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Comparative Analysis of CNN, EFFICIENTNET and RESNET for Grape Disease Prediction: A Deep Learning Approach

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Abstract*:* Despite being an essential part of the world's agricultural economy, grapes are prone to a number of illnesses that can negatively affect crops quality and productivity. In recent years, application of Deep Learning (DL) techniques in agricultural practices has shown promise in disease prediction and early detection. This study investigates the effectiveness of Convolutional Neural Networks (CNN), Efficient Net, and Residual Networks (ResNet) in predicting diseases in grapevines. The study makes use of a database that includes high-resolution photos of both good and diseased grape leaves, including black rot, leaf blight, and grapevine measles. To standardize and enhance data sets for model training and evaluation, methods for pre-processing are used. Three DL classifiers, namely CNN, Efficient Net, and ResNet, are implemented and fine-tuned using transfer learning. To evaluate the models' performance in disease categorization, a subset of the dataset is used for training, and another subset is used for validation. Assessment criteria includes accuracy, recall, precision and F1-score are utilized to measure the ability to forecast the methods. The outcomes of the experiments demonstrate the comparative performance of CNN, Efficient Net, and ResNet. In this CNN shows the accuracy of 90%, the Efficient Net with an accuracy of 97%, and finally the ResNet with the maximum efficiency of 98%.

Keywords: *Convolutional Neural Networks; Efficient Net; ResNet; Deep Learning.*

1. Introduction

Advances in technology have drastically revolutionized traditional methods in today's agriculture, bringing new and inventive ways to boost crop yield and reduce hazards [1]. Grapes are a significant contributor to global agricultural yield among the many crops that contribute to the total global agricultural yield. They are essential in the production of wine, juices, and a range of gastronomic delights [2]. But in the context of grape agriculture, illnesses of plants can significantly affect both quantity and quality.

Deep learning, a subfield of artificial intelligence fashioned after the neural networks of the human brain, has demonstrated extraordinary successes in a variety of domains, ranging from picture recognition to natural language processing [3]. Its ability to alter agriculture is based on its ability to analyse large data sets, discern intricate trends, and forecast outcomes with unmatched accuracy. When applied to grape farming, DL for disease prediction offers the possibility of recognizing difficulties early, reacting quickly, and eventually increasing crop health [4].

The global demand for premium grape-related products and the grape industry's economic significance make the fusion of technology and agriculture all the more pertinent [5]. The majority of conventional illness identification techniques rely on visual inspections, which can be a time-consuming and inaccurate process. Using DL models in grape cultivation offers a more reliable and efficient way to identify illnesses. This gives farmers the ability to better optimize their production and proactively handle possible hazards [6].

Using cutting-edge technology, particularly those with sophisticated DL algorithms, has emerged as a viable solution to this problem. These algorithms are at the forefront of a revolution in grape plant disease prediction. This work explores the use of Residual Networks (ResNets), Efficient Nets, and Convolutional Neural Networks (CNNs) as powerful tools for disease prediction and identification in grape plants.

The CNN, a fundamental framework in DL for analysing images, dissects images into smaller parts to identify specific patterns [7].Efficient Net, recognized for its exceptional efficiency and precision, employs a compound scaling approach to maintain a balance between model depth, width, and resolution [8]. Conversely, ResNet applies residual learning, allowing the construction of significantly deeper networks while addressing the challenge of the vanishing gradient problem [9].

The research compares and assesses how well various classifiers use picture information to forecast illnesses in grape plants. Images of both good and diseased grapevines shall be used in the training and testing of classifiers on this

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dataset. Evaluation metrics includes recall, precision, accuracy, and F1-score will be utilized to assess every classifier.

Through analysing the outcomes generated by these classifiers, this research seeks to pinpoint the most reliable classifier for predicting grape plant diseases. These findings not only promise to enhance agricultural techniques but also offer valuable insights for creating strong and effective models to identify infections in other crops.

2. Literature Survey

Poonam Dhiman et al [10] suggested a deep neural network model can detect citrus fruit disease at various degrees of severity is trained and pre-processed using a citrus fruit dataset. Combining broad search with graph-based segmentation, the model makes use of tagged images and a selective search methodology. 98% of high severity levels, 96% of low severity levels, and 96% of healthy situations are predicted by the model. In terms of identifying medium severity levels, the model similarly demonstrates 97% accuracy. According to the research, the citrus fruit disease has four different intensity degrees, and the suggested approach is both valid and effective for diagnosing it.

Xiaoyue Xie et al [11] suggested use of deep CNN as an actual detector for grape leaf diseases. By applying digital image processing technology, Grape Leaf Disease dataset (GLDD) is enlarged. A Faster DR-IACNN model, established on DL, is presented that has a greater capacity for feature extraction. The model achieves 15.01 FPS detection speed and 81.1% mAP precision on GLDD. It appears from this study that the Faster DR-IACNN gives a workable approach for diagnosing grape leaf disease and guidance for other plant diseases.

Four grapevine illness, leaf blight, black rot, stable, and black measles—were examined by Prabhjot Kaur et al. [12]. Even while earlier ML techniques were limited to detecting one or two diseases, none of them offered a comprehensive diagnosis. The study retrains the EfficientNet B7 deep architecture with transfer learning, down sample structures with Logistic Regression, and detects discriminant qualities with a constant accuracy of 98.7% after 92 epochs. The paper recommends a suitable classifier for this application and validates the effectiveness of the suggested technique in comparison to existing procedures.

Sammy V. Militante et al [13] developed a technique to recognize numerous illnesses in a wide range of plant species, such as tomato, sugarcane, corn, apple, potato, and grapes. 35,000 images of both good and bad leaves are used in the process. DL simulations with a 96.5% accuracy rate were trained to identify and diagnose various illnesses. The technology can detect and recognize plant variety and disease type with up to 100% accuracy.

Feng Jiang et al [14] used CNNs for extracting attributes from pictures of rice leaf disease. Next, the particular disease is classified and predicted using SVM method. The optimal SVM model parameters are determined using the 10-fold cross validation method. Studies show that the rice disease recognition model that utilizes DL and SVM has an average correct identification rate of 96.8% when penalty parameter $C = 1$ and the kernel parameter $g = 50$. Compared to standard back propagation neural network designs, this accuracy is superior. This work offers a novel method for future crop illness diagnostics research utilizing DL.

Miaomiao Ji et al [15] presented UnitedModel, a united CNN architecture intended to distinguish between fresh and diseased grape leaves, including those with isariopsis leaf spot, black rot, and esca. The model employs multiple CNNs to extract complementing discriminative characteristics, hence improving its representativeness. With an average validation accuracy of 99.17% and a test accuracy of 98.57%, the algorithm was evaluated and contrasted with other CNN algorithms on the PlantVillage dataset, demonstrating its usefulness as a decision support instrument for agriculturalists.

Javed Rashid et al [16] utilizing the YoLOv5 image segmentation method, leaves were extracted from plant pictures to develop a multi-level DL algorithm for identifying potato leaf illness. A unique DL method using a CNN was developed to identify both earlier and later blight potato illnesses from leaf pictures. With the use of a 4062-image datas from Central Punjab region of Pakistan, the algorithm was trained and assessed, and it demonstrated 99.75% accuracy. When the performance was evaluated against modern algorithms utilizing the Plant Village dataset, significant enhancements in accuracy and computational cost were observed.

3. Research Methodology

This research looks into a number of diseases that affect grape leaves, including black rot, leaf roll disease, and grapevine measles. Globally, these conditions present serious difficulties for vineyards. A fungus called black rot causes brown patches on leaves that eventually get darker and smaller. This damage to the fruit finally leads to its decomposition and withering. Grapevine measles causes colour changes and curling of the leaves, which interferes with photosynthesis and lowers fruit quality. Different fungi or bacteria can produce leaf blight, which results in sporadic brown patches on leaves and may eventually cause the vines to weaken and lose some of their leaves.

Strategies that work are essential in the fight against chronic illnesses. Fungicides, good hygiene, and cultivating disease-resistant grape varietals are all necessary to keep grapevines healthy and productive. The focus of this work is to use a collection of grape leaves and sophisticated image processing based on DLto identify these diseases. Comparing different DLplatforms such as CNN, Efficient Net, and ResNet is necessary to find the most efficient model for illness diagnosis. This comparison aids in developing better methods for the industry's management of grapevine diseases. The process flow diagram for this procedure is shown in Figure 1.

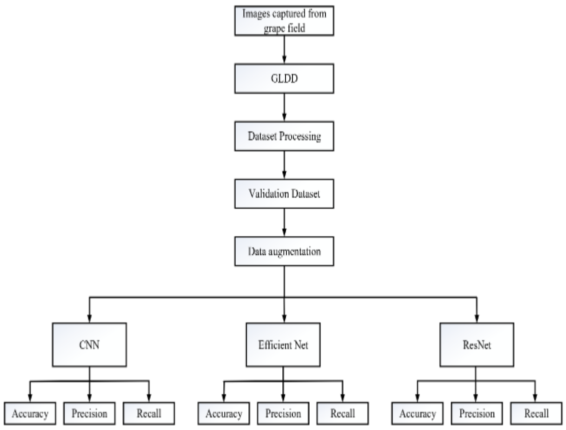

Fig. 1 Work Flow Chart

3.1. Pre-Processing

Data preparation serves as the foundation for fine-tuning the initial leaf dataset and is essential for forecasting grape leaf diseases. Prior to entering the data into a machine learning model for in-depth analysis, this complex process entails careful stages. Data cleaning is the first and most important step in this procedure. Here, the dataset is carefully examined to look for anomalies, discrepancies, or missing data. This crucial stage ensures the accuracy and dependability of the dataset by correcting mistakes and discrepancies.

3.1.1. Grey scale conversion

Grayscale conversion is similar to taking a painting's vibrant colour range and replacing it with a world of black, white, and numerous hues in between. Every pixel becomes less vibrant, changing from a wide variety of hues to a number of tones that make up the grayscale range. The unique qualities that were formerly characterized by vivid colours are now apparent through modest adjustments to brightness and contrast. Highlights get more noticeable, while shadows take on a richer, deeper tone. This monochrome world is fascinating because the lack of colour draws attention to the image's core, which is the underlying structure, arrangement, and interaction of light and dark that colours usually hide [18]. The schematics of grey scale conversion has been shown in Figure.2.

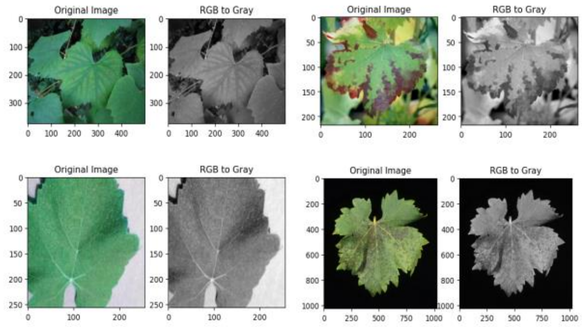

Fig. 2 Grey scale image

3.1.2. Image enhancement

Enhancing a picture's quality to make it more suitable for analysis or human perception is the aim of pre-processing strategies for enhancing images. These methods include a variety of filters and algorithms that highlight details, cut down on noise, and enhance clarity overall. They include adjustments to colour balance and saturation for better visual representation, contrast to accentuate details by enhancing the contrast between light and dark areas, sharpening to highlight edges and finer elements, and noise reduction to remove unwanted pixel irregularities that distort the image. By using these pre-processing techniques, photos are improved and more suitable for further inspection or analysis. This makes it easier to understand and analyse visual content [19]. The schematics of image enhancement has been shown in Figure.3.

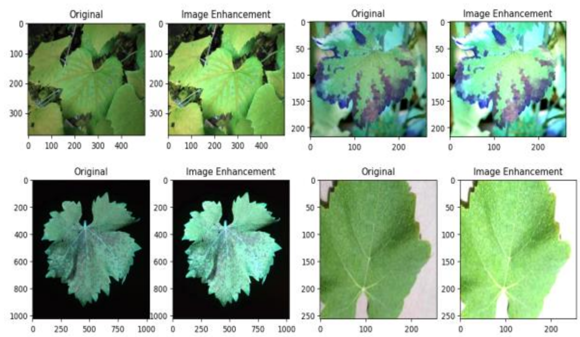

Fig. 3 Image enhancement

3.1.3. Image resizing

Resize or alter an image's dimensions is one of several crucial initial steps in computer vision. This is an essential step to ensure consistency in size, shape, and quality before inspecting or modifying photos. It has benefits in that it helps computers process images quickly while consuming less memory. It also contributes to the creation of a uniform image collection that is used to train models, increasing the effectiveness of machine learning algorithms. Resizing requires careful treatment in order to maintain the key qualities of the image and avoid distortion or loss of important information [20]. The schematics of Image resizing has been shown in Figure.4.

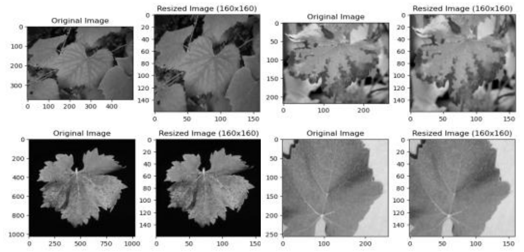

Fig. 4 Image resizing

3.2. DL Models

3.2.1. Convolutional neural network:

A CNN, a DL model frequently employed for tasks involving images, is recommended as a solution for this task. CNNs are created by neurons with programmable weights and biases, just like CNNs. After processing several inputs from unprocessed picture matrices, a neuron applies an activation function, computes a weighted total, and produces an output. The network operates under a loss function that diminishes progressively with each iteration, aiding the network in learning a specific set of parameters ideal for the classification task. Ultimately, the outcome is a vector displaying probabilities for each class. Unlike conventional neural networks that handle flat vectors as input, CNNs manage multi-channel images. During a convolution operation, a filter (e.g., 5x5x3) moves across the entire image, performing dot product computations among the filter and segments of input image [21]. Figure 5 depicts the layout of the suggested CNN, offering detailed insights into its layers and the steps involved in the CNN process.

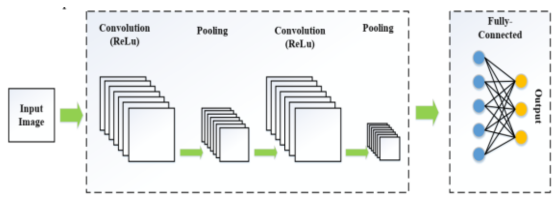

Fig. 5 CNN Layers

3.2.1.1. Convolutional layers

The convolutional layer is a crucial part of CNN. This layer is made up of several different filters. Through convolution, every filter works independently on the picture to produce unique feature maps. Typically, when convolving an M x N-sized image with a w×h-sized filter, it produces an output feature map of size σw×σh, as represented in Equation 1.

$$o_w = \frac{M-w+2p_w}{s_w} + 1$$
$$o_h = \frac{N-h+2p_k}{s_h} + 1 \qquad (1)$$

The symbols p_F and p_h denote the zero-padding applied in the width and height dimensions, while s_w and s_h indicate stride in horizontal and vertical directions. Figure 5 displays convolutional process where a 7x7 input map is passed through a 3x3 filter.

After applying a linear filter for convolution, adding a bias term, and applying a non-linear function—usually represented by the formula in Eq. 2—the final feature map is produced from the input maps.

$$X_j^d = f\left(\sum_{i\in l_j} X_i^{i-1} * W_{ij}^{i} + b_j^{I}\right) \qquad (2)$$

In this context, the convolutional layer within a CNN achieves scale invariance by utilizing various elements: the layer number denoted as 'l', the convolutional kernel expressed as W_{ij}, the bias represented by b_j, the input map set denoted as l_j, and the activation function denoted as f . This combination allows the network to operate independently of scale.

In a convolutional neural network, the activation function is crucial because it allows the network to learn to handle complex tasks. These functions operate as the nonlinear modifications that are applied to the input to ascertain whether the data that is received is pertinent to the task at hand. The rectified linear unit (ReLU), hyperbolic tangent (tanh), and sigmoid (logistic) are examples of frequently used activation functions. The nonlinear transformation for this project is the ReLU activation function.

Due to its nonlinear nature, the ReLU function makes error back propagation simple and can activate neurons across numerous layers. Its ability to selectively activate neurons rather than all of them at once gives it a major edge over other activation processes. Because of this, a sparse network that is computationally efficient is produced, in which only a small number of neurons fire at any given time. One drawback is that it may result in dead neurons, which stop updating weights when back propagation occurs because there is a gradient of zero for negative inputs. Fig. 6 shows the representation of the ReLU function, and Eq. 3 gives its formula.

$$f(X) = \max(0, X)\, f(X) = \begin{cases} X, & X \ge 0 \\ 0, & X < 0 \end{cases} \qquad (3)$$

The initial convolutional layer captures various basic features like edges, lines, and corners, while adding more of these layers enables the network to grasp higher-level, broader features. In this study, we've employed two convolutional layers to facilitate this process.

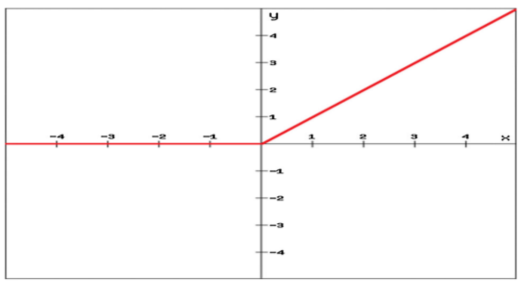

Fig. 6 ReLU activation function

3.2.1.2. Pooling layers

At times, between consecutive convolutional layers in a CNN, a pooling layer is inserted. Its role is to gradually shrink spatial dimensions of representation. This reduction in size curbs excessive parameters and computations in the network, thereby reigning in over fitting. Additionally, pooling layers confer translation invariance to the CNN. They autonomously operate on each input layer, resizing it spatially through pooling operations. A common pooling layer employs a 2 x 2 filter with a stride of 2, downsizing each depth slice in input by 2 along both width and height, discarding 75% of activations. Spatial pooling take various forms: max, min, average, sum, etc. In max pooling, for instance, a 2 x 2 window is defined as the spatial neighbourhood, and the major element from feature map within that window is selected. For two reasons, max pooling produces better results: initially, it removes non-maximal values from upper layers' computations, and secondly, it adds a type of translation variance [22]. Because of the way that this variance supports positional robustness, max pooling is a clever way to lower dimensionality of intermediate illustrations.

3.2.1.3. Fully connected layers

All neurons in current layer are linked to all neurons in prior layer when a neuron is said to be fully connected. Their activations are calculated by multiplying matrices and then adding bias. The last fully connected layer has identical amount of neurons as the prediction classes; output layer size in standard LeNet design for digit recognition is 10. The output layer size in our research, which tackles a four-class problem, is four. Convolutional and subsampling layer features are useful for classification, but together, they can produce even better outcomes. All of the retrieved features from earlier convolutional and subsampling layers are combined in fully connected layer. The softmax activation function, an extended logistic function frequently used in multi-class classification, is applied in this last fully linked layer [23].

3.2.2. Efficient Net:

The inception of convolutional neural networks marked a significant advancement in deep learning, evolving from the basic architecture of LeNet, AlexNet, and VGG-16, which comprised convolutional, pooling, and fully connected layers. The progression continued with more sophisticated models like ResNet, Inception, and GoogleNet. Increasing network depth and widening channel size enhanced complexity of network, leading to improved recognition accuracy and richer fine-grained features in image data. However, this expansion also introduced challenges, notably the high computational cost associated with gradient explosion parameters.

Efficient Net addresses these issues by integrating features from various networks. It achieves this by carefully setting composite ratio coefficients to balance network's width, depth, and resolution. This balanced approach results in an improved model performance across 3D of network. The following is the formula to determine the composite proportion coefficient:

$$\begin{cases} \text{depth: } d = \alpha^{\phi} \\ \text{width: } w = \beta^{\phi} \quad \text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \\ \text{resolution: } r = \gamma^{\phi} \end{cases}$$

For α, β, and γ, each greater than or equal to 1, values of w, d, and r are employed to scale network's width, depth, and resolution coefficients. The provided ϕ determines the extent of effective resource expansion in the model. Constants α, β, and γ play a crucial role in distributing these resources across network's depth, width, and resolution dimensions [24]. Refer to Fig.7 for an illustration of the Efficient Net architecture.

Table 1. Efficient net-B0 network parameter table

Stage	***Operator***	***Resolution***	***#Channels***	***#Layers***
i	$\hat{\mathcal{F}}_i$	$\hat{H}_i \times \hat{W}_i$	$\hat{C}_i$	$\hat{L}_i$
1	**Conv** 3×3	224×224	**32**	**1**
2	**MBConv1,** $k3 \times 3$	112×112	**16**	**1**
3	**MBConv6,** $k3 \times 3$	112×112	**24**	**2**
4	**MBConv6,** $k5 \times 5$	56×56	**40**	**2**
5	**MBConv6,** $k3 \times 3$	28×28	**80**	**3**
6	**MBConv6,** $k5 \times 5$	28×28	**112**	**3**
7	**MBConv6,** $k5 \times 5$	14×14	**192**	**4**
8	**MBConv6,** $k3 \times 3$	7×7	**320**	**1**
9	**Conv1 1 &Pooling&FC**	7×7	**1280**	**1**

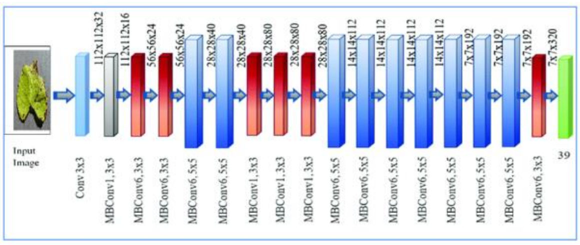

Fig. 7 Efficient Net Architecture.

3.2.3. ResNet 50

ResNet50 represents a significant CNN architecture with 50 layers organized into residual blocks. Its innovative approach incorporates skip connections, which address the issue of vanishing gradients often encountered in deep networks. With 48 convolutional layers, 1 MaxPool, and 1 Average Pool layer, ResNet50's design aligns perfectly with our objectives in the diabetic retinopathy application. This architecture enables later layers to focus on learning more specific and refined features by leveraging foundational semantic information captured in the initial layers.

Using a 3 × 3 filter for spatial convolution, along with subsequent max-pooling, greatly contributes to the model's effectiveness. This strategic setup aids in reducing spatial dimensions while retaining crucial features. Figure 5 offers a clear visualization of the ResNet50 model's complex structure, illustrating its 48 convolution layers intricately linked with 16 skip connections. This interconnected layout facilitates efficient information flow and gradient propagation across different depths, empowering the model to discern intricate patterns vital for detecting and analysing diabetic retinopathy [25].

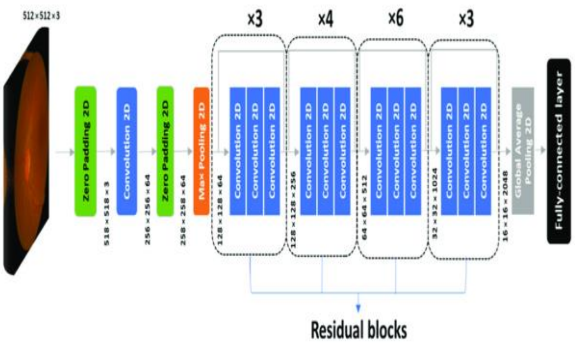

Fig. 8 ResNet Architecture

4. Result and Discussion

This part delves into the full results gathered and provides a detailed analysis of the outcomes for a deeper comprehension.

4.1. Dataset and tools used

The leaf dataset utilized for this analysis was sourced from Kaggle. To execute the proposed models, Python was the chosen platform, operating on a Windows 11 system with 8GB of RAM. This environment was selected to ensure robust implementation and accurate results. The dataset description has been displayed in Table.2.

Table 2: Dataset Description

	Black rot	**Grape vine Measle**	**Leaf Blight**	**Healthy leaves**
Number of Images	**1180**	**1383**	**1076**	**783**

4.2. Result obtained by cnn model

A CNN model's performance throughout 25 epochs in terms of training and validation accuracy is displayed in Fig. 9. Over the course of these epochs, the model exhibits a remarkable accuracy rate of 90%, showcasing its proficiency in learning patterns and making correct predictions. Notably, the validation accuracy—a crucial metric reflecting the model's generalization ability on unseen data—follows a similar trajectory as the training accuracy, indicating that the model effectively learns without over fitting to the training set.

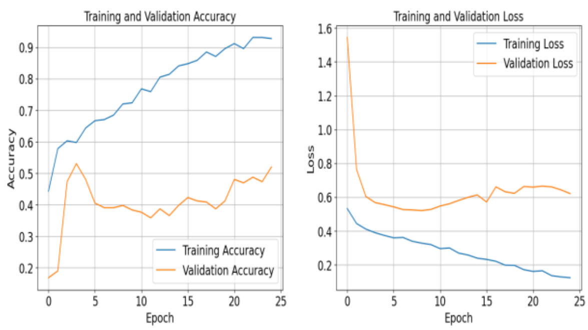

Fig. 9 Training and Validation Graph for CNN Model

Additionally, the minimal loss of 10% achieved by the model signifies its efficiency in minimizing errors during the learning process. Lower loss values correspond to better performance, suggesting that the model effectively minimizes discrepancies between predicted and actual values. This graph's portrayal of consistently high accuracy coupled with low loss underscores the model's robustness and effectiveness in learning complex patterns within the data, making it a promising solution for various tasks and applications.

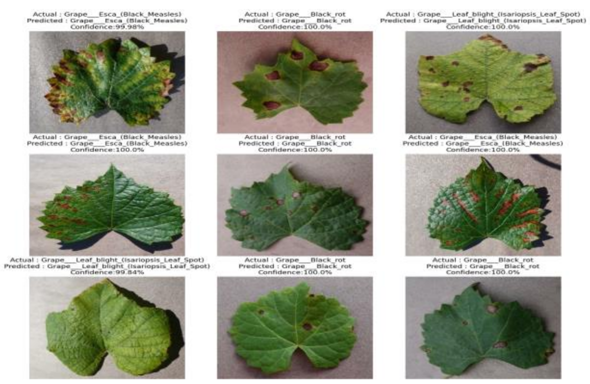

Fig. 10 Output from CNN Model

4.2.1. Performance metrics for CNN model

The Table.2 evaluates disease classification performance in four categories: Black Rot, Grapevine Measle, Leaf Blight, and Healthy Leaves. The model shows a low rate of false positives and high recall, with a balanced performance of 0.83 for Black Rot and 0.85 for Grapevine Measle. The model also has a strong ability to correctly classify positive cases, with a F1-score of 0.87 for Leaf Blight and 0.87 for Healthy Leaves. Leaf Blight has exceptional precision, recall, and F1-score values, with 95 instances. Healthy Leaves, the absence of disease, also shows high precision at 0.98, a low rate of false positives, and a perfect recall of 1.00, indicating the model effectively identifies all true negative instances. The F1-score for Healthy Leaves is 0.99, with 41 instances.

Table 3: Performance Metrics for CNN model

DISEASES	PRECISION	RECALL	F1-SCORE	SUPPORT
Black Rot	**0.83**	**0.87**	**0.85**	**123**
Grapevine measle	**0.89**	**0.85**	**0.87**	**148**
Leaf Blight	**0.99**	**0.99**	**0.99**	**95**
Healthy leaves	**0.98**	**1.00**	**0.99**	**41**

4.3. Result obtained by efficient net model:

The Fig 11 and fig 12 illustrates the performance of an Efficient Net model across 25 epochs, showcasing both training and validation accuracy. Throughout training process, this model exhibits substantial progress, reaching an impressive accuracy rate of 97% on validation dataset. Simultaneously, it maintains a remarkably low loss, bottoming out at a minimal 3%. This graph represents an important milestone in the model's training process by demonstrating its strong learning capacity and good generalization to new input.

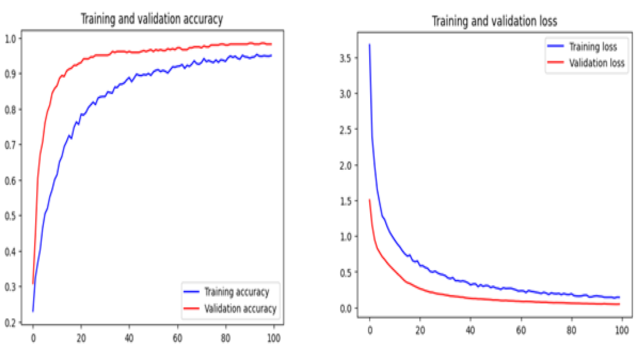

Fig. 11 Training and Validation curve for Efficient Net Model

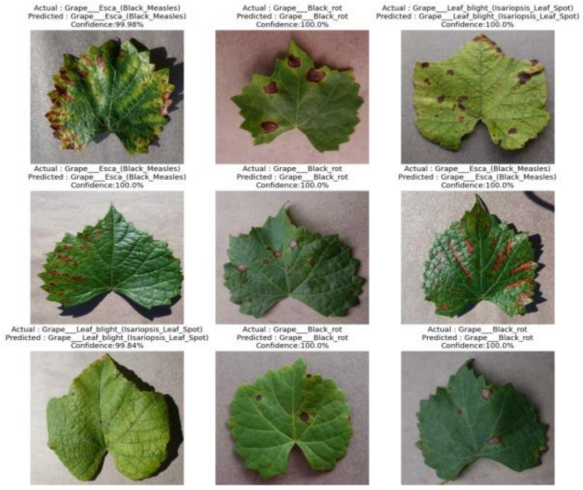

Fig. 12 Output from Efficient Net Model

4.3.1. Performance metrics for efficient net model:

The Table.3 presents performance metrics for identifying diseases affecting grapevines and a category for healthy leaves. The model is assessed on precision, recall, F1-score, and support. "Black Rot" category has a high precision of 0.98, demonstrating a strong ratio of correctly identified cases. However, it might miss some instances. The F1-score that combines both precision and recall, is 0.94, suggesting a balanced performance. The "Grapevine Measles" category has a precision of 0.92, indicating a slightly lower ratio of correctly identified cases compared to Black Rot. However, its recall is higher at 0.98, implying a better ability to capture most actual instances. The "Leaf Blight" category has a perfect score of 1.00, indicating accurate identification of all instances without false positives or negatives. The "Healthy Leaves" category also displays flawless performance, with perfect scores across all evaluation metrics. Overall, the classification model shows impressive accuracy and reliability, particularly in identifying Leaf Blight and Healthy Leaves.

Table 4: Performance metrics for Efficient Net

DISEASES	PRECISION	RECALL	F1-SCORE	SUPPORT
Black Rot	**0.98**	**0.91**	**0.94**	**237**
Grapevine measle	**0.92**	**0.98**	**0.95**	**258**
Leaf Blight	**1.00**	**1.00**	**1.00**	**232**
Healthy leaves	**1.00**	**1.00**	**1.00**	**86**

4.4. Result obtained by resnet model

The depicted graph illustrates training and validation accuracy for state-of-the-art ResNet design across 9 epochs. Remarkably, this model showcases an outstanding accuracy of 98%, reflecting its robust learning capability. Concurrently, it achieves an impressively low loss, minimizing to a mere 2%. These metrics underline model's proficiency in understanding and generalizing complex patterns within the dataset, positioning it as a high-performing solution for the given task.

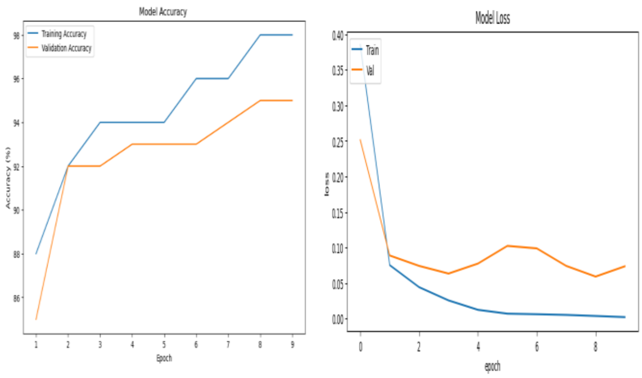

Fig. 13 Training and Validation curve for ResNet Model.

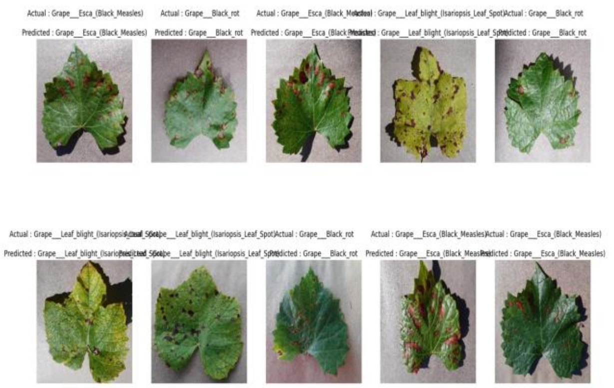

Fig. 14. Output from ResNet model

4.4.1. Performance metrics for cnn model

The Table.4 shows metrics for identifying four plant conditions: Black Rot, Grapevine measles, Leaf Blight, and Healthy leaves. Black Rot detection had a precision rate of 96%, indicating high accuracy, while Grapevine measles detection had a precision rate of 98% and a recall rate of 97%. Leaf Blight detection had a perfect precision, recall, and F1-score of 100%, indicating flawless identification. Healthy leaves had a high precision of 99%, indicating a high proportion of accurately classified instances. The overall performance for Healthy leaves was 99%, indicating excellent overall performance in detecting and distinguishing between plant ailments. These measurements offer insightful information on how well illness identification methods work.

Table 1: Performance metrics for ResNet model

DISEASES	PRECISION	RECALL	F1-SCORE	SUPPORT
Black Rot	0.96	0.98	0.97	237
Grapevine measle	0.98	0.97	0.97	258
Leaf Blight	1.00	1.00	1.00	232
Healthy leaves	0.99	1.00	0.99	86

5. Conclusion

In the field of viticulture, keeping grapevines healthy and productive requires the early identification and control of diseases such as black rot, leaf blight, and grapevine measles. Utilizing cutting-edge DL models, such as ResNet, Efficient Net, and CNN, has greatly improved the precision and effectiveness of disease detection and classification in grapevines. With a 90% efficiency rate, CNN has shown to be a reliable tool for diagnosing diseases in grapevines. Its capacity to recognize patterns and characteristics in images has made it possible to reliably identify these prevalent grape diseases.With its impressive 97% efficiency, Efficient Net has shown to be an excellent tool for diagnosing and categorizing grape illnesses. Measuring grapevine measles, leaf blight, and black rot has become more accurate thanks to its scalable architecture and balanced network depth, width, and resolution. In addition, ResNet has proven to be a reliable solution for grapevine disease identification, with a 98% efficiency rate as demonstrated. By addressing the problem of disappearing gradients and making complex disease-related feature extraction easier, its deep residual learning system has produced impressive accuracy rates.

DECLARATIONS

Ethics approval and consent to participate

This article does not contain any studies with human participants or animals performed by any of the authors

Consent for publication

All contributors agreed and given consent to Publication.

Availability of data and material

Data that has been used is confidential

Competing interests

On behalf of all authors, the corresponding author states that they have no competing interest.

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