Effective Classification of Plant Diseases Using Blend Unity Resqueeze With ResNet Model

*1S.Reena

Research Scholar, Department of Computer applications, Madurai kamaraj university, Madurai, India.

2Dr.R.Rathinasabapathy

Associate professor Department of computer applications, Madurai kamaraj university, Madurai, India.

***1Corresponding Author Mail ID**: reenarajmca@gmail.com

2Co Author: saba.dca@mkuniversity.ac.in

Abstract:

Agricultural is the primary source of essential provisions almost all nation and remains as a vital survival tool for human race for past, present and future. Agriculture, the bedrock of civilizations, is frequently affected by devastating plant diseases leading to the loss of economy and food shortage. The manual testing requires high expertise, time and often leads to human error. Recent advancements in computer vision and AI models have highlighted the potential for building automatic plant disease detection models based on visible signs using image classification tasks. However, the task becomes complex and erroneous due to the complex nature of data. Consequently, Deep Learning (DL) models tend to outperform others traditional methods through utilizing network topology with convolution layers in core. Projected system uses high quality Cotton Disease dataset sourced by Kaggle and provide a suitable solution to the aforementioned problem using advanced DL neural network namely Blend Unity Resqueeze Resnet approach. It yields high accuracy with modification including Resqueeze layer and blend unity weights applied to do the tedious job of diagnosing plant diseases on image based classification. In the blend unity Resqueeze, the element shows a better feature extraction method using multiple convolution layers, and by including a squeeze-and-excitation method to include dynamic importance to those features based on their relevance to the classification task. The proposed research outperforms the conventional methods achieving better accuracy of 92% with better precision and reliability. The outcome of the respective research is analyzed with suitable metrics and compared with the recent developed conventional algorithms in which the proposed model proves to be a better suited for the efficient plant disease classification. Hence, the proposed method is intended to contribute in the plant disease classification and assist the agriculturists significantly to prevent the losses due to crop diseases.

Keywords: Crop disease, Artificial Intelligence, Cotton Disease, Deep learning, Cotton Rust, Blend Unity Resqueeze Resnet.

I. Introduction

Agriculture is a fundamental sector that significantly contributes to the domestic revenue for numerous nations, as well as for India. Crop damage is a significant issue worldwide, making it crucial to detect signs of disease factors as early as possible. Plant diseases and pests are known to be the primary causes of such damage. Various manual techniques, including physical examination, microscopic analysis, spectral analysis, and others, is used to identify features associated with plant diseases. One of the major challenges in farming is diseases that occur in plant, which may expressively decrease both quantity and quality of crop production, leading to economic losses. Hence, the detection and classification of crop diseases are important. Signs of crop disease can occur on various parts of a crop, but leaf is the commonly used for disease detection [1]. In reality, around 60% of the people are involved in certain arrangement of farming, either by direct or indirect. Besides, the one of the important factor which influences the success of agricultural cultivated in fields is the prior identification, classification and severity assessment of crop leaf disease [2].The traditional methods employed by farmers for predicting and identifying plant leaf diseases are often tedious and prone to error. Manual attempts to predict disease types can lead to misinterpretation. The failure to swiftly detect and categorize crop disease can lead to the mass destruction of crop plants, resulting in a substantial reduction in yield [3]. In simpler terms, researchers are using DL and computer techniques to automate the detection of crop disease from digital images of crop leaves. The use of DL in agriculture has revolutionized to identify diseases in plant leaves, making it an essential tool for diagnosing and controlling plant diseases. Since DL became a part of artificial intelligence, a lot of research has been done on image classification. As the technology has evolved, identifying plant diseases has become an important area of interest in agriculture, building on the basics of image classification. However, traditional systems often underperform in the important areas like accuracy, precision, and sensitivity [4]. To leverage the power of DL and computer vision techniques, several studies are examined to automate the process of detecting plant diseases from images of plant leaves. The innovative application of DL in the agricultural sector has transformed the way to diagnose and manage plant diseases, making it a crucial tool in the fight against plant diseases. However, traditional systems often fall short in critical areas such as accuracy, precision, and sensitivity. DL models, with their ability to learn and adapt, have proven to be more effective and reliable. In conclusion, the integration of DL and computer vision techniques in agriculture has revolutionized the way to identify and manage plant diseases, making it an indispensable tool in modern agriculture [5].

The advancement of smart farming has led to the digitalization and data-driven identification [6] of plant diseases, which facilitates sophisticated decision-making, analysis and planning. Identifying and safeguarding crops against diseases is time consuming and requires a lot of labor, thus making it impossible for humans to examine every plant2. As such, there has been research on integrating and using new technology to efciently identify disease, and now, research on identifying plant disease in leaves by using artifcial intelligence (AI) is ongoing3. Ongoing development of better classifcation models, like disease detection, or plant health monitoring, could make AI-assisted decision-making systems for smart agriculture4 feasible. Numerous studies have been conducted to implement deep learning algorithms more accurately for disease detection, like implementing newly established architectures5,6, automatic detection and classifcation of lesions in plant images7, or researching preprocessing techniques for incomplete images8 for real-world applications [7]. Traditional detection methods, while still prevalent, often require significant effort and are prone to errors, highlighting the urgent need for more efficient, scalable, and immediate solutions. Another conventional research utilizes a comprehensive dataset of nearly 87,000 RGB leaf images of various crops. These images cover 38 unique classes, including both healthy and diseased specimens. For effective model development and evaluation, the data is divided into training and validation subsets, with an 80/20 split. The existing study primarily focuses on Convolutional Neural Network (CNN) and MobileNet architectures for the early and accurate detection of plant diseases. It also incorporates eXplainable Artificial Intelligence (XAI) with GradCAM. Upon thorough testing, the CNN model achieved an accuracy of 89%. The MobileNet model also performed better in comparison to the CNN model, yet it needs to improve the accuracy further to be useful in the field [8].

Recent progress in DL methodologies has yielded encouraging results across a range of AI applications which leads to the AI implementation in detecting diseases in citrus fruits and leaves. In this traditional research, a CNN was trained and tested using a total of 2293 digital images from citrus dataset [9] to categorize healthy leaves and fruits and the ones which are infected by citrus diseases such as melanose, scab, black spot, canker and greening. The CNN model demonstrated superior test accuracy, making the conventional system a valuable tool for farmers to classify diseases in citrus fruits and leaves [10] in the future. A conventional automated system utilizes DL and optimal feature selection [11] for the classification [12]. The experiments are conducted on a publicly accessible dataset. The employed dataset includes six different disease classes, each with 150-200 images, which are expanded to 2000 [13]. In an existing process, required data are derived from the images and further refined using the Entropy-ELM system. In the subsequent steps, the features from multiple systems are combined, and the Entropy-ELM system[14] is applied again, before being fused with the selected feature from first phase. Ultimately, these combined features are processed using ML system for the ultimate categorization. The system achieved the highest accuracy on these datasets [15].

The projected research aims to address existing limitations and enhance the classification of subjects into diseased and normal cotton plants using DL technology which is accomplished by implementing Blend Unity Resqueeze with Resnet Model for multiclass classification. The experiment leverages a Cotton Disease Dataset, comprising of high-resolution images of cotton plants. The data undergoes preprocessing to improve its usability, reduce noise, and prepare it for classification. The data is partitioned in 80:20 ratios for training and testing phases. The proposed method utilizes Blend Unity and Resqueeze technologies to tackle performance issues commonly found in conventional methods. The dataset is preprocessed to balance any missing data and extract features more efficiently, thereby boosting performance. Blend Unity is integrated into the Conv layer to provide initial biases to the model, enhancing prediction accuracy that usually necessitates additional training. Blend Unity is an enhanced technique that improves feature representation and then it attains this using initial biases, which is given to convolutional layers, employing multi-scale channel weight fusion, and refining the model's ability to capture contextual data. However, Blend Unity decreases computational intricacy, improves feature retaining, and allows more effectual learning of multi-scale feature.The proposed ResNet-50 model processes images and retains long-range memory through the use of resqueeze, allowing for a wide range of inputs for training within a shorter time frame. Once the images are loaded, the layers in the ResNet-50 architecture uses normalization process, accelerating the training process and improving data compatibility. This normalization is mathematical formula, which is used to enhance the performance of the feature extraction. The efficacy of the research is validated using performance metrics such as f1-score, precision, accuracy, and recall. Through regression analyses, significant metrics for assessing the performance error of the presented method are calculated and analyzed.

The key contributions of the proposed system is to classify diseased and normal cotton plants with improved accuracy and precision using the Blend Unity Resqueeze with ResNet model, which combines Blend Unity and Resqueeze to provide an advanced image processing function. This method will aim to outperform existing models such as MLP, CNN, and standard ResNet for cotton disease detection via multiclass classification. The proposed method will be rigorously tested using standard performance metrics to assess the efficiency of results in the study.

1.1 Paper Organization

The structure of the research is precisely designed to effectively represent the techniques utilized in classifying diseased and healthy cotton crops using image processing and DL approaches. Section II delves into an examination of earlier research in the same domain, employing a variety of methodologies. Next, the Section III introduces the methodology employed in the proposed system. The outcomes achieved by the respective model are detailed in Section IV. The final section, Section V, draws the conclusion and outlines the future work of the proposed method.

II. Literature Review

In the agricultural sector, the detection of leaf diseases is of paramount importance. However, the process requires significant labor, extensive preparation time, and in-depth knowledge of plant pathogens. The dataset utilized in the existing study is manually collected from center of research for citrus in Sargodha town. Images are taken using a DSLR camera at a high quality. The dataset comprises both healthy and infected citrus fruits and leaves. Researchers have developed and tested various ML and DL methods for plant disease detection. Many traditional methods have shown substantial results in the field of plant disease detection. Drawing inspiration from these existing works, the study evaluates the performance of ML systems such as SVM, RF, SGD, [16] for plant disease detection. The achieved accuracy through the experiments is quite remarkable, with DL methods surpassing the machine learning methods in disease detection. The results are SGD-86.5%, SVM-87% and RF-76.8%. The crop infection categorization is in high demand in agricultural sector. Numerous traditional systems have been put forward to address this task, with DL emerging as the recommended approach due to its exceptional performance. The study recently done utilizes the VGGNet, ImageNet and the Inception module. The traditional approach achieves an accuracy of at least 91.83%. In a conventional system DRNN is utilized for detection of disease in cassava. The dataset contains 5,656 images of leaves: 466 images of CBB, 1,443 images of CBSD, 773CGM, and 2,658 CMD [17].These images were collected from farmers who took pictures of unhealthy and healthy cassava plants. The existing DRNN system is used to strengthen the argumentation and significantly surpasses PCNN by a margin of 9.25%. With the cassava mosaic disease dataset. But the existing system still needs to improve in the overall performance and accuracy [18].

The evaluation of multiple CNN models had been conducted based on efficacy indicators. The selected DL systems have been trained utilizing PlantVillage dataset, including twenty six distinct diseases from fourteen respective crops. Keras, TensorFlow [19] have been utilized for training the DL architectures. An inference is noted that the Xception system can achieve better validation accuracy [20]. The existing system has been validated against a benchmark dataset of tomato leaf diseases, which comprises 5452 images of healthy and diseased leaves. The Optimal Mobile Network-Based CNN operates in various stages, including preprocessing, segmentation, feature extraction, and classification. The experimental results have demonstrated the superior accuracy of the traditional method over recent methods, indicating its promising potential [21]. Numerous diseases, such as angular leaf spot disease and bean rust disease, affect bean leaves and impede their production. To resolve the aforementioned issues at an early stage, accurate classification[22] of bean leaf diseases is crucial. An existing DL approach is suggests to identify and classify bean leaf diseases using TensorFlow and MobileNetV2. The earlier approach utilizes a public dataset of leaf images and the MobileNet model, along with the open-source library TensorFlow. The traditional model has been trained using a publicly accessible dataset and tested on 1296 bean leaf images. The same controlled conditions as MobileNet has been used to achieve faster training times, high accuracy and effortless retraining. The average classification accuracy of the conventional method surpasses that of other systems [23].

An existing system built with transfer learning has been suggested for detection of diseases from tomato leaves using 54,309 pictures of both normal and abnormal leaves from fourteen different crops, all labeled by experts in plant pathology [24]. The system employs a combined model that extracts features by a MobileNetV2 structure along with a classifier system for effective prediction. When evaluated with tomato leaf imageries from the PlantVillage dataset, the prevailing structure demonstrates superior accuracy [25]. Traditional methods such as visual inspection by expert and laboratory testing are commonly used by farmers to identify diseases that occur in plant. However, DL methods have recently proven to be effective tools for diagnosing diseases in olive leaves and various other areas. In similarly, a recent research used 5400 diverse images of olive leaves have been collected from the Al Jouf region, which is located in the Kingdom of Saudi Arabia. The existing research employed a DFC system to include extracted features against input images using dual improved pre-trained CNN models, namely, ResNet-50 and MobileNet. The traditional methods demonstrated superior accuracy compared to other technologies [26].

Tomato, being one of the most vital and widely consumed crops globally, has its yield quantity significantly influenced by the way it is composted. Moreover, disease which occurred in leaf is a primary factor that affects the quantity and quality of the crop yield. Therefore, accurate diagnosis [27] and classification of these diseases are crucial. Various diseases impact tomato production and early detection of these diseases can mitigate their effects on tomato plants, leading to improved crop yield. The dataset used in the existing study comprises three thousand images of tomato leaves, affected by nine different diseases, along with images of healthy leaves. The aim of conventional work is to assist farmers in accurately identifying diseases at an early stage and educating them about these diseases. A CNN is employed for effective identification and classification of tomato diseases. The results indicate that the predictions made by the existing model are highly accurate [28]. Rice leaf infections, including Brown Spot Disease, Bacterial Leaf Bligh, and Blast Disease are common and significantly impact paddy leaf health. Early and accurate detection of these diseases can substantially decrease crop failure and prevent farmers' losses. An automated classification approach using DL CNN [29] models has been found to provide the best results for rice leaf infection detection. The previous approach offers higher accuracy compared to the traditional, time-consuming manual disease identification methods in which the accuracy is unstable. A number of existing models, namely Xception, VGG-19, ResNet-101, and Inception-Resnet-V2 has been analysed, with the Inception-ResNet-V2 model yielding suitable accuracy. However the system needs improvement in other important aspects like speed, reliability, flexibility and precision [30].

2.1 Problem Identification

The accuracy metric is essential for determining the performance of the model. Several traditional studies attempted to achieve effective classification of normal and diseased plant, but the accuracy metric was absent [16, 17] . In these previous works there was difficulty for the network to learn from earlier layers due to vanishing gradients leading to slow or non-optimal performance. Earlier works also failed to achieve other important metrics such as flexibility, precision, recall and overall reliability in the disease detection [22, 27] .

III. Proposed Methodology

However, these traditional methods are often error-prone, time-consuming, and labor-intensive. To provide a solution to aforementioned issue, AI methods are now utilized for precise identification and categorization of crop diseases, making the detection process more efficient and functional for agriculturists. DL methods proved to be effective in the classification based on image dataset with better accuracy than other existing approaches. Moreover, Blend Unity Resqueeze approach presents a substantial enhancement over standard Squeeze-and-Excitation techniques by providing more flexible channel weight assignments, which allow for a more granular representation of the feature at varying scales. This greater flexibility increases the model efficiency to attend to relevant features that reduce computational burden, all with no loss of accuracy. In addition, increased multi-scale feature learning allows the model to collect more information from the input data. Overall, these improvements combine to create a more powerful feature extraction mechanism that is vital for challenging tasks, such as plant disease classification.The proposed study utilizes ResNet system, which is better known for its object detection performance. Integrated with blend unity Resqueeze, the projected model performs effective and precise crop disease classification. The overall mechanism is depicted in Figure.1.

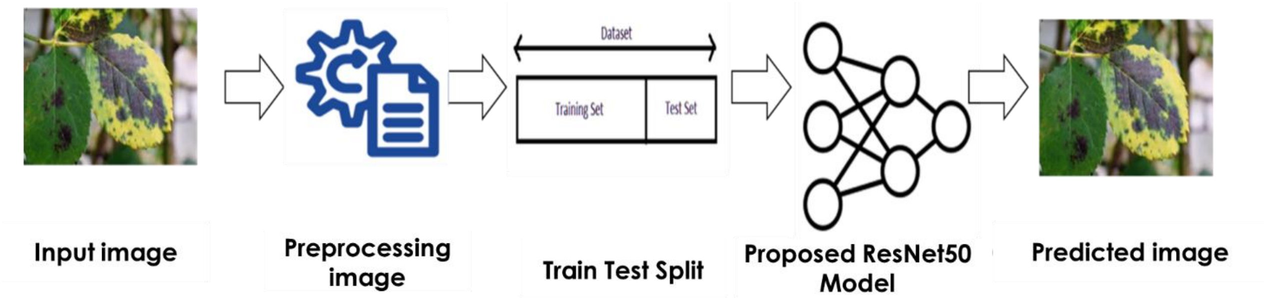

Figure 1. Overall Flow of the Proposed Model

Figure.1 depicts the overall proposed plant disease identification workflow for cotton leaves begins by loading an input image, followed by crucial pre-processing steps to standardize and enhance the image data. This prepared data is then split into training and testing sets to facilitate model learning and evaluation. The core of the system is a proposed deep learning architecture, ResNet 50, potentially enhanced with a Blend Unity Resqueeze mechanism for improved feature extraction. After training, the model analyzes new input images, and the final output is the predicted disease affecting the cotton leaf or not. This process aims for accurate and automated disease identification to aid in timely agricultural interventions.

3.1 Pre-Processing

Pre-processing primarily serves to enhance the model's precision and dependability by eliminating inconsistent and noisy data from the images.

- Image pre-processing is a key step in enhancing the accuracy and dependability of a model by removing inconsistent and noisy data from images.
- Image resizing is involved to modify the dimensions of an image by adjusting the pixel count, while maintaining the image's aspect ratio.
- Image normalization method, is the process to scale pixel values towards a definite range, frequently among 0 and 1/ -1 and 1, to confirm reliable intensity values with improved model training efficiency.
- Feature Extraction is aimed at reducing data complexity by selecting the most relevant features required for the model. Such techniques are employed for identifying and extracting pertinent features from raw data, thereby enhancing the model's performance.
- Contour processing methods are utilized in shape detection, object detection, measuring the dimensions of the objects. The contour image facilitates clear recognition of disease characteristics on the cotton leaf.
- The image pre-processing steps included resizing images to a consistent dimension of 224x224 pixels, normalizing pixel values to a range of [0, 1] for improved training efficiency, and employing contour detection to identify disease-specific features on cotton leaves, thereby aiding in the classification process. It is employed OpenCV library for essential pre-processing tasks such as resizing, normalization, and contour detection, while PIL enabled image manipulation and enhancement. NumPy facilitated efficient numerical and array operations, and Matplotlib, along with Seaborn, is used for visualizing training metrics and generating informative statistical graphics like confusion matrices

3.2 Traditional ResNet Model

ResNet stands for Residual Networks; it is a cutting-edge variant of Convolutional Neural Networks (CNNs). Specifically, ResNet-50 is an improved model of CNN composed of 50 layers, consisting of 48 convolutional layers, one MaxPool layer, and an average pool layer. A distinctive feature of ResNet is the introduction of the residual unit with identity mapping which allows deeper layers to learn directly from the shallower ones, enhancing the network's convergence and learning capacity. The training of these neural networks required million parameters.

ResNet-50 is a deep convolutional neural network architecture comprising 50 layers, including 48 convolutional layers, one MaxPooling layer, and one Average Pooling layer. It is built around the concept of residual blocks, which use shortcut (skip) connections to enable the network to learn residual functions, effectively addressing the vanishing gradient problem and allowing for much deeper architectures. Here, the bottleneck Residual block is used to minimize the computational load when having the greater accuracy through the shortcut connection, which permits gradients to move effectually in training phase. In this proposed model deeper networks are used to mitigate vanishing gradient issues and enable ResNet-50 to learn difficult features without raise in computational cost. The model is typically trained using the Adam optimizer with an initial learning rate of 0.001, which is decayed over time, and a batch size of 32. Training is conducted over 20 epochs. To prevent overfitting, a dropout rate of 0.5 is applied, and batch normalization is used after convolutional layers to stabilize and accelerate the learning process. For multi-class classification tasks, categorical crossentropy is employed as the loss function. This combination of architectural depth, residual learning, and robust regularization techniques makes ResNet-50 a powerful model for plant leaf disease identification. The table 1 depicts the hyper parameter details

Table 1. Hyper parameter details

Parameters	Value
No. of Layers	50 layers (48 Convolutional layer * 1Maxpooling layer*1 Avg pooling layer)
Optimizer	Adam
Batch size	32
Epochs	20
Dropout rate	0.5
Loss function	Categorical Crossentropy

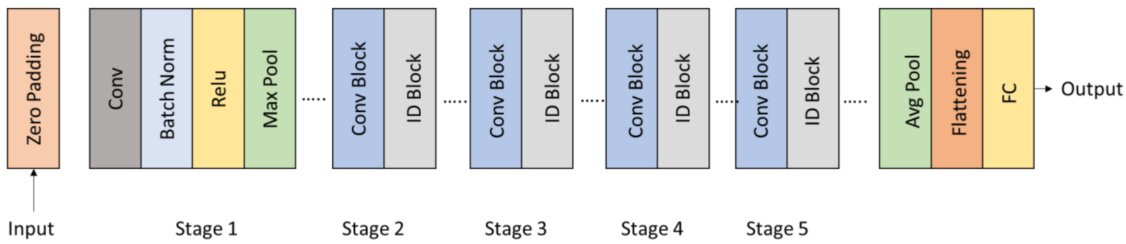

Figure 2. Mechanism of Classification Using Conventional ResNet Model

Figure 2. Illustrates the ResNet-50 which starts with an input image, applies zero padding to preserve spatial dimensions, and applies a convolutional layer. Next is the Batch Normalization to normalize the inputs, and a Rectified Linear Unit (ReLU) activation function. Max Pooling is used to reduce dimensionality, and is followed by a series of Convolutional Blocks and Identity Blocks. After these blocks, average pooling is applied, followed by Flattening to convert the 2D arrays into a single vector. A FC layer connects every neuron in one layer to every neuron in another layer. The final output layer provides the probabilities for each class for multi-class classification problems.

The Bottleneck Residual Block, utilized in ResNet-50, is composed of three convolutional layers. Each of these layers continues to normalization in batch method and ReLU activation. The initial convolutional layer typically employs a 1x1 filter size, which decreases the counts of channels in the input data. The subsequent convolutional layer possibly uses a 3x3 filter size to derive spatial features from the data. The final convolutional layer reverts to a 1x1 filter size to reinstate the original number of channels before the output is combined with the shortcut connection. By strategically incorporating bottleneck residual blocks and shortcut connections, ResNet-50 effectively tackles the vanishing gradient problem. This approach is enhanced the weight and feature extraction and facilitating the development of more sophisticated and powerful image classification models.

3.3 Classification – Proposed Blend Unity Resqueeze With ResNet Model

The proposed model employs ResNet-50 in conjunction with a blend unity resqueeze technique to enhance the efficiency of classification process. Moreover, the term “Blend Unity Resqueeze” is defined as the recent method in feature extraction processes that relies on Blend Unity and Resqueeze. Blend Unity integrates multi-scale channel weight fusion by performing element-wise summation of the channel weights, which facilitates thorough multi-scale feature representation and gives initial biases to the model. Also, Resqueeze concentrates on adaptive feature recalibration which reduces computation effort while improving feature retention. This includes the use of global average pooling, the gating mechanism with a sigmoid function, and a non-linear feature transforming the feature’s reflexive property. All these components construct a durable structure for feature extraction and improve the efficiency of models in different tasks like plant disease classification. The projected system is designed to efficiently minimize the mathematical complications and network parameters, without compromising the efficacy of intended classification. The intensity of a ResNet can enhance the image classification challenge due to the significant number of layers and compatibility to millions of parameters to train the neural networks. Figure.3 shows the mechanism involved in the classification of cotton disease identification.

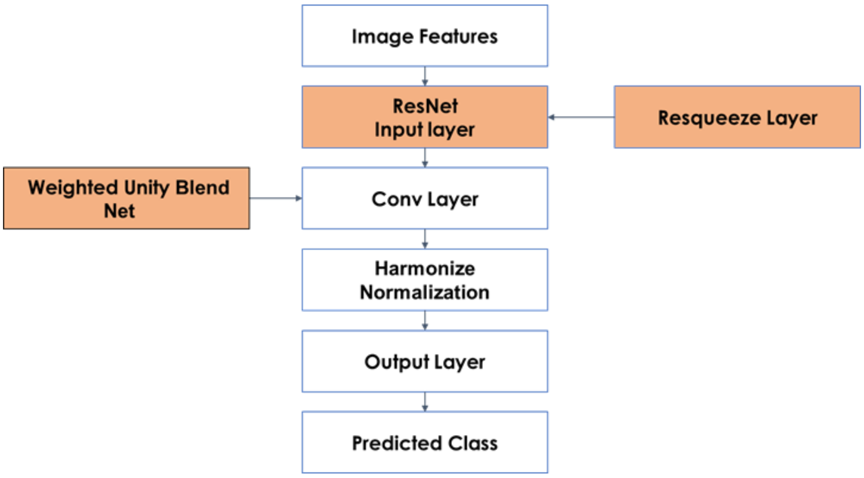

Figure 3. Overall Mechanism of Blend Unity Resqueeze with ResNet Model

Figure 3 represents the Blend Unity Resqueeze ResNet model is trained with multiclass dataset. The classes consists (Diseased Leaf) DL, (Disease Plant) DP, (Fresh Leaf) FL and (Fresh Plant) FP, by category. Pre-processing in the proposed ResNet-50 model helps in feature enhancement by explicitly modelling channel interdependencies leading to increased sensitivity to informative features. Further, incorporation of blend unity module in Conv Layer helps, not only in terms of capturing the long term dependencies between the different channels of network but also helps in retaining the specific location information with the aim to enhance the accuracy of classification of Cotton disease.

ResNet-50 primarily solves the issue of performance deterioration in deep neural networks. As the networks increase in depth, it tends to reach a peak in accuracy, after which the accuracy swiftly declines. The decline is not a result of overfitting, but rather stems from the complexities involved in optimizing the training process. ResNet-50 tackles this issue by employing Residual Blocks, which facilitate a direct information flow via skip connections, thereby alleviating the problem of vanishing gradients.

Resqueeze: It plays a vital role in improving the model by reducing the dimensionality of the feature maps without losing critical information. A lower dimensionality can enable better computational efficiency as well as a smaller model size suitable for deployment in restricted environments. This layer used to calculate lightweight feature which ensuring overall more efficient training results with CNN architectures. A Squeeze-and-Excitation block is a computational component that can be constructed on top of a transformation, denoted as F_{tr}. The transformation maps an input o, which belongs to the space $o \in \mathbb{R}^{b' \times y' \times c'}$ to feature maps that belong to the space $o \in \mathbb{R}^{b \times y \times c}$. In the subsequent notation, it is considered F_{tr} as a convolutional operator and use $V = [v_1, v_2 \dots . v_C]$ to represent the trained filter kernels. Here, v_c refers to the parameter of the c^{th}filter. The result can be given as $U = [u_1, u_2 \dots . u_C]$, where each u_c corresponds to the output of the c^{th}filter.

$$u_c = v_c * o = \sum_{s=1}^{C'} v_c^s * o^s \quad (1)$$

The term v_c^s represents a 2D kernel that corresponds to a solo channel of v_c and operates on the matching channel of o. To make the notation simpler, bias terms are left out. The output is generated by summing across all channels, which means that channel dependencies are inherently included in v_c. However, these dependencies are intertwined with the local spatial correlation that the filters capture.

Each learned filter functions with a receptive field of local, which means that every unit of the transformation result U cannot utilize contextual data beyond the space. To address the issue, it is suggested that condensing global position data into a channel descriptor which is accomplished through employing global average pooling to produce statistics channel-wise. In formal terms, $z \in R^C$is created by reducing U through its dimension$b \times y$; the c^{th}element of z is computed in the expression (2),

$$z_c = F_{sq}(U_c) = \frac{1}{b \times W} \sum_{i=1}^{b} \sum_{j=1}^{y} u_c\,(i, j) \tag{2}$$

A straightforward gating mechanism that utilizes a sigmoid activation function is integrated into the model which enhances the model's flexibility and allows for non-mutually-exclusive relationships, as it enables the model to assign significance to multiple channels simultaneously.

$$s = F_{ex}(z, y) = \sigma\big(g(z, y)\big) = \sigma(y_2 \delta(y_1 z)) \tag{3}$$

Where, δ refers to the ReLU function, $y_1 \in R^{\frac{C}{r} \times C}$ and $y_2 \in R^{C \times \frac{C}{r}}$.

The final result of the block is achieved by adjusting U using the activations s, as per the given expression.

$$\widetilde{x_c} = F_{scale}(U_c, s_c) = U_c, s_c \tag{4}$$

The excitation operator transforms the input-specific descriptor, z, into a series of channel weights. Similarly, SE blocks inherently incorporate dynamics that are conditioned on the input which can be viewed as a self-attention function on channels, where the relationships are not limited to the local receptive field.

The Blend Unity Resqueeze with ResNet model decreases the convolution kernels in comparison to conventional models, leading to a reduction in computational complexity. The critical aspects in Resqueeze is to balancing squeeze and expand layer ratios for computational efficiency and classification accuracy. A lower squeeze ratio (SR) reduces parameters and FLOPs by compressing input channels but risks creating bottlenecks that degrade feature representation. Conversely, higher SR preserves richer spatial information at the cost of increased computational demands. Integrating mechanisms like squeeze-excitation (SE) blocks dynamically prioritizes critical channels, enhancing discriminative power without altering layer ratios, while bypass connections mitigate information loss from aggressive compression. Overall, the proposed model is yielding improved plant disease identification in terms of performance. The proportion of convolution kernels in the expanded layer to the total convolution kernels acts as a hyper-parameter, signifying the balance between the model's efficiency and complexity.

Blend Unity: Blend Unity employs an additive fusion method to obtain channel weights, which involves the element-wise summation of channel weights across two feature scales. These weights are then multiplied with the input features in accordance with their respective channels, enabling multi-scale channel recalibration. After several iterations, the model utilizes average pooling to further diminish spatial dimensions and converts the 2D feature maps into a 1D vector. This vector is then processed through FC layers, enabling the model to recognize global patterns within the data. Finally, the model generates its predictions in the output layer. Moreover, it provides a more fine-grained integration approach that captures the contributions of all channels that can improve a model's ability to detect fine differences in the data. The approach of maximum fusion can lead to outperforming traditional lightweight feature fusion channel weights from stronger features, which can overshadow critical information in less powerful channels. Gaining a deeper understanding of these differences could further enhance our understanding of the overall strength and clinical application of DL in channels of recalibrating the input weights.

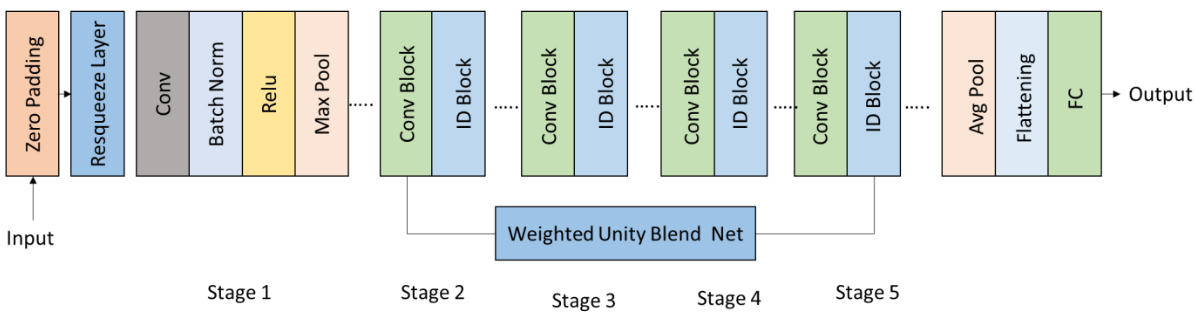

Figure 4. Mechanism of Blend Unity Resqueeze With ResNet Model

Figure 4 illustrates a modified CNN that integrates elements from both ResNet and Resqueeze models. The process begins with an input image that undergoes zero padding to maintain spatial dimensions during the convolution process. A Resqueeze layer, a type of CNN designed for efficiency and compactness is applied. The model proceeds through a series of convolution blocks, ReLU activation functions and batch normalization to extract features and introduce non-linearity. The ReLU activation function is commonly used in plant disease prediction models, particularly in CNNs. It works by outputting zero for any negative input and passing positive values as they are, which introduces nonlinearity into the model and helps it learn complex patterns in plant images. This property allows the network to focus on important features related to disease symptoms, improving the accuracy and efficiency of disease classification. Additionally, ReLU is computationally simple and speeds up the training process, making it highly suitable for large-scale and real-time plant disease detection applications. It helps model train faster by avoiding the vanishing gradient problem, hence speed up convergence make it a preferred choice for activation function. Following that, Max pooling is used to reduce the spatial dimensions. Proposed system alternates between convolution blocks and ID blocks which allow the input to skip one or more layers, mitigating the vanishing gradient problem. Weights are added to the model to include initial biases. These biases can help increase the accuracy of the model and decrease the training time by providing a starting point for the optimization process, which can help the model converge swiftly.

In contrast to additive fusion, maximum fusion chooses the highest weight value under each scale as the channel's weight. When dealing with double scale features, splicing fusion, based on a specific coordinate axis the weights of the channels at every scale concatenates initially. The result is then mapped to the ultimate weight of the channel via layers. The size of the channel weight is given as $N \times C \times 1 \times 1$, where N is the batch image dimension and C represents the channels count of input feature. The specific implementations of splicing fusion are categorized into dual types, depending on the choice of the splicing axis coordinating.

In the additive fusion method, channel weights are derived through an element-wise summation of channel weights across dual feature scales. The weights are applied to the input features in sequence of the respective channels, facilitating recalibration of channels across multiple scales. After a number of iterations, the model employs average pooling to further decrease the spatial dimensions and converts the 2D feature maps into a 1D vector. The vector is then processed by FC layers, which allows the model to identify global patterns within the data. The final predictions are generated in the output layer. Finally, the integration of advanced module such as Blend Unity Resqueeze with ResNet 50 enhances crop disease classification by refining feature extraction and recalibration. These modifications introduce spatial/channel attention to prioritize disease-specific regions, blend multi-scale features for improved generalization, and optimize computational efficiency through depthwise convolutions. Moreover, the enhanced model achieves high accuracy, reduced parameter counts, and real-world adaptability, making it effective for deployment in resource-constrained agricultural environments. Hence, the incorporation of computer vision and DL greatly improves plant disease identification and management in agriculture. Using ANN, the proposed results uses automated analysis of visual information, with a success rate of 92% versus conventional approaches that only get to 76.8.

IV. Results and Discussion

The following section will delve into the details of dataset characterization, evaluation metrics, exploratory data analysis, performance analysis, and comparative analysis utilized for assessing the effectiveness of the model.

4.1. Dataset Description

The respective model employs the Cotton Disease Dataset for multiclass classification between diseased and healthy plants. The dataset is sourced from Kaggle, a prominent online platform for data science and DL research. Kaggle serves as a hub for users to discover datasets for their AI model development needs. Essentially, the dataset is divided into training, testing, and validation sets, with a total of 2310 image samples. These samples are further categorized into four groups: Diseased cotton Leaf, Fresh cotton leaf, Diseased cotton Plant, and Fresh cotton Plant (FP). The training set comprises 1951 cotton crop images, while the remaining 359 images are for testing and validation. Key characteristics of the dataset are outlined in Table 2 and Table 3

Table 2. Significant Features of the Training Dataset

S. no	Features	Feature percentage %
1.	DL	14.77
2.	DP	41.77
3.	FL	21.88
4.	FP	21.58

Table 3. Significant Features of the Validation Dataset

S. no	Features	Feature percentage %
1.	DL	16.97
2.	DP	31.17
3.	FL	24.70
4.	FP	27.16

The utilized dataset is licensed with creative commons attribution 4.0 international. The dataset is acquired from the following link:

https://www.kaggle.com/datasets/janmejaybhoi/cotton-disease-dataset/data

4.2 Performance Metrics

The metrics used for evaluating the system's performance are precision, accuracy, f1-score and recall.

1. **Precision**: The metric signifies the count of accurate positive predictions. Precision is calculated by taking the ratio of true positives to the total number of positive predictions, and it is expressed as a percentage and it is expressed by equation (5),

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

Where, TP, FP are True Positive and False Positive.

2. **Recall:** It is utilized to measure the number of actual positives that were predicted incorrectly in the system. Often referred to as sensitivity or specificity, it is typically represented as a percentage and it provided in equation (6),

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{6}$$

Where, TP, FN are True positive and False Negative.

3. **Accuracy:** It denotes the significant metric used to get the value of correct prediction of the proposed system to the total prediction. It is estimated by (7),

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{7}$$

Where TP, FN, FP, TN are True Positive, False Negative, False Positive and True Negative.

4. **F1-score:** It is employed to evaluate binary classification by focusing on positive class predictions. Essentially, it represents the average of recall and precision. It is calculated by (8),

$$\text{F1} - \text{Score} = 2 * \frac{\text{Recall}*\text{Precision}}{\text{Recall+Precision}} \tag{8}$$

4.3 EDA (Exploratory Data Analysis)

EDA is an important phase in the automated systems development projects as it involves examining and visualizing data to understand the relationships between variables, identify anomalies, and discover patterns in the proposed work. EDA provides valuable insights into the data for further analysis. Additionally, EDA assists in identifying missing values, outliers, and other defects. For instance, consider a set of images of a cotton plant affected by a disease. These images, which feature indications of the disease, can be used to automate its detection. The process underscores the importance of EDA in enhancing our understanding of the data and preparing it for subsequent analysis.

Figure 5. Diseased Cotton Leaf Images From Dataset

Figure 5 shows the diseased leaves from the selected dataset which is taken in resolution configuration for classification suitable for classification problems. The number of images in training set and validating set are 1951 and 324, respectively. The dataset comprises four unique categories of images such as healthy cotton leaves, healthy cotton plants, diseased cotton leaves, and diseased cotton plants. The categories are not evenly distributed, resulting in an imbalanced dataset. The four classes in the training dataset do not have roughly the same proportion. Each diseased image consists of prominent features indicating the presence of diseases which makes the data suitable to train and test the projected system. Also the data set shows more variation in the sizes, angle, shape and shades of the leaves contributing to the flexibility of the trained model. The following Figure.7 shows the Normal Image and Counters Image of Diseased Cotton Leaf. Moreover, in leaf shape identification, plant leaf contours are good indicators of species classification because they are morphological features associated with each plant species. Contour-based techniques also assist in the quantification of plant disease symptoms, such as fungal stromata in tar spots, by offering objective and precise measurements from RGB images. Contour detection is also very important in coping with intricate leaf shapes in natural backgrounds, where it assists in separating leaves from non-leaf regions by making use of geometric features and curvature analysis.

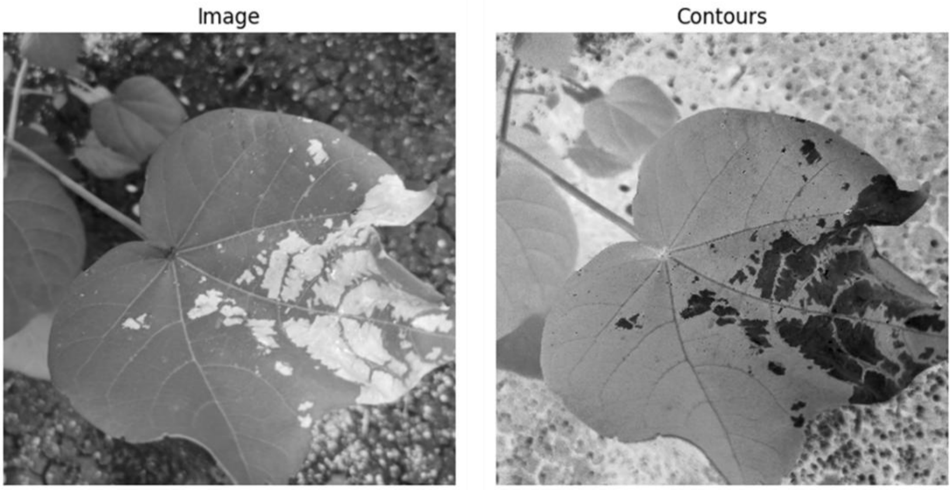

Figure 6. Normal Image and Contour Image of Diseased Cotton Leaf

Figure 6 shows contour processing in plant diseases analysis is important because the boundaries provided by contour processing can help localize features specific to disease and accurately identify areas of interest. Contour processing provides distinction in leaf texture, allowing the observer to determine the health status of the plant and provide clues regarding the predisposition of the plant to the disease. In the case of contour processing, it may potentially indicate areas of separation difficulty. Leaf structures related to the leaves in question cause overlaps in features that may impede accurate boundaries. Overall, contour processing is a tool to support in understanding plant diseases and to better classify leaf features. Images of the diseased cotton leaf with high and low thresholds are depicted in Figure.8.

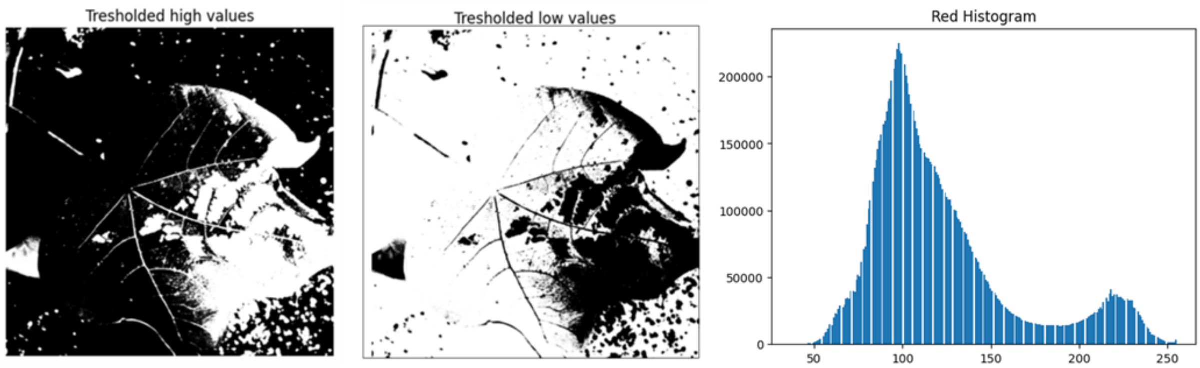

Figure 7. High Threshold, Low Threshold Images and Red Histogram of Diseased Cotton Leaf

Figure.8 represents the high and low threshold Images which involves in dividing the image data into two or more regions based on intensity levels, allowing for easy analysis and extraction of desired features. A low threshold makes the structures bigger and merges some together. A high threshold makes structures smaller. By setting a threshold value, pixels with intensities above or below the threshold images, it easier to analyse and extract relevant information and can be classified accordingly. The technique aids in tasks such as object detection, classification, and image enhancement. Moreover, by modifying threshold values an accurate distinction is done between healthy and diseased plants. Then, the red histogram is used for separating the colour intensity. Hence, the detailed analysis is done by demonstrating its importance in detecting the plant disease detection systems. Figure.8 also shows the spread of pixels from shadows on the left to highlights on the right. The peaks are higher concentrations of pixels, whereas the valleys indicate lower concentrations of pixels. Histogram picks red as the base in which highest peak is observed between 90 and 100 pixels. Hence an inference can be drawn by analysing the histogram of diseased cotton around the specified values.

4.4 Performance Analysis

Evaluating the effectiveness of the proposed framework is crucial, and is achieved by analyzing the systems performance. Various metrics are employed to gauge the value of the proposed work, including the F1 score, accuracy, recall, and precision. Confusion matrix for multiclass classification of Cotton disease using a modified and existing ResNet-50 is illustrated in Figure 9. Similarly, Figure 10 presents the training and validation loss of the proposed and existing models respectively.

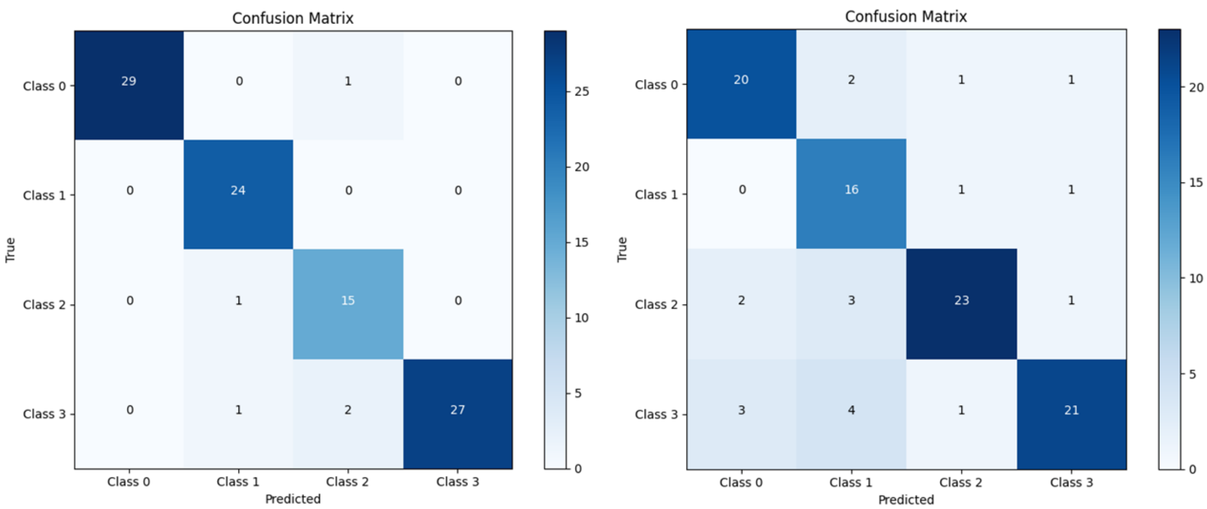

Figure 8. Confusion Matrix of Modified System and Existing System

Figure 8 depicts the confusion matrix for multiclass classification of proposed and conventional system with 4 rows and 4 columns, which indicates that the suggested model possess the ability to classify the correct and incorrect classes in better way. From the confusion matrix a clear improvement can be seen on the modified system when compared to the unmodified ResNet system on the right side. Similarly, Figure.10 represents the training and validation loss of the proposed and existing models respectively.

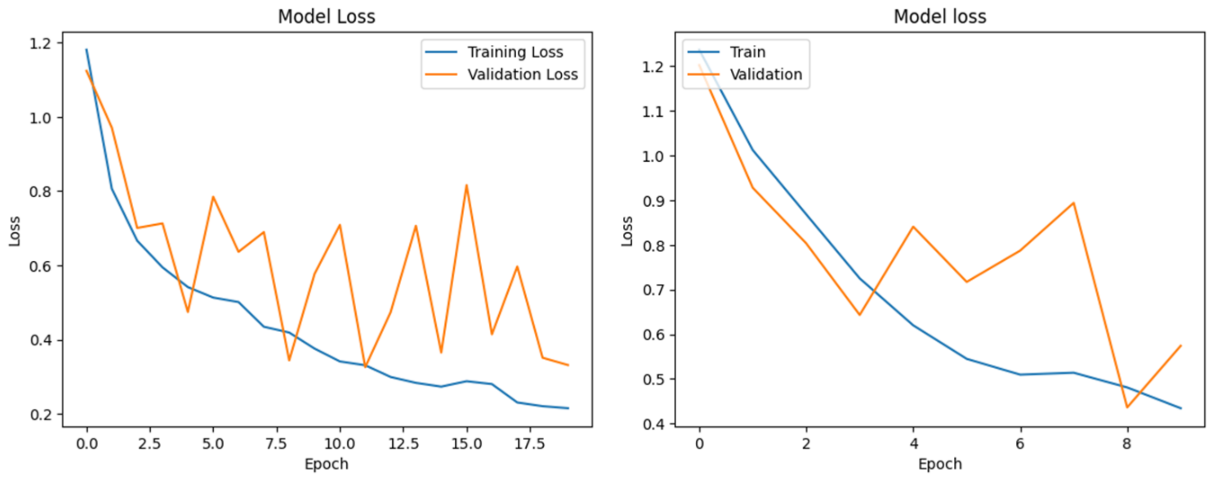

Figure 9. Model Loss of Modified System and Existing System

Figure 9 depicts the model loss of the projected work and the existing method. The training loss should be close to the validation loss. When the training loss is pointedly lower than the validation loss, it typically demonstrates that model is overfitted. However, in proposed model training loss is close to the validation loss, thereby preventing the overfitting of the model. Likewise, training accuracy and validation accuracy is depicted in Figure.11.

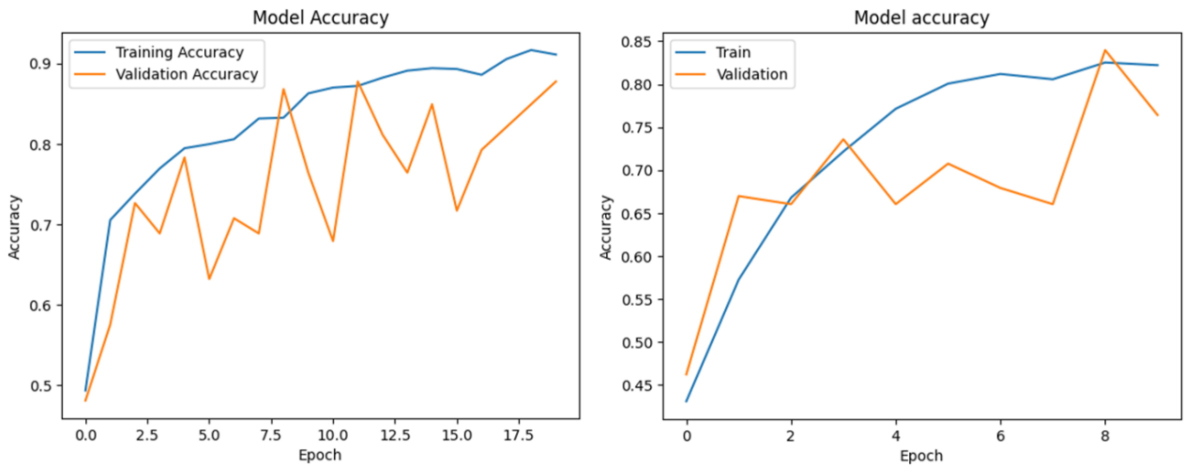

Figure 10. Model Accuracy of Modified System and Existing System

Figure 10 shows the model accuracy attained by the proposed system and existing method, where blue line indicate the training accuracy and orange line imply the validation accuracy. Both the validation accuracy and training accuracy of proposed model is better than the existing model. The projected system achieved the highest accuracy of 92 % after 18th epoch which is better than the convention model.

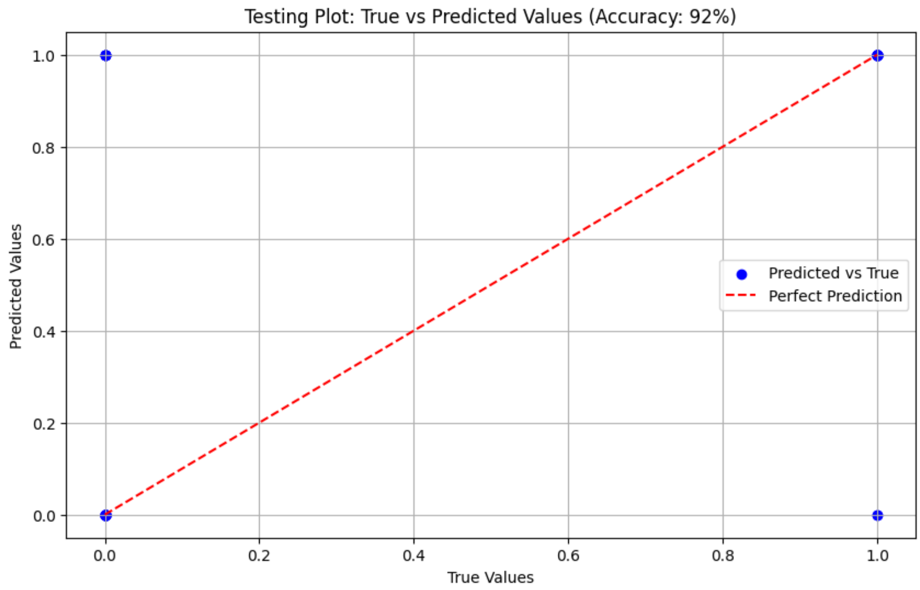

Figure 11. Graphical Representation of Testing Plot

Figure 11 demonstrates the accuracy obtained by the proposed model for testing. Whereas, the red dotted lines shows that the prediction is 92% accuracy.

4.5 Comparative Analysis

Comparative analysis primarily deals with the comparing the metrics of the proposed work with the prevailing works, likewise, Table 4 shows the accuracy attained by the proposed system for classification of diseases is 92% in all four classes and the table 4 shows the accuracy obtained by the existing model which is 85% in all four classes. The graphical illustration of comparative analysis is depicted in Figure 12.

Table 4. Accuracy Comparison of Existing and Proposed System Based on Classes [30]

Models	**class 0 %**	**class 1 %**	**class 2 %**	**class 3 %**
ResNet	85	85	85	85
VGG19	81.43	81.76	80.35	80.41
Xception	89.42	89.63	88.65	88.23
Proposed	92	92	92	92

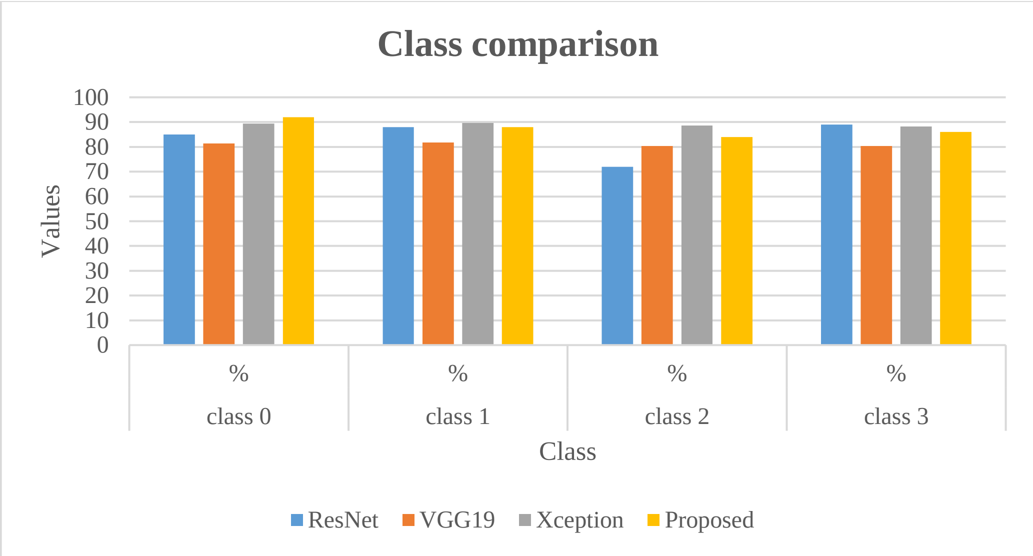

Figure 12. Class Based Accuracy Comparison of Modified and Existing Systems

The figure 12 and table 4 illustrates the examination of outcomes of the proposed model with the conventional CNN (VGG19 and Xception) models. Each number from 1-4 in the x axis represents the internal results of CNN trained model on each data module as DL, DP, FL, FP. From the results, it is recognized that the conventional method, CNN acquired good results in all dataset modules and little lag in DP and better performance in FL detection using the corresponding dataset with the consistent accuracy of 89%. The proposed Blend Unity Resqueeze ResNet method outperforms the conventional model by accomplishing 3% greater than the existing method, which discloses the better efficacy of the projected system.

Table 5. Outcome Analysis of Conventional and Proposed System [30]

Models	**Accuracy %**	**Precision %**	**Recall %**	**F1-score %**
ResNet	85	88	72	89
VGG19	81.43	81.76	80.35	80.41
Xception	89.42	89.63	88.65	88.23
Proposed	92	88	84	86

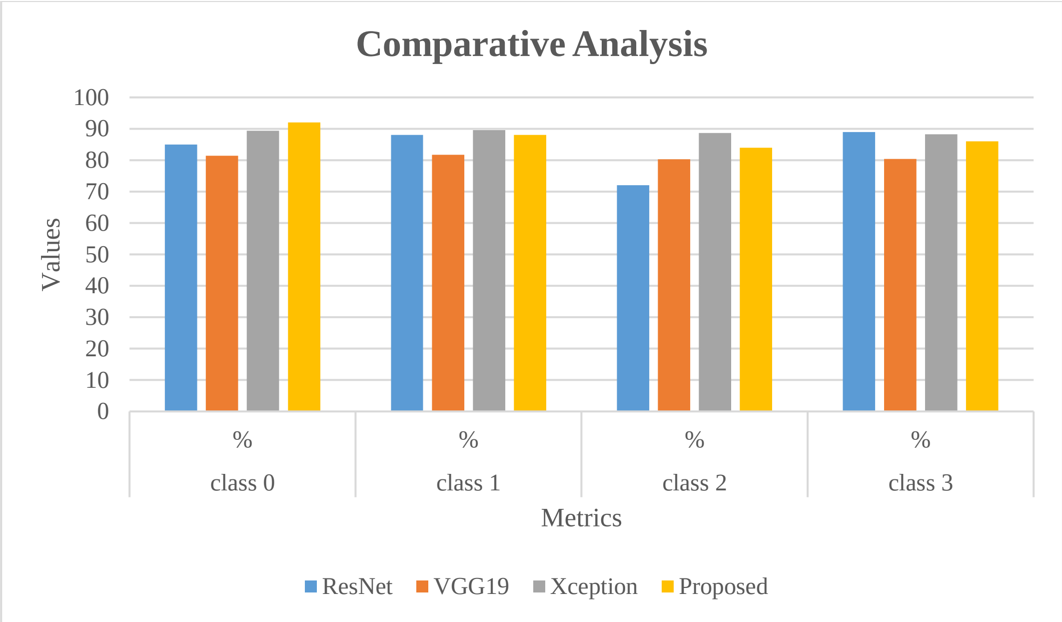

Figure 13. Performance Metrics of Modified System and Conventional Systems

The figure 13 and table 5, presents the performance metrics of conventional methods such as ResNet, VGG19, Xception and the projected system. The existing technologies performed well and yielded 89% whereas the proposed model is achieved the highest accuracy of 0.92. It also shows precision of 0.88, recall of 0.84, and F1-score of 0.86. The projected model is the most effective at correctly classifying the data, making accurate predictions, and balancing both precision and recall. The proposed Blend Unity Resqueeze ResNet method represents a significant improvement in the accuracy accomplishing 7% greater than the existing ResNet method. These results disclose the better performance of the projected model over the conventional models.

V. Conclusion and Future Recommendation

As, the Blend Unity Resqueeze method together with the ResNet model have proven to be very effective for identifying plant diseases in different test conditions, being capable to obtain accuracy rates greater than 92%. This approach introduces more powerful feature extraction through its unique channel weight assignment and adaptive recalibration for more effective multi-scale feature learning. Furthermore, its ability to accurately identify boundaries of disease-specific features and leaf texture variation, along with clearer distinguish-ability of features, encouraged enhanced accuracy, making it valuable in the context of agricultural technology. While these results are promising, it is important to note a few limitations. Initially, the model relies on high-quality training data, which may be difficult to obtain in some circumstances, especially when labeled datasets are limited. Next, contour processing sharpens disease boundary detection, isolating infected areas precisely to improve plant disease identification accuracy. All of these factors could have implications for the overall robustness and generalizability of the model when applied to different plants and environments.

In the future, these limitations can be addressed using distinct data augmentation techniques and improved classifucation algorithms, specifically for boundary detection. The inclusion of other contextual data like weather and soil health may also be beneficial for predictive accuracy. Moreover, the scalability of the Blend Unity Resqueeze model is a major asset since it can be adapted to fit various agricultural contexts, ranging from small family farms to large agricultural businesses. This adaptability suggests it can be applied to conditions such as monitoring the health of plants in real-time, while also enabling a timely response and possible mitigation efforts. Through its application in practice, farmers and agricultural professionals can improve their capabilities of identifying plant diseases and measuring the influence of those diseases. Eventually, the possibility of using the Blend Unity Resqueeze model for real-time applications reflects the need for the research and development in this field to continue, and possibilities forward for innovation in plant disease management and sustainable agriculture.

References

[1] V. K. Vishnoi, K. Kumar, and B. Kumar, "Plant disease detection using computational intelligence and image processing," *Journal of Plant Diseases and Protection*, vol. 128, pp. 19-53, 2021.

[2] K. Indira and H. Mallika, "Classification of Plant Leaf Disease Using Deep Learning," *Journal of The Institution of Engineers (India): Series B,* pp. 1-12, 2024.
[3] W. B. Demilie, "Plant disease detection and classification techniques: a comparative study of the performances," *Journal of Big Data,* vol. 11, no. 1, p. 5, 2024.
[4] W. Yang, Y. Yuan, D. Zhang, L. Zheng, and F. Nie, "An Effective Image Classification Method for Plant Diseases with Improved Channel Attention Mechanism aECAnet Based on Deep Learning," *Symmetry,* vol. 16, no. 4, p. 451, 2024.
[5] P. Singla, V. Kalavakonda, and R. Senthil, "Detection of plant leaf diseases using deep convolutional neural network models," *Multimedia Tools and Applications,* pp. 1-17, 2024.
[6] S. Kumar, S. Pal, V. P. Singh, and P. Jaiswal, "Performance evaluation of ResNet model for classification of tomato plant disease," *Epidemiologic Methods,* vol. 12, no. 1, p. 20210044, 2023.
[7] M. Jung *et al.*, "Construction of deep learning-based disease detection model in plants," *Scientific reports,* vol. 13, no. 1, p. 7331, 2023.
[8] M. M. Khalid and O. Karan, "Deep learning for plant disease detection," *International Journal of Mathematics, Statistics, and Computer Science,* vol. 2, pp. 75-84, 2024.
[9] T. Daniya and S. Vigneshwari, "Deep neural network for disease detection in rice plant using the texture and deep features," *The Computer Journal,* vol. 65, no. 7, pp. 1812-1825, 2022.
[10] A. Khattak *et al.*, "Automatic detection of citrus fruit and leaves diseases using deep neural network model," *IEEE access,* vol. 9, pp. 112942-112954, 2021.
[11] M. A. Khan *et al.*, "Cucumber leaf diseases recognition using multi level deep entropy-ELM feature selection," *Applied Sciences,* vol. 12, no. 2, p. 593, 2022.
[12] B. Kim, Y.-K. Han, J.-H. Park, and J. Lee, "Improved vision-based detection of strawberry diseases using a deep neural network," *Frontiers in Plant Science,* vol. 11, p. 559172, 2021.
[13] W. Zeng and M. Li, "Crop leaf disease recognition based on Self-Attention convolutional neural network," *Computers and Electronics in Agriculture,* vol. 172, p. 105341, 2020.
[14] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, "Identification of plant-leaf diseases using CNN and transfer-learning approach," *Electronics,* vol. 10, no. 12, p. 1388, 2021.
[15] S. Yadav, N. Sengar, A. Singh, A. Singh, and M. K. Dutta, "Identification of disease using deep learning and evaluation of bacteriosis in peach leaf," *Ecological Informatics,* vol. 61, p. 101247, 2021.
[16] R. Sujatha, J. M. Chatterjee, N. Jhanjhi, and S. N. Brohi, "Performance of deep learning vs machine learning in plant leaf disease detection," *Microprocessors and Microsystems,* vol. 80, p. 103615, 2021.
[17] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," *Computers and electronics in agriculture,* vol. 173, p. 105393, 2020.
[18] D. O. Oyewola, E. G. Dada, S. Misra, and R. Damaševičius, "Detecting cassava mosaic disease using a deep residual convolutional neural network with distinct block processing," *PeerJ Computer Science,* vol. 7, p. e352, 2021.
[19] M. Nawaz *et al.*, "A robust deep learning approach for tomato plant leaf disease localization and classification," *Scientific reports,* vol. 12, no. 1, p. 18568, 2022.
[20] M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant disease classification: A comparative evaluation of convolutional neural networks and deep learning optimizers," *Plants,* vol. 9, no. 10, p. 1319, 2020.
[21] S. Ashwinkumar, S. Rajagopal, V. Manimaran, and B. Jegajothi, "Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks," *Materials Today: Proceedings,* vol. 51, pp. 480-487, 2022.
[22] M. Nahiduzzaman *et al.*, "Explainable deep learning model for automatic mulberry leaf disease classification," *Frontiers in Plant Science,* vol. 14, p. 1175515, 2023.
[23] E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans leaf diseases classification using mobilenet models," *IEEE Access,* vol. 10, pp. 9471-9482, 2022.
[24] O. Attallah, "Tomato leaf disease classification via compact convolutional neural networks with transfer learning and feature selection," *Horticulturae,* vol. 9, no. 2, p. 149, 2023.
[25] S. Ahmed, M. B. Hasan, T. Ahmed, M. R. K. Sony, and M. H. Kabir, "Less is more: Lighter and faster deep neural architecture for tomato leaf disease classification," *IEEE Access,* vol. 10, pp. 68868-68884, 2022.
[26] A. Ksibi, M. Ayadi, B. O. Soufiene, M. M. Jamjoom, and Z. Ullah, "MobiRes-net: a hybrid deep learning model for detecting and classifying olive leaf diseases," *Applied Sciences,* vol. 12, no. 20, p. 10278, 2022.
[27] B. Sai Reddy and S. Neeraja, "Plant leaf disease classification and damage detection system using deep learning models," *Multimedia tools and applications,* vol. 81, no. 17, pp. 24021-24040, 2022.
[28] N. K. Trivedi *et al.*, "Early detection and classification of tomato leaf disease using high-performance deep neural network," *Sensors,* vol. 21, no. 23, p. 7987, 2021.

[29] S. K. Upadhyay and A. Kumar, "A novel approach for rice plant diseases classification with deep convolutional neural network," *International Journal of Information Technology*, vol. 14, no. 1, pp. 185-199, 2022.

[30] M. A. Islam, M. N. R. Shuvo, M. Shamsojjaman, S. Hasan, M. S. Hossain, and T. Khatun, "An automated convolutional neural network based approach for paddy leaf disease detection," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 1, 2021.

Author biography

*corresponding author:

Mrs.S.Reena:

I am S.REENA is a Research Scholar from the Department of Computer applications in Madurai Kamaraj university and working in Thiruvalluvar Arts & Science College For women, Soolappuram, Elumalai,Madurai District.. I am 8 years of teaching experience. My major area of research include machine learning and image processing. She has 1 publication in journals and as conference proceedings.

Co-Author:

Dr.R.Rathinasabapathy:

Dr.R.Rathinasabapathy is an associate professor from the department of computer applications, working in Madurai Kamaraj University, Madurai, India. He has thirty year of teaching experience. His major areas of research include design and analysis of data mining algorithms, machine learning and image processing. He has more than 15 publications in journals and as conference proceedings.