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# EFFINET-CL: A FRAMEWORK FOR LEAF DISEASE DETECTION AND CLASSIFICATION USING CONTINUAL LEARNING

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**ABSTRACT**

This paper presents an innovative approach to detect and classify leaf diseases using EfficientNetB3 combined with continual learning strategies. The proposed model leverages data augmentation techniques for improved generalization and integrates continual learning through Elastic Weight Consolidation (EWC) and Replay Memory to prevent catastrophic forgetting. This approach keeps the model's knowledge of formerly learnt diseases intact while permitting it to learn continually from new disease classes. The integration of an Out-of-Distribution (OOD) detection mechanism further improves the ability of the model to recognize unknown diseases, making it a reliable tool for real-time agricultural applications. The model demonstrated excellent performance with an accuracy of 98.44%, highlighting the potential of deep learning combined with continual learning for plant disease diagnosis, and outperformed ResNet50, DenseNet121, InceptionV3, and MobileNet-V2 algorithms.

**KEYWORDS:** *Leaf Disease Detection, Feature Extraction, Classification, Deep Learning, Continual Learning*

## 1. INTRODUCTION

Agriculture remains the backbone of many economies and is essential in maintaining global food security [1]. However, plant diseases, particularly those affecting leaves, pose a significant challenge to agricultural productivity, often resulting in severe food shortages and financial losses [2]. Conventional methods to detect and diagnose plant diseases largely depend on hands-on examination by professionals, which can be both laborious and prone to human error. The visual symptoms of different diseases frequently overlap, further complicating accurate diagnosis, even for experienced professionals [3]. This has highlighted the growing need for automated, high-accuracy methods that can help with early identification and classification of leaf diseases, enabling timely interventions to mitigate their impact on crop yields [4].

Recent advancements in deep learning have shown promise in addressing these challenges [5]. Specifically, Convolutional neural networks (CNNs), have showcased extraordinary outcomes in tasks associated with image recognition, consistently outperforming traditional machine learning methods in terms of both accuracy and efficiency. CNNs are capable of learning complex patterns and features from large datasets, making them highly suitable for classifying diseases based on leaf images [6]. However, the efficiency of deep learning models is heavily reliant on the underlying architecture. Selecting the most appropriate model for specific tasks has thus become a focal point of research. Among the various deep learning architectures, EfficientNet has emerged as a leading choice for image classification [7]. The EfficientNet family

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of models, developed by Google, scales network dimensions (depth, width, and resolution) in a fair manner, achieving superior performance with lesser parameters and lower computational costs. EfficientNetB3, a variant in this family, offers an optimal balance between accuracy and efficiency, making it ideal for utilization in settings with low resources such as mobile or edge devices [8]. Its capacity to preserve high accuracy while lowering computational needs makes it an ideal candidate for leaf disease identification and classification, particularly in field conditions where resources may be limited.

Despite the strengths of EfficientNetB3, conventional deep learning models, including EfficientNet, typically suffer from a critical limitation: once trained, they struggle to adapt to new, unseen diseases without compromising performance on previously learned diseases [9]. This study addresses that limitation by incorporating continual learning strategies, specifically Replay Memory and Elastic Weight Consolidation (EWC), into the EfficientNetB3 architecture [10]. Replay Memory allows the model to retain examples from previously learned diseases, while EWC helps prevent catastrophic forgetting by selectively consolidating important parameters. These enhancements enable the model to match with new or unknown diseases while maintaining its performance on already learned ones, overcoming a significant drawback of traditional models. This paper presents an enhanced EfficientNetB3-based leaf disease detection and classification system, capable of learning from new data while maintaining accuracy on past tasks. The study begins by outlining the limitations of traditional disease detection approaches and the need for adaptive, automated solutions. It then delves into the technical aspects of the EfficientNetB3 architecture and the integration of continual learning methods. Inorder to improve generalization, the suggested model is trained using a large and varied dataset of leaf images utilizing a variety of data augumentation strategies. The outcomes reveal the potential of the model to precisely determine and classify a variety of leaf diseases, even in cases where symptoms overlap, while also adapting to new disease classes without performance degradation. The block diagram of the proposed model is given below (fig 1):

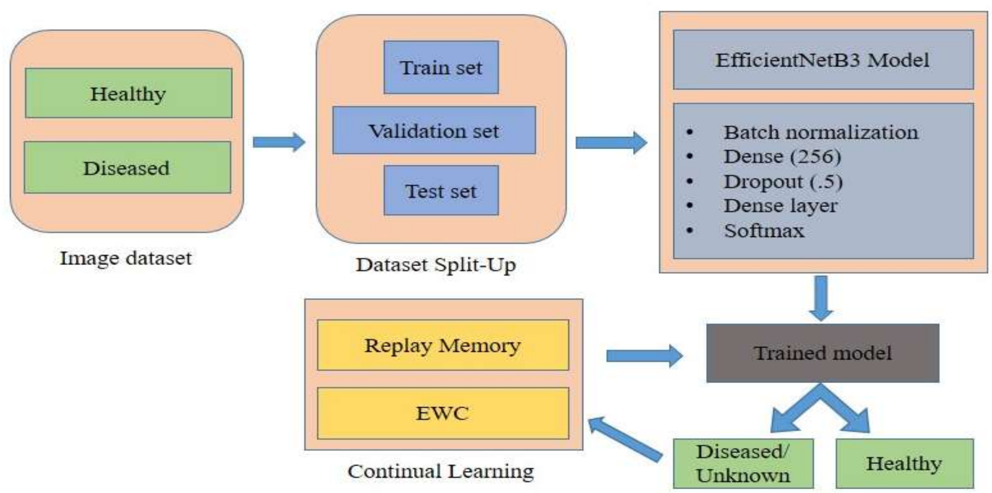


Fig 1: Block diagram of the proposed model

Unlike prior studies that rely mainly on fixed deep learning models for leaf disease classification, this research introduces a continual learning enabled EfficientNetB3 framework. The proposed approach not only delivers strong classification performance but also effectively tackles the problem of catastrophic forgetting, a limitation that is often neglected in traditional plant disease detection methods. By integrating Replay Memory and Elastic Weight Consolidation into a compact and computationally efficient architecture, the model supports progressive learning of new disease categories without the need for complete retraining or loss of previously learned

information. In addition, the application of comprehensive data augmentation techniques along with a heterogeneous dataset improves the system's robustness in real world agricultural environments. Collectively, these innovations establish the proposed model as an adaptive, scalable, and resource conscious solution that surpasses existing deep learning based leaf disease detection approaches. Incorporation of continual learning strategies into EfficientNetB3 represents a significant advancement in precision agriculture. By combining state-of-the-art deep learning techniques with adaptive learning mechanisms, this study advances the development of intelligent tools that assist agricultural professionals and farmers in taking quick, well-informed choices. These findings possess the capacity to improve food security, lower agricultural losses, and serve as a foundation for future research into adaptive deep learning models in agriculture.

Contributions are detailed below:

- A new model, EffiNet-CL has been developed to detect and classify the leaf diseases.
- EfficientNet-B3 algorithm is modified using Continual Learning approaches such as Replay memory and Elastic Weight Consolidation (EWC) to overcome the limitations of catastrophic forgetting.
- The system has the ability to identify new/unkown diseases while preserving its performance on the previously learned ones.
- The model is evaluated and compared with current cutting-edge algorithms such as Resnet50, DenseNet121, InceptionV3 and MobileNet-V2.

The remaining sections of the article are structured as follows. Section 2 discusses the background on leaf disease detection and classification. Section 3 depicts the experimental materials and methods, as well as the model architecture and parameters. Section 4 discusses the findings and the time required to train and predict the models. Finally, the conclusion and future work are represented in section 5.

## 2. BACKGROUND

### 2.1. Conventional Methods for Leaf Disease Detection

Historically, leaf disease detection has been predominantly carried out through manual observation supported by expert judgment. In traditional agricultural practices, disease identification is performed by visually examining plant leaves for symptoms such as color changes, lesions, deformities, or abnormal growth patterns. Although this approach is widely adopted due to its simplicity, it presents several notable drawbacks [11]. Manual inspection is highly labor-intensive and demands continuous field monitoring, which becomes impractical in large-scale farming systems. Moreover, the accuracy of diagnosis largely depends on the experience and skill level of the observer [12]. Even well-trained agronomists may find it challenging to differentiate between diseases that exhibit similar visual symptoms, particularly during the early stages of infection. External factors such as lighting conditions, seasonal variations, and differences in plant maturity can further influence symptom appearance, increasing the likelihood of misdiagnosis [13]. Since visual assessment is inherently subjective, diagnostic outcomes often vary between individuals, leading to inconsistencies in disease identification and management decisions.

A further limitation of conventional disease detection techniques is the delay in recognizing infections [14]. In many cases, visible symptoms appear only after the disease has advanced significantly, reducing the effectiveness of control measures. Late-stage detection often results in severe yield loss, deterioration in crop quality, and increased economic burden on farmers [15]. Additionally, the limited availability of trained plant pathologists, especially in rural and resource-limited regions, restricts the scalability and accessibility of expert-based diagnosis. These challenges collectively demonstrate the inadequacy of traditional approaches and underline the necessity for automated, accurate, and scalable systems for leaf disease detection and classification [16].

### 2.2. Deep Learning-Based Methods

To address the shortcomings of manual disease identification, deep learning techniques have gained considerable attention for automating leaf disease detection and classification. Deep learning, a branch of machine learning, utilizes multilayer neural networks trained on large volumes of data to automatically learn discriminative features and generate predictions [17]. Among these techniques, Convolutional Neural Networks (CNNs) have proven particularly effective for image centric tasks, including plant disease recognition, due to their ability to extract spatial and hierarchical features directly from raw images [18][19]. Despite their success, many CNN based solutions proposed in the literature operate under a static learning framework, where models are trained once using a fixed dataset. Such approaches assume a stable data distribution, which is rarely realistic in agricultural environments. The emergence of new disease types or variations in existing diseases often necessitates complete retraining of the model, resulting in increased computational cost and time. Moreover, conventional deep learning models are susceptible to catastrophic forgetting, where learning new information leads to the degradation of previously acquired knowledge, an issue that remains insufficiently addressed in most existing plant disease detection studies.

EfficientNet, a family of convolutional architectures introduced by Google, represents a major advancement in image classification by employing a compound scaling strategy that uniformly adjusts network depth, width, and input resolution [20]. This approach enables EfficientNet models to achieve high accuracy with fewer parameters and reduced computational overhead compared to traditional architectures such as ResNet and VGG [21]. Within this family, EfficientNetB3 provides a balanced compromise between performance and efficiency, making it suitable for applications with limited computational resources [22]. EfficientNetB3 has demonstrated strong capability in capturing intricate visual characteristics of leaf images, including texture, shape, and color variations, which are essential for accurate disease discrimination [23]. Its lightweight design also facilitates deployment on resource-constrained platforms such as mobile devices and edge systems used in agricultural fields [24]. However, existing applications of EfficientNetB3 in plant disease detection largely focus on static classification performance and do not consider the dynamic nature of real-world agricultural data. Most studies overlook the need for models to continuously adapt to new disease classes while retaining previously learned information.

To bridge these gaps, the proposed work enhances the EfficientNetB3 architecture by incorporating continual learning strategies that support incremental learning without performance degradation. By leveraging Replay Memory and Elastic Weight Consolidation, the model is designed to mitigate catastrophic forgetting while maintaining computational efficiency. This approach directly addresses the limitations of existing deep learning-based methods and offers a more adaptive and scalable solution for practical, real-world leaf disease detection scenarios.

## 3. MATERIALS AND METHODS

### 3.1 Dataset

The PlantVillage dataset was used in this research, consisting of 15 classes of leaf diseases from crops such as tomatoes, brinjal, cucumber, cluster beans, potatoes, and peppers. The dataset includes healthy leaf images as well as images exhibiting signs of various diseases, ensuring a varied and broad set of data for model training and evaluation.

The image dataset consisting of diseased and normal crop leaves were collected online from the Kaggle website. It contains a total of 20000 images of size 256 x 256, which were taken at 100x magnification. The dataset is of imbalanced distribution and is divided into 2 classes, normal and diseased. Figure (fig 2) given below shows the sample images:

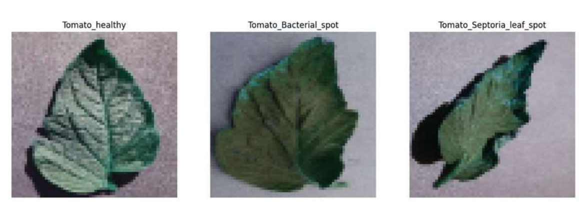


Fig 2: Sample images

The image patches are separated into three categories using the popular train-test split approach. The testing dataset is further separated into test and validation sets. The given table 1 shows details of the Image dataset.

*Table 1: Dataset Split-Up*

| Image Dataset | Total Images | Train set | Validation set | Test set |
|---|---|---|---|---|
| Normal | 8000 | 4000 | 2000 | 2000 |
| Diseased | 12000 | 6000 | 3000 | 3000 |

### 3.2 Model Architecture

The proposed model employs EfficientNetB3 as the backbone for feature extraction. EfficientNetB3 was pre-trained on ImageNet and optimized for the leaf disease classification task. This pre-training step allows the model to leverage a set of convolutional layers optimized on millions of images to recognize intricate patterns relevant to leaf diseases. Mathematically, each convolutional layer in EfficientNetB3 applies a set of learned filters to the input image, where each filter is represented as a weight matrix $W$. This operation can be defined as:

$$f(x) = W * x + b \quad (1)$$

where $x$ is the input image or feature map, $*$ denotes the convolution operation, and $b$ is the bias term. This process captures spatial hierarchies in leaf images, including edges, textures, and complex disease-related patterns.

Following feature extraction, Global Average Pooling (GAP) condenses the spatial dimensions of the EfficientNetB3 output, resulting in a feature vector $v$. This is achieved by computing the average of each feature map across its spatial dimensions:

$$v_i = \frac{1}{H \times W} \sum_{h=1}^{H} \sum_{w=1}^{W} x_{i,h,w} \quad (2)$$

where $H$ and $W$ represents the height and width of each feature map $x_i$, respectively. GAP reduces the high-dimensional feature map into a compact vector while preserving critical information, streamlining the model for subsequent dense layers.

To adapt the EfficientNetB3 backbone for leaf disease classification, the feature vector passes through a custom classification head. First, Batch Normalization normalizes the extracted features, stabilizing training by ensuring that inputs to each layer maintain a consistent mean of 0 and standard deviation of 1. For each feature vector $v$, this can be expressed as:

$$\hat{v} = \frac{v - \mu}{\sigma} \quad (3)$$

where $\mu$ and $\sigma$ are the mean and standard deviation of the vector $v$.

Next, a fully connected Dense layer with 256 neurons refines the extracted features by introducing learnable weights $W_d$ and $b_d$ biases , generating high-level representations of disease patterns:

$$y = ReLU(W_{d^v} + b_d) \quad (4)$$

$L_1$ and $L_2$ penalties are Regularization techniques, which are applied to the weights $W_d$, formulated as $\lambda_1 \sum |W_d|$ for $L_1$ and $\lambda_2 \sum {W_d}^2$ for $L_2$, where $\lambda_1$ and $\lambda_2$ are hyperparameters. Additionally, by promoting robust feature learning and zeroing out 50% of the neurons during training a dropout layer with a dropout rate of 0.5 reduces overfitting.

The model concludes with a final Dense layer that outputs a vector $o$ of probabilities for each disease class. The Softmax function converts the output into a probability distribution across the 15 classes:

$$o_i = \frac{e^{z_i}}{\sum_{j=1}^{15} e^{z_j}} \quad (5)$$

where $z^i$ represents the output logits for each class $i$, and $o_i$ is the probability that the image belongs to class $i$. The model predicts the class with the highest probability, facilitating precise classification of each leaf image according to its disease type.

To support the model's adaptability to new diseases, continual learning techniques such as Replay Memory and Elastic Weight Consolidation (EWC) are incorporated. Replay Memory allows the model to retain knowledge of previous diseases by periodically retraining on a subset of old data, helping prevent catastrophic forgetting. Additionally, EWC imposes a regularization term $R$ on the loss function to preserve essential parameters for previously learned tasks:

$$R = \frac{\lambda}{2}\sum_i F_i \left(\theta_i - \theta_{i,old}\right)^2 \quad (6)$$

where $\theta_i$ are the current parameters, $\theta_{i,old}$ are the parameters from prior training, $F_i$ is the Fisher Information Matrix capturing the importance of each parameter, and $\lambda$ is a regularization factor. EWC thus permits the model to acquire new skills while preserving performance on already learned diseases. This architecture, combining EfficientNetB3 with continual learning strategies, enables precise, adaptive leaf disease detection across evolving datasets. The overview of the model architecture is depicted below (fig 3):

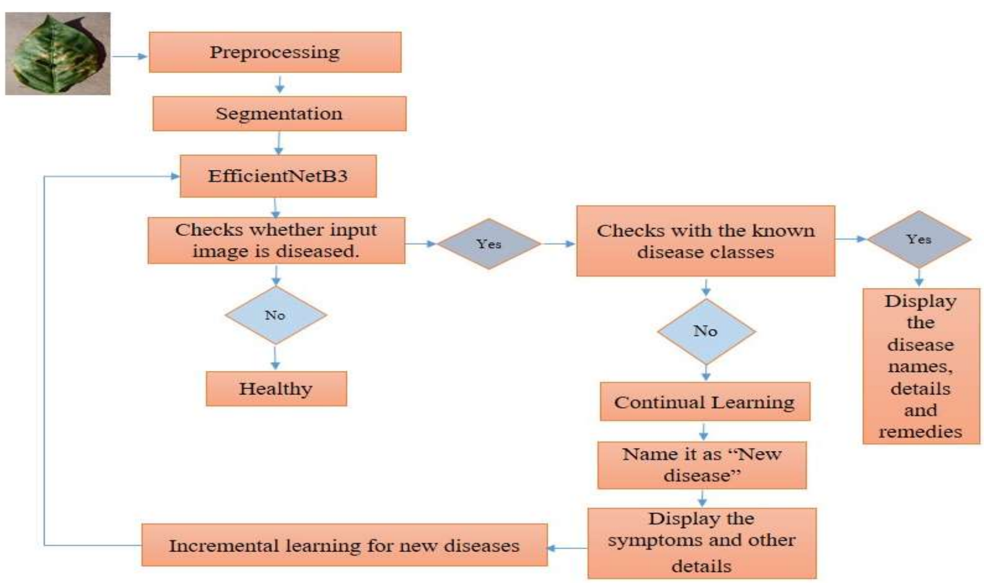


*Fig 3: Architectural Diagram Of Effinet-CL Model*

The architectural design and training configuration were selected to ensure efficiency, adaptability, and robustness in real-world agricultural applications. The PlantVillage dataset was chosen for its diversity across crops and disease categories, while preserving class imbalance to reflect practical conditions. Images were resized to 256 × 256 to balance feature retention with computational cost. EfficientNetB3 was adopted as the backbone due to its favorable accuracy efficiency trade off and suitability for resource constrained environments, with ImageNet pre-training used to enhance feature extraction. Regularization techniques, including batch normalization, dropout, and weight penalties, were applied to improve generalization, and Global Average Pooling was employed to reduce model complexity. To support incremental learning and mitigate catastrophic forgetting, Replay Memory and Elastic Weight Consolidation were incorporated, enabling the model to adapt to newly introduced disease classes.

Algorithm 1

Input:

- X: Input image dataset
- $\lambda_1$ and $\lambda_2$: Regularization factors for L1 and L2 penalties
- λ: Regularization factor for EWC
- $D_{old}$: Replay memory with prior disease data (for continual learning)
- $\theta_{old}$: Parameters from previous training (for EWC)
- $F_i$: Fisher Information Matrix for parameters

Output:

- $O$: Predicted probabilities for disease classes

Steps:

1. Load the dataset X.
2. Initialize the EfficientNetB3 model pre-trained on ImageNet. Fine-tune the model using X by optimizing the convolutional operation, $f(x) = W * x + b$
3. For each feature map $x_i$, compute the compact feature vector $v$ using, $v_i = \frac{1}{H \times W} \sum_{h=1}^{H} \sum_{w=1}^{W} x_{i,h,w}$
4. Apply batch normalization to stabilize feature distribution. Then, pass normalized features through a Dense layer with 256 neurons and regularize the Dense layer weights $W_d$ using: $\lambda_1 \sum |W_d|$ and $\lambda_2 \sum {W_d}^2$.
5. Apply Dropout (rate = 0.5) to prevent overfitting.
6. Use a Dense layer to output logits $z$ and convert logits into class probabilities using the Softmax function.
7. Add a regularization term R to the loss function and update parameters while preserving performance on previously learned tasks.
8. For a new input image $x_{new}$, extract features using EfficientNetB3 and classify using the trained model to predict $O_{new}$.

### 3.3 Continual Learning Mechanism

To increase the model's flexibility and prevent catastrophic forgetting, two continual learning strategies are incorporated: Replay Memory and Elastic Weight Consolidation (EWC).

- Replay Memory: To maintain performance on previously learned diseases, the model selectively retains a subset of training examples from earlier tasks. This replay data is periodically presented to the model during training on new disease classes [25]. By revisiting these older examples, the model prevents forgetting previously learned patterns, ensuring it can generalize across both new and old diseases.
- Elastic Weight Consolidation (EWC): Based on the Fisher Information Matrix EWC adds a regularization term to the loss function, which quantifies the importance of different model parameters. Parameters crucial for prior tasks are less likely to change during the learning of new diseases, effectively consolidating knowledge from earlier tasks. This mechanism enables the system to adapt to new diseases while maintaining its performance on already learned tasks [26].

The model is trained using the Adamax optimizer, a variant of the Adam optimizer well-suited for handling sparse gradients. Categorical cross-entropy is used for the loss function, as it is the most common option for problems involving multi-class classification. The continual learning strategies are integrated into the training loop, ensuring that while the model learns new diseases, it retains and consolidates its knowledge of previously learned classes. Overall, this architecture combines the powerful feature extraction capabilities of EfficientNetB3 with continual learning techniques, addressing a critical limitation of conventional models that tend to forget previously learned tasks. This enables the model to be highly adaptable, making it appropriate for real-world agricultural implementations where new leaf diseases might emerge over time.

### 3.4 Out-of-Distribution (OOD) Detection

An OOD detection mechanism was implemented to handle novel disease classes. In classification tasks, models are typically trained on a predefined set of classes using labeled data. However, in real-world applications, models often encounter inputs that do not belong to any of these known classes. These inputs are referred to as Out-of-Distribution (OOD) data [27]. It is a system designed to identify such novel or unseen inputs during inference and handle them appropriately, ensuring robust and reliable model performance. During inference, if the predicted probability of the most likely class was below a defined threshold (0.5), the image was classified as "Unknown Disease." This feature is critical in real-world applications where the model may encounter previously unseen diseases.

### 3.5 Training

The Adam optimizer was used to train the model for 50 epochs with a batch size of 64. The learning rate was reduced dynamically using a ReduceLROnPlateau callback, and checkpoints were saved to store the best-performing model. Data augmentation was applied during training to further improve the model's robustness.

Standardization of the hyperparameters has been taken into consideration throughout all trials in order to allow for a fair comparison of the results of all the models. The following values (table 2) were selected for the standard hyperparameters for each model after conducting several experiments.

*Table 2: Hyperparameter Setup*

| Optimizer | Base learning rate | Momentum | Weight decay | Batch size |
|---|---|---|---|---|
| Adam | 0.001 | 0.9 | 0.0001 | 64 |

### 3.6 Experimental Setup

For this study, the model was run on Google Colab with a runtime environment set up to use a T4 GPU. This approach was chosen to take advantage of the considerable processing power required for deep learning tasks, guaranteeing that the model is trained and evaluated efficiently. The use of a T4 GPU enabled rapid picture data processing, allowing complex neural network architectures such as EfficientNetB3 to be trained on a huge dataset in a reasonable amount of time.

## 4. RESULTS AND DISCUSSION

The experimental results indicate that the proposed EffiNet-CL model achieves consistently high performance across all evaluation metrics. High precision and recall values confirm the model's ability to accurately identify diseased leaves while limiting false predictions. The confusion matrix shows strong diagonal dominance, demonstrating reliable classification for most disease categories. Minor misclassifications occur primarily between visually similar diseases, indicating that errors arise mainly from overlapping symptom characteristics rather than model instability.

Some limitations were observed during training. Slight fluctuations in validation loss at later epochs suggest mild overfitting, despite regularization. In addition, class imbalance led to marginal performance variation in less-represented disease classes. These observations highlight opportunities for further improvement through advanced sampling methods and adaptive training strategies.

### 4.1 Model Performance

This study uses benchmark metrics such as accuracy, precision, recall, and F-measure to assess the efficiency of the proposed model. The ratio of correctly detected images to all positive images is known as the classifier's recall or true positive rate (TPR). The ratio of accurately classified positive images to positively predicted images is called precision, or positive predictive value (PPV). The mean of precision and recall is represented by the F-measure, sometimes referred to as the F-score.

The performance metrics used in this work are given by the following equations:

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

$$Precision, PPV = \frac{TP}{(TP+FP)}$$
(2)

$$Recall, TPR = \frac{TP}{(TP+FN)}$$
(3)

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Reca}$$
(4)

*The Performance Metrics Of The Proposed Method Is Given As (Table 3):*

| Algorithm | Precision | Recall | F1 Score | Accuracy |
|---|---|---|---|---|
| Proposed method | 0.9805 | 0.9841 | 0.9823 | 0.9844 |

The proposed EffiNet-CL model demonstrated excellent performance in classifying the disease classes. The final model achieved an accuracy of 98% on the validation set, indicating its effectiveness in distinguishing between different leaf diseases. The model was also compared and tested with other cutting-edge algorithms such as InceptionV3, ResNet50, DenseNet121,VGG16 and MobileNetV2. The results shows that the proposed method is giving more accurate resutls than the other methods. The below given table 4 shows the analysis that compares the suggested approach with the other cutting-edge algorithms and fig 4 is its graphical representation.

*Table 4: Comparison Study Of The Proposed Method And Other Algorithms*

| Algorithm | Epoch | Accuracy | Loss | Val_accuracy | Val_loss | Learning rate |
|---|---|---|---|---|---|---|
| InceptionV3 | 27 | 0.9336 | 0.2132 | 0.8045 | 0.6868 | 0.001 |
| ResNet50 | 33 | 0.9587 | 0.1339 | 0.9253 | 0.9253 | 0.001 |
| DenseNet121 | 20 | 0.9327 | 0.2193 | 0.7384 | 1.5480 | 0.001 |
| VGG16 | 25 | 0.8812 | 0.3872 | 0.6072 | 1.8384 | 0.001 |
| MobileNetV2 | 21 | 0.9172 | 0.2806 | 0.8892 | 0.4864 | 0.001 |
| Proposed Method | 22 | 0.9844 | 0.0498 | 0.9557 | 0.1982 | 0.001 |

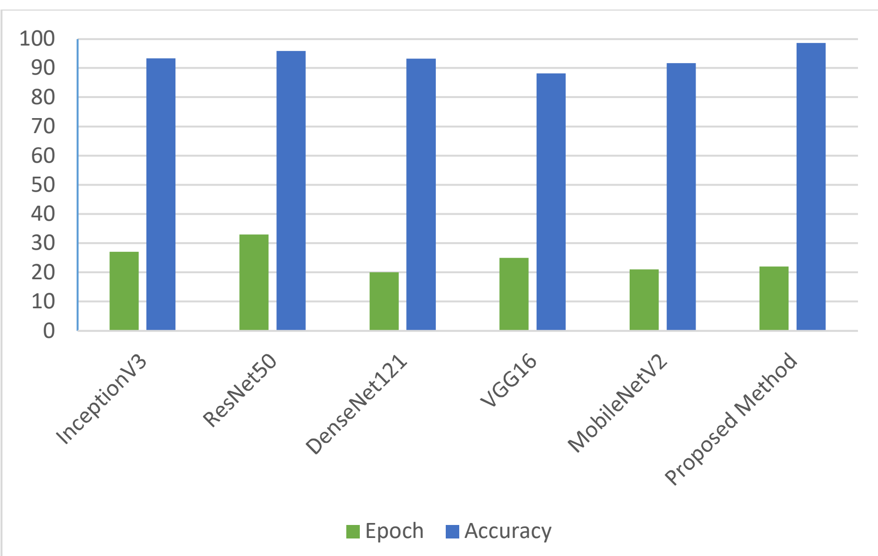


*Fig 4: Graphical Representation of the Comparison Study*

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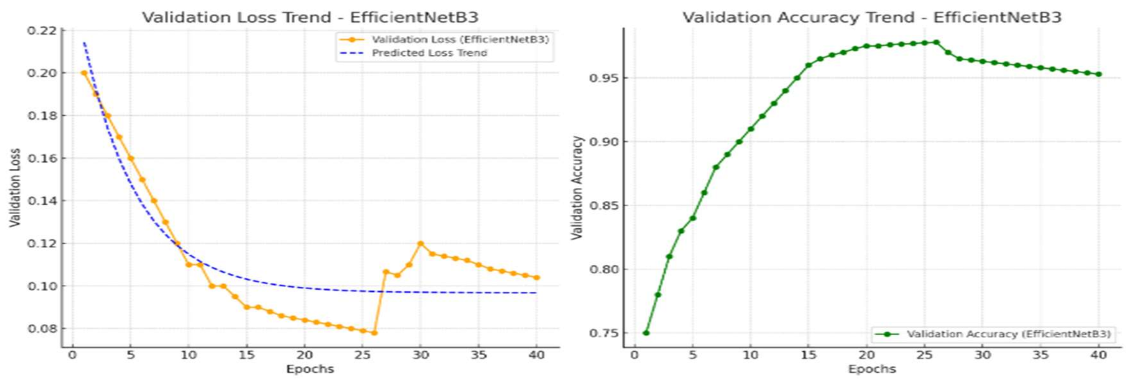


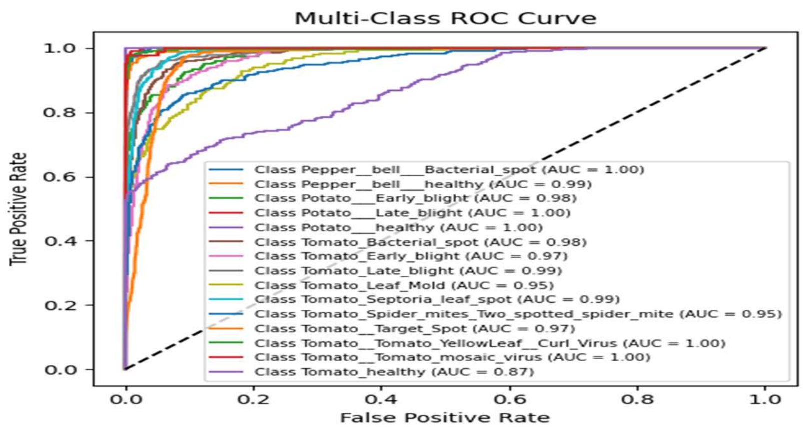


*Fig 5: Validation Loss And Accuracy Of Efficientnetb3 Fig 6: The Multi-Class ROC Curve*

The figure 5 illustrates the validation loss and accuracy trends for the EfficientNetB3 model during training. The validation loss decreases significantly in the initial epochs, indicating effective learning, but begins to fluctuate and slightly increase after epoch 30, suggesting potential overfitting. The predicted loss trend provides a smoothed overview of this progression. The validation accuracy shows rapid improvement in the early epochs, plateauing at around 98-99% by epoch 20, demonstrating the model's high classification effectiveness. Figure 6 presents the multi-class ROC curve, showcasing the model's capacity to distinguish between various leaf disease classes. Each curve corresponds to a specific class, with AUC values close to 1 indicating excellent performance for most classes. Together, these results highlight the EfficientNetB3 model's strong overall performance in leaf disease classification.

### 4.2 Out-of-Distribution Detection

The OOD detection mechanism successfully identified leaf images from unknown diseases with high confidence, reducing the likelihood of misclassification. This feature is essential for deploying the model in environments where new diseases may emerge, as it alerts users to potential novel threats. A sample image (fig 7) is given below depicting the successful OOD detection using Continual Learning mechanisms.

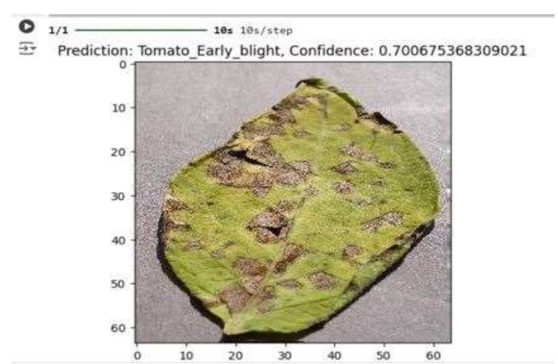


*Fig 7: Sample Output Image With Prediction Details*

### 4.3 Confusion Matrix

A confusion matrix (fig 8) was developed to visualize the performance of model across the 15 classes. The model showed high precision and recall values for most disease classes, with only minor misclassifications between similar diseases.

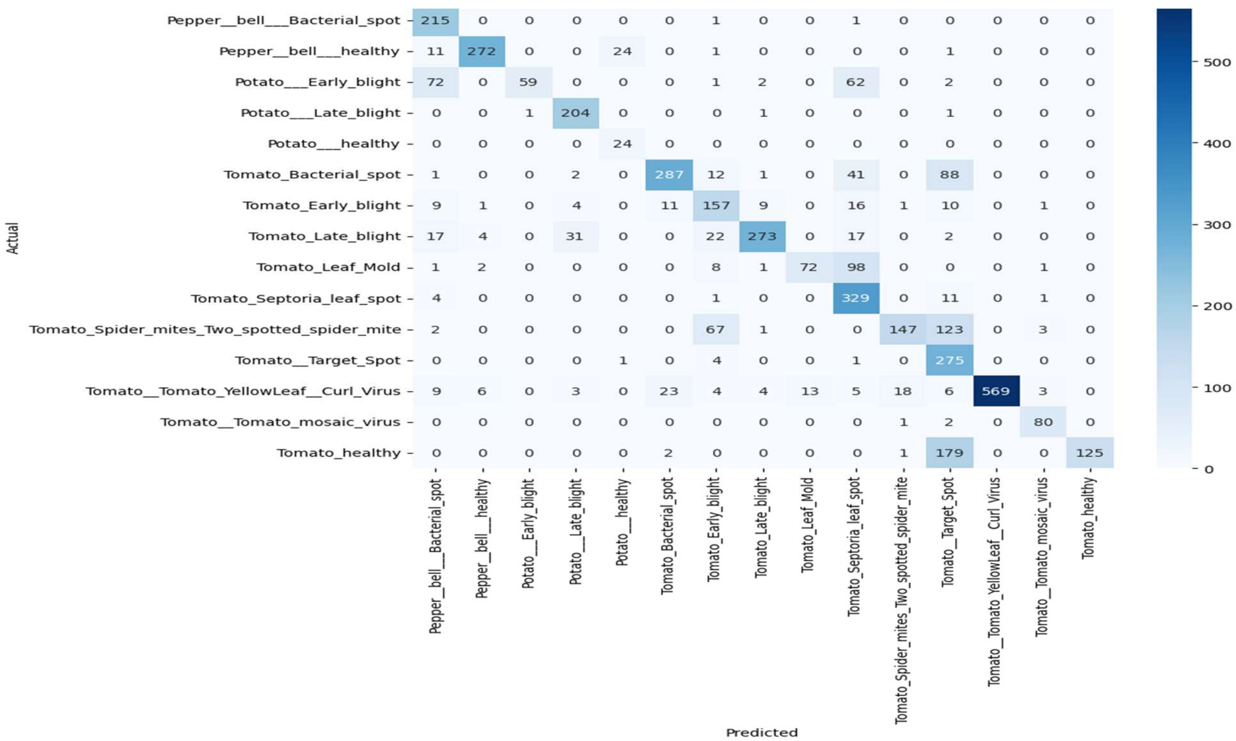


*Fig 8: Confusion Matrix Of The Proposed Method*

Here, the vertical axis which is marked as Actual represents the true labels (ground truth) for the data. And the horizontal axis which is marked as Predicted represents the labels predicted by the model.

Each cell of the confusion matrix depicts the count of samples classified in a particular way. The off-diagonal values indicate misclassifications (false positives or false negatives), whereas the diagonal values show accurate predictions (true positives). Also the heatmap uses color intensity to visualize the magnitude of the counts. Darker shades represent higher counts, helping to identify patterns easily.

### 4.4 Loss and Accuracy Curves

The model's accuracy and loss curves over the training epochs indicate smooth convergence, with a significant reduction in validation loss and consistent improvement in accuracy, proving that the model can effectively generalize to new/unseen data. This is given in fig 9.

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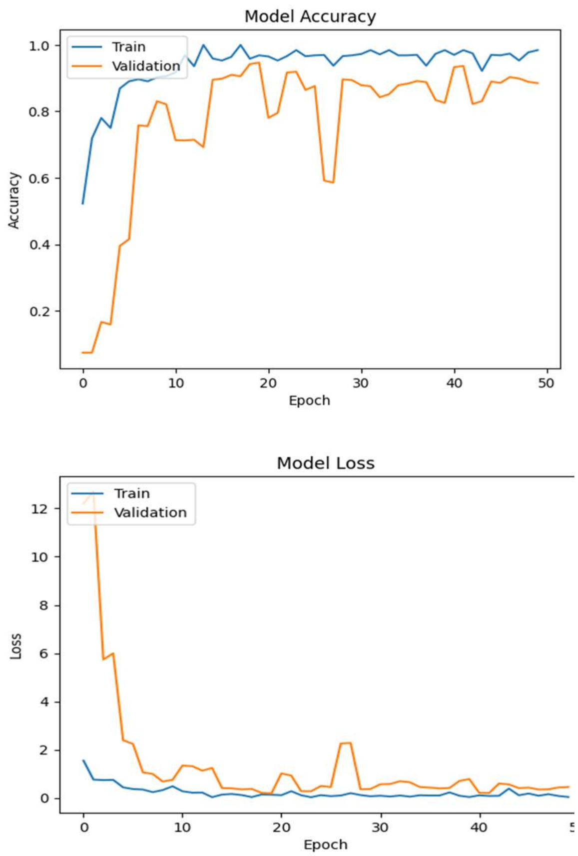


*Fig 9: Accuracy And Loss Of Proposed Model Over Training Epochs*

### 4.5 Discussion

This study demonstrates that incorporating continual learning strategies into EfficientNetB3 significantly enhances model adaptability compared to conventional static deep learning approaches. The proposed model outperforms established architectures such as InceptionV3, ResNet50, and MobileNetV2, achieving higher accuracy with lower validation loss. These results indicate that the integration of Replay Memory and Elastic Weight Consolidation effectively mitigates catastrophic forgetting while maintaining computational efficiency.

The successful detection of out-of-distribution samples further strengthens the model's suitability for real world agricultural deployment, where new disease patterns may emerge. However, the use of publicly available datasets limits exposure to complex field conditions such as background noise and lighting variations. Future work may focus on real-field data integration and improved memory selection mechanisms to enhance long-term generalization. Overall, the findings contribute a scalable and adaptive solution that advances current leaf disease detection frameworks.

## 5. CONCLUSION

This research introduce a robust and efficient model for leaf disease identification using EfficientNetB3 and continual learning strategies. The integration of Elastic Weight Consolidation and Replay Memory permits the model to adapt to new tasks without catastrophic forgetting, making it suitable for real-time agricultural applications. Additionally, the Out-of-Distribution detection mechanism enhances the model's reliability by identifying novel diseases. Future work will explore the scalability of the model to larger datasets and additional disease classes, as well as its deployment in real-world environments.

## AUTHOR CONTRIBUTIONS

Sreya John: Conceptualization, Methodology, Formal analysis and investigation, Writing – original draft.

P. J. Arul Leena Rose: Conceptualization, Validation, Writing – review & editing, Supervision.

## CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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