.

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