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

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Research Article

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

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Abstract: Grapes and potato, both a crucial component of the global agricultural economy, are susceptible to various diseases that can adversely affect crop quality and yield. Recently, the use of Deep Learning (DL) techniques in agriculture has shown potential for predicting and detecting diseases early. This study explores the effectiveness of Convolutional Neural Networks (CNN), Efficient Net, and Residual Networks (ResNet) in identifying diseases in grape and potata leavess. It employs a database containing high-resolution images of healthy and diseased grape leaves, including conditions like leaf blight, and grape and potata leaves browny mildew. Data pre-processing methods are used to standardize and enhance the datasets for model training and evaluation. The study implements and fine-tunes three DL classifiers—CNN, Efficient Net, and ResNet—using transfer learning. To assess the models' performance in disease classification, the dataset is divided into training and validation subsets. Metrics such as accuracy, recall, precision, and F1-score are used to evaluate the models' predictive capabilities. The experimental results show that CNN achieved 94% accuracy, ResNet attained the highest efficiency with 96% accuracy, and Efficient Net reached 97% accuracy.

Keywords
CNN, grape downy mildew, potato blight disease, crop diseases, EfficientNet, ***ResNet-50***

1. Introduction

Rises in Information technology have severely reformed traditional methods in present's field of agriculture, bringing innovative and altered ways to promot crop yield and curb hazards [1]. Grapes and potatoes are a significant contributor to global agricultural yield among the many crops that contribute to the total global agricultural yield. Grapes gives production of wine, juices, and a range of gastronomic delights in the meantime potato are being served as vegetable, crispy and junk food items [2]. But in the context of grape and potato agriculture, illnesses of plants can significantly affect both quantity and quality particularly in emerging nations like Bangladesh.

Artificial intelligence (AI) subfield is deep learning where methods are machine learning based, their prevalent models such as Convolutional neural networks (CNNs) have garnered significant interest within the agricultural domain include plants-based detection [3]. These models are fashioned after the neural networks alike human brain, has successfully applied in a range of domains, either picture recognition to natural language processing [3]. Its potential to revolutionize agriculture lies in its capacity to analyze extensive data sets, discern complex patterns, and predict outcomes with unparalleled precision. When applied to grape and potato farming, deep learning (DL) for disease prediction enables early problem detection, swift response, and ultimately enhanced crop health [4]. The global demand for high-quality grape and potato products and the significant economic role of the grape industry underscores the relevance of integrating technology with agriculture [5]. Traditional methods of disease identification often rely on visual inspections, which can be time-consuming and inaccurate. Implementing DL models in grape and potato cultivation provides a more reliable and efficient approach to disease detection, empowering farmers to optimize production and proactively manage potential risks [6].

The adoption of advanced technologies, particularly those utilizing sophisticated DL algorithms, presents a promising solution to this issue. These algorithms are spearheading a revolution in predicting grape and potato plant diseases. This study investigates the application of Residual Networks (ResNets), EfficientNets, and Convolutional Neural Networks (CNNs) as robust tools for disease prediction and identification in grape and potato plants.

CNNs, a foundational framework in DL for image analysis, break down images into smaller segments to detect specific patterns [7]. EfficientNets are renowned for their exceptional efficiency and accuracy, employing a compound scaling method to balance model depth, width, and resolution [8]. Conversely, ResNets utilize residual learning to construct significantly deeper networks while addressing the vanishing gradient problem [9].

This research evaluates the effectiveness of various classifiers in using image data to predict diseases in grape and potato plants. Images of both healthy and grape downy mildew for grape crops and early and late blight for potato will be employed for training and testing these classifiers. Evaluation metrics such as recall, precision, accuracy, and F1-score will be used to assess each classifier.

By analyzing the results produced by these classifiers, this research aims to identify the most reliable classifier for predicting grape and potato plant diseases. These findings not only promise to improve agricultural practices but also provide valuable insights for developing robust and efficient models for identifying infections in other crops.

2. Literature Survey

Usama Mokhtar et al. [10] introduced a method for identifying healthy and infected rice leaves with a remarkable accuracy of 99.83%. Their technique involved preprocessing the input images by removing the background and using erosion techniques to eliminate noise. They extracted texture features using the Gray Level Co-occurrence Matrix (GLCM) and classified the images with a Support Vector Machine (SVM). However, the study did not differentiate between various types of diseases or provide detailed information about the specific conditions identified.

Poonam Dhiman et al. [11] proposed a deep neural network model for detecting citrus fruit disease at different severity levels. The model was trained and pre-processed using a citrus fruit dataset, combining broad search with graph-based segmentation and leveraging tagged images and a selective search methodology. The model predicted 98% of high severity levels, 96% of low severity levels, and 96% of healthy conditions, while also achieving 97% accuracy for medium severity levels. The study identified four intensity levels of citrus fruit disease and validated the model's effectiveness for diagnosis.

Xiaoyue Xie et al. [12] advocated for the use of a deep CNN as an effective detector for grape leaf diseases. They expanded the Grape Leaf Disease dataset (GLDD) using digital image processing technology and introduced a Faster DR-IACNN model based on deep learning, which demonstrated enhanced feature extraction capabilities. The model achieved a detection speed of 15.01 FPS and an 81.1% mAP precision on the GLDD, suggesting that the Faster DR-IACNN is a viable approach for diagnosing grape leaf diseases and offers insights for other plant diseases.

Prabhjot Kaur et al. [13] examined four grape and potata leaves diseases: leaf blight, black rot, stable, and black measles. While earlier machine learning techniques were limited to detecting one or two diseases, this study provided a comprehensive diagnosis by retraining the EfficientNet B7 deep architecture with transfer learning. It downsampled structures using Logistic Regression and identified discriminant qualities with a consistent accuracy of 98.7% after 92 epochs. The study recommended an appropriate classifier for this application and validated the technique's effectiveness compared to existing methods.

Sammy V. Militante et al. [14] developed a technique to recognize multiple diseases across various plant species, including tomato, sugarcane, corn, apple, potato, and grapes. The process involved 35,000 images of healthy and diseased leaves. Deep learning simulations achieved a 96.5% accuracy rate in identifying and diagnosing various diseases, with the technology capable of detecting and recognizing plant varieties and disease types with up to 100% accuracy.

Feng Jiang et al. [15] used CNNs to extract features from images of rice leaf disease and classified the specific diseases using the SVM method. Optimal SVM model parameters were determined through the 10-fold cross-validation method. The study showed that the rice disease recognition model using DL and SVM had an average correct identification rate of 96.8% with penalty parameter C = 1 and kernel parameter g = 50, surpassing standard backpropagation neural network designs in accuracy. This work presents a novel approach for future research in crop disease diagnostics using DL.

Miaomiao Ji et al. [16] introduced UnitedModel, a combined CNN architecture designed to differentiate between fresh and diseased grape leaves, including those with isariopsis leaf spot, black rot, and esca. The model employed multiple CNNs to extract complementary discriminative features, enhancing its representativeness. The algorithm achieved an average validation accuracy of 99.17% and a test accuracy of 98.57%, demonstrating its effectiveness as a decision support tool for agriculturalists when evaluated against other CNN algorithms on the PlantVillage dataset.

Javed Rashid et al. [17] used the YoLOv5 image segmentation method to extract leaves from plant images and develop a multi-level DL algorithm for identifying potato leaf diseases. They created a unique DL method using a CNN to identify both early and late blight potato diseases from leaf images. The algorithm was trained and assessed using a dataset of 4062 images from the Central Punjab region of Pakistan, achieving 99.75% accuracy. Performance evaluations against modern algorithms using the PlantVillage dataset showed significant improvements in accuracy and computational cost.

Chambon et al. [18] focused on classifying mineral deficiencies in rice using digital image processing and neural networks with texture and color features. Their method, which achieved 88.56% accuracy, also categorized blast and brown spot diseases, demonstrating versatility. These studies highlight the potential of digital image processing and machine learning in diagnosing and managing rice crop health, supporting agricultural efforts.

Another research on CNN achieved accuracy of 96.09% by author akther et al [19] for potato leaves infected by early and late blight and healthy leaves and the model can be utilized for android mobile devices by the author akther et al [20]. Both of this work has some decisions of skilled crop checkers.

The instances above illustrate the potential of employing RGB images at the leaf level within the computer vision basis for identifying crop diseases. Yet, effectively training models for image recognition demands a certain volume of annotated images captured under diverse conditions, times, and locations to ensure dependable predictions. Annotating images necessitates significant effort according to time, and expertise; hence, the scarcity of annotated images poses a constraint on the technique. Moreover, challenges emerge from the worth of the pictures utilized to train the model; subpar resolution or insufficient annotation may diminish accuracy.

3. Research Methodology

This research looks into a number of diseases that affect grape and potato leaves, including downy mildew, potato early blight, and potato late blight disease.

Globally, Downy mildew is a highly severe fungal disease affecting grapes. The pathogen infects all green parts of the vine, with leaves being particularly affected. The leaves exhibit angular, yellowish lesions that can occasionally appear oily and are found between the veins. As the disease progresses, a white, cotton-like growth can be seen on the underside of the leaves [21].

Early blight of potato, marked by small dark spots on mature leaves ranging from 3-8 inches in size and irregular in shape, poses significant challenges with yellowing of the leaves [22]. Similarly, Late blight infection in potatoes, caused by the pathogen Phytophthora infestans, is a devastating disease affecting potato foliage and tubers, leading to rapid defoliation and decay [23]. Consequently, there is a pressing need for innovative approaches to disease surveillance, prevention, and management in potato cultivation.

A dataset comprising approximately 4000 images was collected from the secretary latu's garden, situated in Sonaimuri,Noakhali, Bangladesh, at coordinates 23.23° N and 91.65° E. The data acquisition involved manually positioning individual grapes and potatoes leaves and capturing images using various latest smart devices, including iphone 15 pro max tha is iOS platforms. To address the challenge of distinguishing among classes like grape (fungal leaves downy mildew infections and healthy) and poato (early and late blight) during collection Leaves was developed in 2023. The leaves were selected by the author's mom, Jesmin, an agriculture expert with lifelong experience in vegetable harvesting. Additionally, the authors and an expert farmer collaborated to identify and label leaves infected with laboratory. All images were taken under consistent weather conditions, including uniform shooting distance, lighting, and environmental backgrounds of sunny and gloomy conditions, ensuring clear visibility of the leaves and disease spots. The leaves were manually grouped into three datasets: training, testing, and validation. Each group was further subdivided into grape downy mildew, grape healthy, potato early blight and late blight categories before image capture. To maintain high image resolution, photos with nuances or noticeable inscriptions were manually removed. Additionally, images with multiple leaves were cropped and enhance quality to focus on each leaf and the physical appeal of the disease.

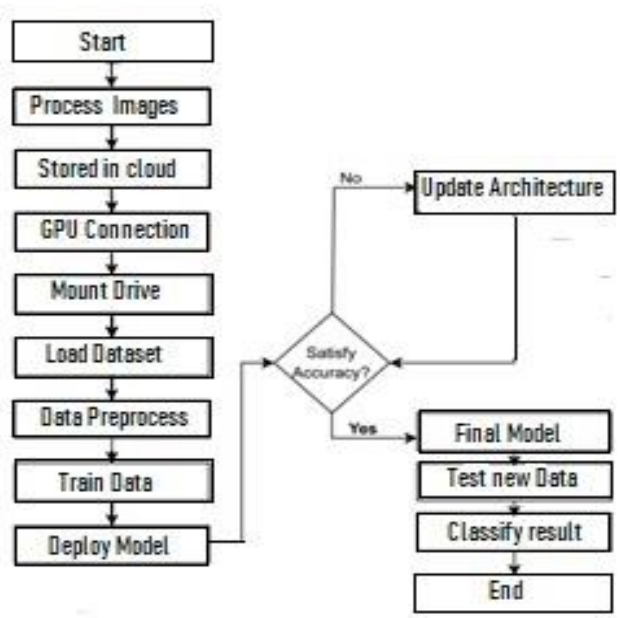


Fig. 1 Workflow Chart

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.

Effective strategies are crucial in combating chronic illnesses in crops. Utilizing fungicides, maintaining good hygiene, and cultivating disease-resistant grape and potato varieties are essential for ensuring the health and productivity of these crops. This work focuses on employing a collection of grape and potato leaf images and advanced image processing based on deep learning (DL) to identify diseases. Comparing different DL platforms such as CNN, EfficientNet, and ResNet is necessary to determine the most efficient model for disease diagnosis. This comparison aids in developing improved methods for managing grape and potata leaves diseases in the industry. The process flow diagram for this procedure is illustrated in Figure 1. Raw leaves pictures are first gathered, analysed, and then saved in the google drive cloud. Before the model is trained, the data is then pre-processed, standardized, and shuffled and the trained model undergoes evaluation and normalization. Then deploy model CNN,RestNet and EfficientNet model till satisfy accuracy modify hyper-parameter and enumber of epochs and check with the real unused normalized data employed to validate the outcomes. The ultimate selection of the disease prediction model occurs upon achieving satisfactory consequences compared to other models in the training, testing, and validation phases ensuring no overfitting issues.

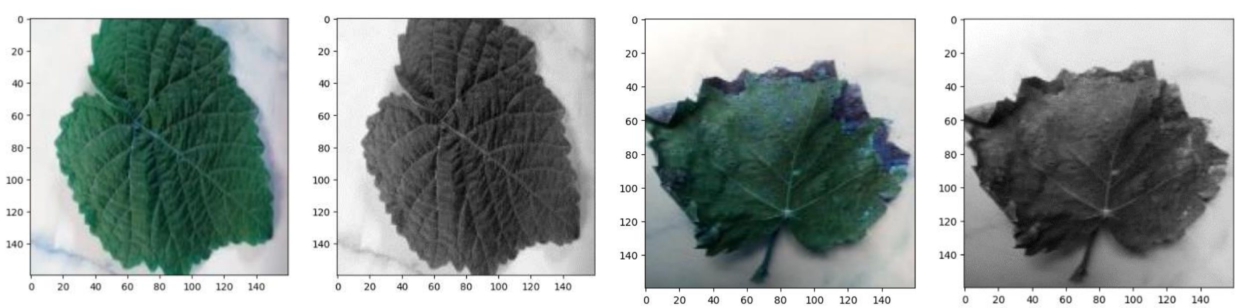
3.1. Pre-Processing

Data preparation is fundamental for refining the initial leaf dataset and is crucial for accurately forecasting grape leaf diseases. Before feeding the data into a machine learning model for detailed analysis, it undergoes a complex, multi-step process. The first and most critical step in this process is data cleaning. During this stage, the dataset is meticulously reviewed to identify and address anomalies, discrepancies, or missing data. This essential step ensures the dataset's accuracy and reliability by correcting any errors and inconsistencies.

3.1.1. RGB to Grey scale convert

Grayscale conversion is akin to transforming a painting's vibrant color spectrum such as red, green, blue that is three channels into a monochromatic (Grey) world of black, white, and various shades of gray. Each pixel loses its color, transitioning from a broad array of hues to the limited tones within the grayscale range. The unique features previously defined by vivid colors become evident through subtle changes in brightness and contrast. Highlights become more prominent, and shadows gain a richer, deeper quality. This monochromatic transformation is captivating as the absence of color emphasizes the image's core elements: the underlying structure, arrangement, and interplay of light and dark, which colors often obscure [24]. The schematics of grayscale conversion are illustrated in Figure 2.

Original image RGB to Gray Original image RGB to Gray



Original image RGB to Gray Original image RGB to Gray

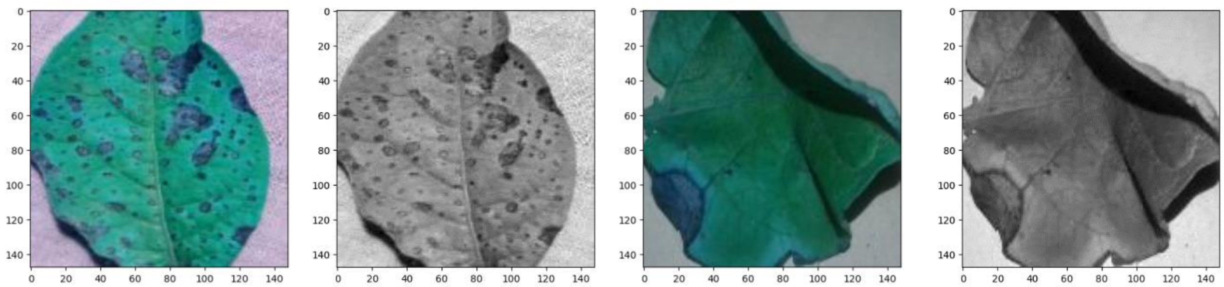
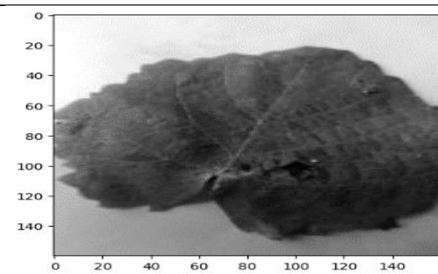


Fig. 2 Grey scale image

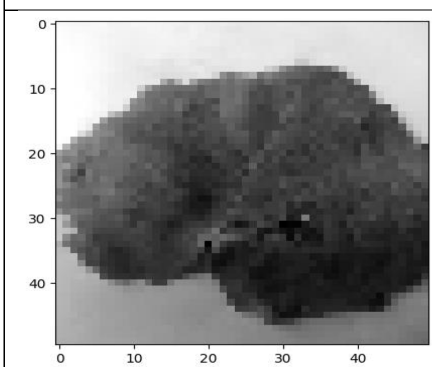
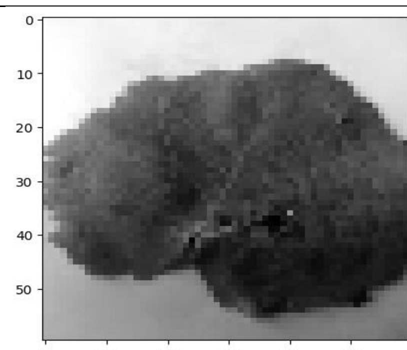
3.1.2. Image resizing

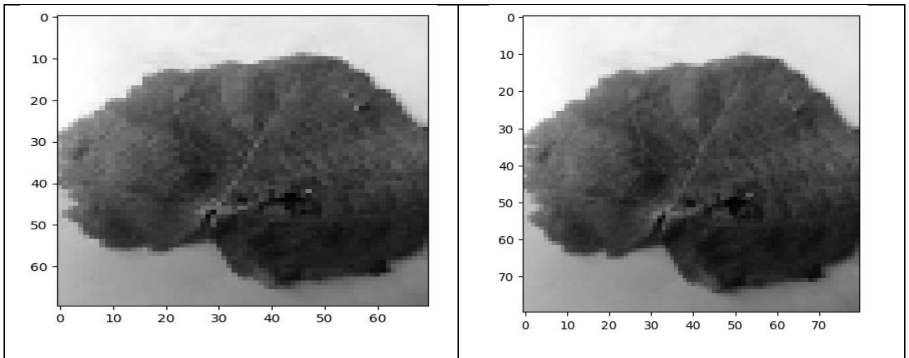
Resizing or altering an image's dimensions is an essential preliminary step in computer vision, ensuring uniformity in size, shape, and quality before further inspection or modification. The optical zoom lens of the iPhone 15 Pro Max reaches up to 5 times the capability of the default camera, which is equivalent to a focal length of 120mm. Meanwhile, the smaller variant, the non-Max model, retains its impressive 3 times zoom lens. So, resize and reshape applied for training data This step offers several advantages, such as speeding up image processing and reducing memory usage. Moreover, it aids in creating a consistent image collection for training models, thereby improving the efficiency of machine learning algorithms. It is crucial to handle resizing with care to preserve the image's essential features and avoid distortion or the loss of significant information [25]. The schematics of image resizing are depicted in Figure 3.



Original image in Gray Color

Resize Image into four different dimensions

	
50 x50	60 x60



70 x70	80 x80

Fig. 3 Image resizing

3.2. DL Models

3.2.1. Convolutional neural network:

A CNN, a DL model commonly utilized for image-related tasks, is proposed as a solution for this endeavor. CNNs consist of neurons with adjustable weights and biases, akin to traditional neural networks. Upon receiving multiple inputs from raw image matrices, a neuron applies an activation function, calculates a weighted sum, and generates an output. The network operates under a loss function that gradually decreases with each iteration, aiding the network in learning a specific set of parameters suited for the classification task. Ultimately, the outcome is a vector indicating probabilities for each class. In contrast to conventional neural networks, which process flat vectors as input, CNNs handle multi-channel images. During a convolution operation, a filter (e.g., 5x5x3) traverses the entire image, conducting dot product computations between the filter and segments of the input image [6]. Figure 4 delineates the architecture of the proposed CNN, providing detailed insights into its layers and the steps involved in the CNN process.

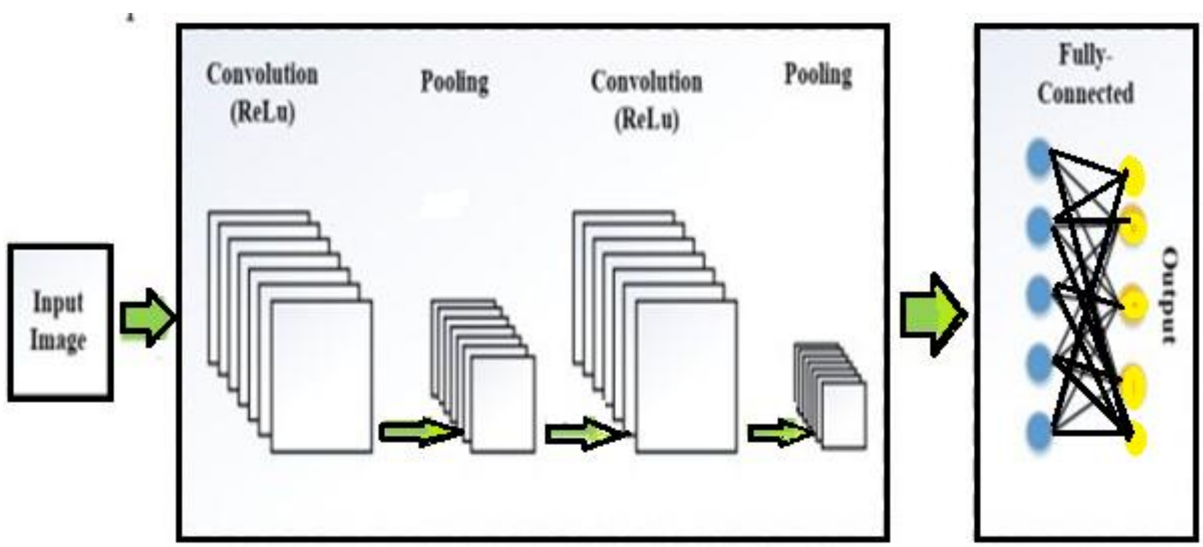


Fig. 4 CNN Layers

3.2.1.1. Convolutional layers

The convolutional layer plays a pivotal role in CNN architecture. Comprising numerous filters, this layer independently processes the image through convolution to generate distinct feature maps. Generally, convolving an M x N-sized image with a w x h-sized filter yields an output feature map of size σw x σh, as depicted in Equation 1.

$$O_w = \frac{M - w + 2p_w}{s_w} + 1$$

$$O_h = \frac{N - h + 2k}{s_h} + 1$$

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.

$$\mathrm{X}_d^j = f(\sum\nolimits_{i \in lj} X_i^{i-1} * W_{ij}^i + b_j^i$$

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. 5 shows the representation of the ReLU function, and Eq. 3 gives its formula.

$$f(x) = \max(0, \mathrm{X}).\mathrm{f(X)} \; = \; \{^{X, X \geq 0}_{0, X < o}$$

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.

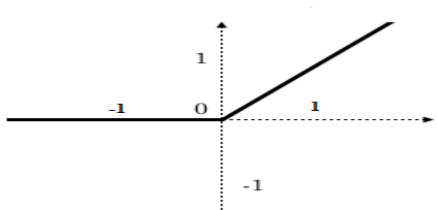


Fig. 5 ReLU activation function

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 takes 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 nonmaximal values from upper layers' computations, and secondly, it adds a type of translation variance [26]. 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 number 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 [27].

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:

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

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 [28]. Refer to Fig.6 for an illustration of the Efficient Net architecture.

Table 1. Efficient net-B0 network parameter table

Stage	***Operator***	***Resolution***	***#Channels***	***#Layers***
[redacted]	[redacted]	$\hat{H}_i \times \hat{W}_i$	[redacted]	[redacted]
1	**Conv** 3×3	224×224	**32**	**1**
2	**MBConv1,** $k3 \times 3$	112×112	**16**	**1**

3	$k3 \times 3$ **MBConv6,**	112×112	**24**	**2**
4	**MBConv6,** $k5 \times 5$	56×56	**40**	**2**
5	$k3 \times 3$ **MBConv6,**	28×28	**80**	**3**
6	$k5 \times 5$ **MBConv6,**	28×28	**112**	**3**
7	$k5 \times 5$ **MBConv6,**	14×14	**192**	**4**
8	$k3 \times 3$ **MBConv6,**	7×7	**320**	**1**
9	**Conv1 1 &Pooling&FC**	7×7	**1280**	**1**

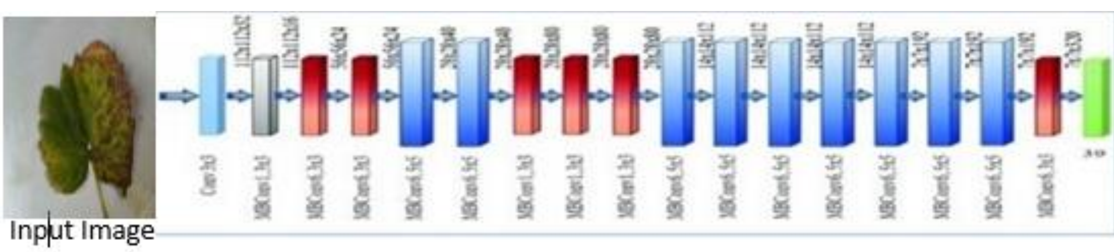


Fig. 6 Efficient Net Architecture.

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 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 [29].

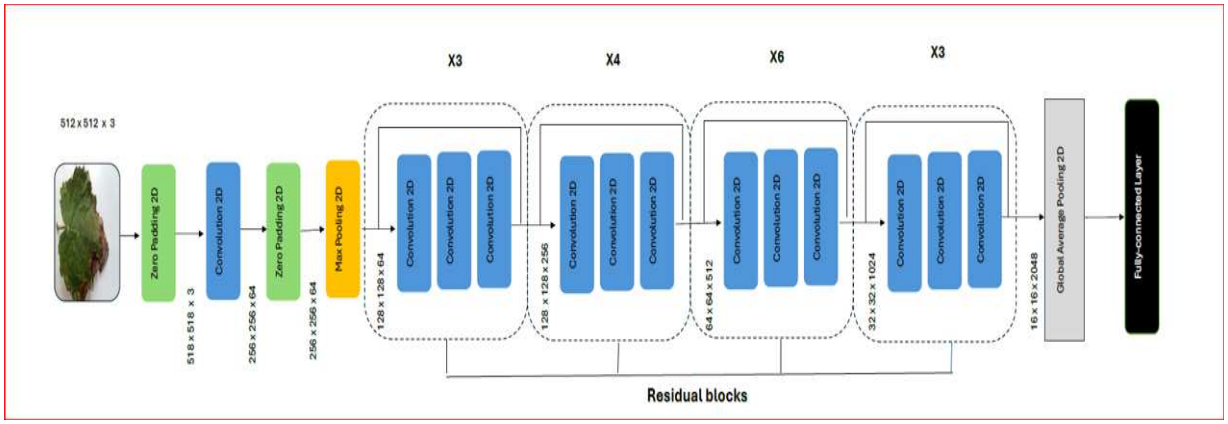


Fig. 7 ResNet Architecture

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 10 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. **The research employs various dl techniques, namely CNN, ResNet, and EfficientNet pre-trained models. The models are trained using 80% of the dataset [19], while 10% of data validity is essential for assessing performance without overfitting problems and fine-tuning the model with leftover 10% real unused images[11] and** the model can be utilized for Android mobile devices [20].

Table 2: Dataset Description

Number of Images	**Grape healthy**	**Grape downy mildew**	**Potato Leaf early Blight**	**Potato Leaf late Blight**	**Healthy leaves**
Model	**1000**	**1000**	**1000**	**1000**	**1000**
Test	**200**	**200**	**200**	**200**	**200**

4.2. Result obtained by CNN model

A CNN model's performance throughout 20 epochs in terms of training and validation accuracy is displayed in Fig. 8. Over the progression of these epochs, the model revelations a remarkable accuracy rate of 94%, 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.

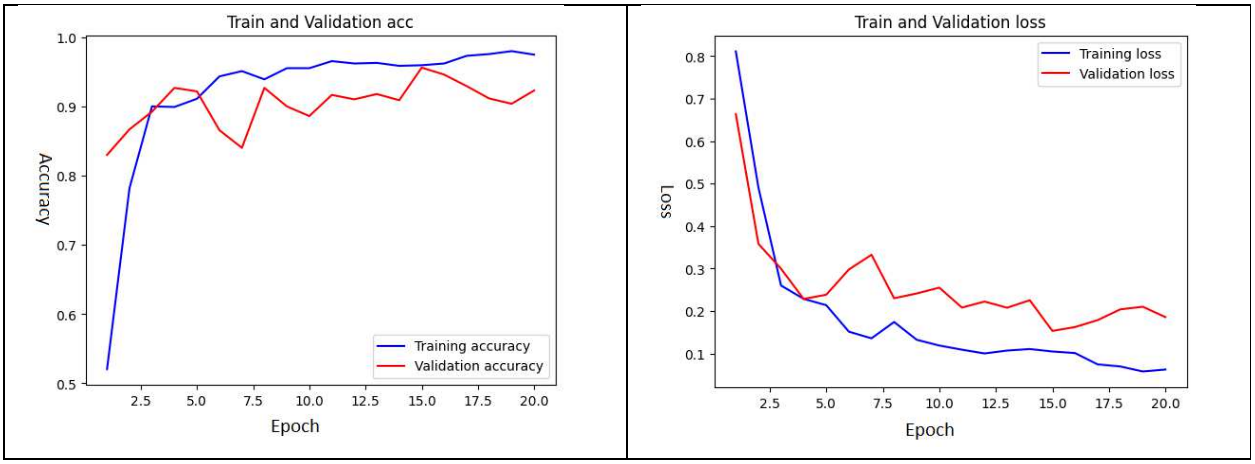


Fig. 8 Training and Validation Graph for CNN Model

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.

Original:Grape_Healthy Detected: Grape_Healthy Confidence 99.98%	Original:Grape_Downy_mildew Detected: Grape_Healthy Confidence 99.98%	Original:Potato_Healthy Detected: Potato_Healthy Confidence 99.98%
		
Original: Potato _Early_Blight Detected: Potato _Early_Blight Confidence 99.98%	Original: Potato _Late_Blight Detected: Potato _ Late_Blight Confidence 99.98%	

Fig. 9 Output from CNN Model

4.2.1. Performance metrics for CNN model

The CNN model demonstrated robust performance in diagnosing grape and potata leaves diseases and identifying healthy leaves. For Grape Healthy, it achieved a precision of 0.86, recall of 0.97, and an F1-score of 0.95, indicating high accuracy with a good balance between precision and recall. In detecting Grape Downy Mildew, the model showed high performance with a precision of 0.90, recall of 0.88, and an F1-score of 0.97. The model performed well for Early Leaf Blight with a precision of 0.91, recall of 0.98, and an F1-score of 0.90. It achieved excellent results for Late Leaf Blight with precision, recall, and F1-score all at 0.99, indicating near-perfect classification. For Healthy Leaves, the model achieved a precision of 0.97, perfect recall of 1.00, and an F1-score of 1.00, reflecting high accuracy and reliability. These metrics highlight the model's effectiveness and balanced performance with high precision and recall across different categories.

Table 3: Performance Metrics for CNN model

DISEASES AND NON-DISEASE IMAGE	PRECISION	RECALL	F1- SCORE
Grape healthy	**0.86**	**0.97**	**0.95**
Grape downy mildew	**0.90**	**0.88**	**0.97**
Early Leaf Blight	**0.91**	**0.98**	**0.9**
Late Leaf Blight	**0.99**	**0.99**	**0.99**
Healthy leaves	**0.97**	**1.00**	**1.00**

4.3. Result obtained by efficient net model:

The Fig 10 and fig 11 illustrates the performance of an Efficient Net model across 20 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.

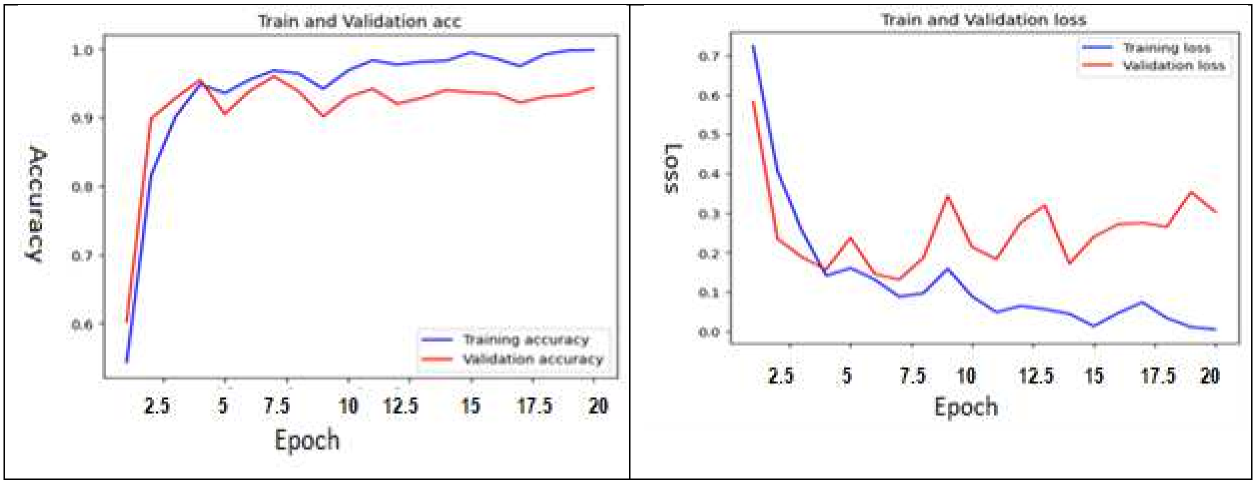


Fig. 10 Training and Validation curve for Efficient Net Model

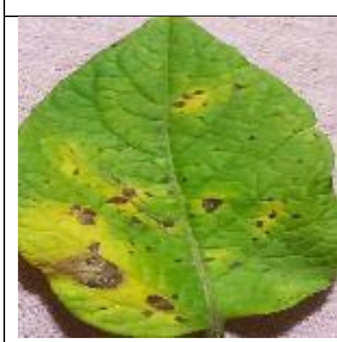
Original:Grape_Healthy Detected: Grape_Healthy Confidence 99.98%	Original:Grape_Downy_mildew Detected: Grape_Healthy Confidence 100.0%	Original:Potato_Healthy Detected: Potato_Healthy Confidence 100.0%
		
Original: Potato _Early_Blight Detected: Potato _Early_Blight Confidence 99.88%	Original: Potato _Late_Blight Detected: Potato _ Late_Blight Confidence 100.0%	
		

Fig. 11 Output from Efficient Net Model

4.3.1. Performance metrics for efficient net model:

The Table.4 presents performance metrics for identifying diseases affecting grape and potata leavess and a category for healthy leaves. The model is assessed on precision, recall, and F1-score. The EfficientNet model demonstrated robust performance in diagnosing grape and potata leaves diseases and identifying healthy leaves. For Grape Healthy, it achieved a precision of 0.98, recall of 0.91, and an F1-score of 0.94, indicating high accuracy with a few false negatives. In detecting Grape Downy Mildew, the model showed strong performance with a precision of 0.92, recall of 0.98, and an F1-score of 0.95. The model performed exceptionally well for Early Leaf Blight, Late Leaf Blight, and Healthy Leaves, achieving perfect scores of 1.00 for precision, recall, and F1-score in all three categories. These metrics reflect the model's effectiveness in identifying these cases and its high accuracy and reliability in distinguishing healthy leaves from diseased ones. The high F1-scores across different categories indicate a well-balanced model with both high precision and recall.

Table 4: Performance metrics for Efficient Net

DISEASES AND NON-DISEASE IMAGE	**PRECISION**	**RECALL**	**F1-SCORE**
Grape healthy	**0.98**	**0.91**	**0.94**
Grape downy mildew	**0.92**	**0.98**	**0.95**
Early Leaf Blight	**1.00**	**1.00**	**1.00**
Late Leaf Blight	**1.00**	**1.00**	**1.00**
Healthy leaves	**1.00**	**1.00**	**1.00**

4.4. Result obtained by ResNet model

The depicted graph illustrates training and validation accuracy for state-of-the-art ResNet design across 20 epochs. Remarkably, this model showcases an outstanding accuracy of 96%, reflecting its robust learning capability. Concurrently, it achieves an impressively low loss, minimizing to a mere 4%. These metrics underline model's proficiency in understanding and generalizing complex patterns within the dataset, positioning it as a highperforming solution for the given task.

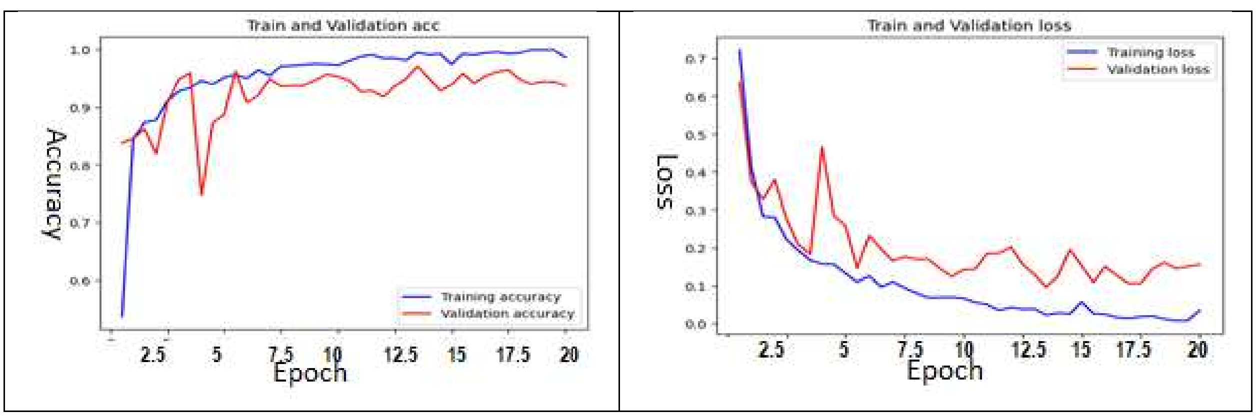


Fig. 12 Training and Validation curve for ResNet Model.

Original:Grape_Healthy	Original:Grape_Downy_mildew	Original:Potato_Healthy

Detected: Grape_Healthy Confidence 100.0 %	Detected: Grape_Healthy Confidence 100.0%	Detected: Potato_Healthy Confidence 100.0%
		
Original: Potato _Early_Blight Detected: Potato _Early_Blight Confidence 99.88%	Original: Potato _Late_Blight Detected: Potato _ Late_Blight Confidence 100.0%	
		

Fig. 13. Output from ResNet model

4.4.1. Performance metrics for CNN model

The table 5 shows that the CNN model demonstrated excellent performance across all categories. For Grape Healthy, it achieved a precision of 0.97, recall of 0.99, and an F1-score of 0.98, indicating very high accuracy with minimal false negatives. In detecting Grape Downy Mildew, the model showed high performance with a precision of 0.99, recall of 0.98, and an F1-score of 0.98, reflecting its reliability with very few false positives. The model performed exceptionally well for Early Leaf Blight and Late Leaf Blight, achieving near-perfect precision, recall, and F1-scores of 0.99 or 1.00, indicating perfect or near-perfect classification. For Healthy Leaves, the model achieved a precision of 0.99, recall of 1.00, and an F1-score of 0.99, demonstrating high accuracy and reliability. These metrics highlight the model's effectiveness and balanced performance, with high precision and recall across different categories.

Table 5: Performance metrics for ResNet model

DISEASES AND NON-DISEASE IMAGE	**PRECISION**	**RECALL**	**F1-SCORE**
Grape healthy	**0.97**	**0.99**	**0.98**
Grape downy mildew	**0.99**	**0.98**	**0.98**
Early Leaf Blight	**0.99**	**1.00**	**1.00**

Late Leaf Blight	**1.00**	**1.00**	**1.00**
Healthy leaves	**0.99**	**1.00**	**0.99**

5. Conclusion

In the field of viticulture, keeping grape and potata leavess healthy and productive requires the early identification and control of diseases such as leaf blight and grape and potata leaves mildew. 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 crops grape and potato. With a 94% efficiency rate, CNN has shown to be a reliable tool for diagnosing diseases both of the crops. Its capacity to recognize patterns and characteristics in images has made it possible to reliably identify these prevalent among crop diseases. In addition, ResNet has proven to be a reliable solution for grape and potata leaves disease identification, with a 96% 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. With its impressive 97% efficiency, Efficient Net has shown to be an excellent tool for diagnosing and categorizing grape and potato illnesses. Measuring grape downy mildew and leaf blight has become more accurate thanks to its scalable architecture and balanced network depth, width, and resolution.

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Conflicts of interest
The authors do not have any conflicts of interest to disclose.

Author's Role Disclosure
Jesmin Akther: The tasks accomplished gathering data, idealization leading to composing the initial draft manuscript, training the process data, and analyzing and interpreting outcomes. Muhammad Harun-Or-Roshid: at a same time, conceptualization investigation, data curation, suggested draft writing, and reviewing and editing. Aminul Islam: participating in the review and editing of the writing.

Data Availability
The data considered in this study were gathered from the Noakhali. The data are not freely accessible. Nevertheless, the data may be on condition that by the first author upon realistic appeal.

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