[1]Rathiya R
[2]Kalamani M

Multi-Plant Disease Detection and Classification Using Multi-Scale Dynamic Spatial Gating - Squeeze and Excitation (MDSG-SE)

Abstract: - The increasing influence of plant illnesses on worldwide agricultural yield demands sophisticated technologies for prompt identification and categorization. Multi-Plant Disease Detection and Classification using Multi-Scale Dynamic Spatial Gating - Squeeze and Excitation (MDSG-SE) is a novel approach that is introduced in this study. The suggested model improves the ability to discriminate in plant imagery by utilizing multi-scale dynamic spatial restricting to capture complex patterns at various scales. By combining the Squeeze and Excitation mechanisms, MDSG-SE allows the model to adaptively recalibrate the responses of individual channel features. By improving the network's empathy to disease-specific features, this dynamic recalibration maximizes classification accuracy. The multi-scale feature enables the model to manage plant diseases with different spatial features. Using a variety of datasets, a thorough performance analysis is to demonstrate the model's resilience across various crops. According to experimental results, MDSG-SE performs better than current techniques for both recognition and categorization accuracy. The model is resilient to changes in the environment and shows outstanding responsiveness to subtle disease symptoms. The general efficacy of plant disease identification systems is synergistically enhanced by the combination of multi-scale fluid spatial gating, squeeze, and excitation in MDSG-SE.

Keywords: MDSG-SE, Pre-processing, Segmentation, Classification, Deep Learning

I. INTRODUCTION

Maintaining food security in the face of growing threats to global agriculture. The Multi-Plant Disease Detection and Classification using Multi-Scale Dynamic Spatial Gating - Squeeze and Excitation (MDSG-SE) is a novel approach that is presented in this work. The model overcomes the shortcomings of current techniques. The Squeeze and Excitation mechanism and multi-scale dynamic spatial gating are combined in MDSG-SE to improve feature extraction and recalibrate adaptive features, respectively. The model can identify subtle disease patterns and adjust to different spatial characteristics thanks to this special fusion. Plant diseases can present with a variety of symptoms, so the multi-scale approach of MDSG-SE is crucial for precise identification in a variety of crop types. Its capacity to interpret photos at different resolutions and capture both fine-grained details and wider geographical information highlights the model's versatility. This flexibility, along with its capacity to learn from big datasets, makes MDSG-SE a flexible instrument for use in a variety of international agricultural applications.

An extensive performance analysis demonstrates the MDSG-SE, exhibiting increased sensitivity and classification accuracy. The model demonstrates robustness against environmental fluctuations, demonstrating its effectiveness in practical agricultural situations. This work establishes the foundation for future developments in automated crop protection and precision agriculture in addition to providing a cutting-edge solution. The technical details, methodology, experimental configuration, and in-depth results analysis of MDSG-SE are covered in the following sections. In [1], In order to improve plant disease identification, this study uses transfer learning in conjunction with a modified MobileNet and squeeze-and-excitation block (SE-MobileNet). A model with remarkable efficiency is produced by the two-phase transfer learning procedure; The suggested SE-MobileNet exhibits efficacy and viability, highlighting its promise as a very precise plant disease categorization solution.

According to [2], Dise-Efficient, a new convolutional neural network that is built on top of EfficientNetV2, transforms agricultural plant disease and pest identification. Its robust performance is demonstrated on the PlantVillage dataset, where it achieves an astonishing 99.80% accuracy using dynamic learning rate decay and transfer learning. The model uses the IP102 dataset to retain a recognition accuracy of 64.40% in real-world

[1] *Assistant Professor, Department of Information Technology , Dr.N.G.P Institute of Technology, Coimbatore, Tamilnadu, India

[2] Professor, Department of Electronics and Communication Engineering, KPR Institute of Engineering and Technology, Coimbatore, Tamilnadu, India

scenarios, despite its small size of 13.3 MB. Zhe Tanga,b et,al [3], To improve the ShuffleNet architecture, the model combines channel wise attention (CA) mechanism with squeeze-and- excitation (SE) blocks. Dataset of 4,062 grape leaf images with four classes, yielding a 99.14% best-trained model accuracy.

In [4], This study addresses rice, the main crop in India, and how growing both brown and white rice contributes significantly to the GDP and employment of the nation. The research examines techniques for identifying rice diseases from plant photos in the context of agriculture and contemporary technology, examining different classifiers and tactics employed during the last ten years. Furthermore, the research suggests a model that utilizes an improved CNN to precisely identify rice diseases. CASE-Net incorporates evidence-based modules to highlight contextual information localization in biomedical segmentation by leveraging Cross Attention Squeeze Excitation Network. The suggested framework outperforms existing competitive segmentation architectures with an impressive segmentation Dice score of 87.36% in a retrospective investigation including 34 cases. [5]

In [6], This study uses deep learning-based Convolutional Neural Networks (CNNs) to investigate how rice plant diseases affect global agriculture and food security. Learning of minor lesions, an attention mechanism is incorporated with MobileNet-V2 pretrained on ImageNet as a backbone. With an accuracy of 99.67% and 98.48% accuracy even in difficult situations, the suggested method achieves higher performance through optimized loss functions and dual transfer learning, demonstrating its efficacy for rice disease identification. According to [7], The model provides a quick and simple deployment in practice, as it can identify 13 different types of plant illnesses and discriminate leaves from their surroundings. The constructed model, which makes use of the deep learning framework Caffe, demonstrates its usefulness in the identification of plant diseases by achieving an impressive precision range of 91% to 98%, with an average precision of 96.3% in independent class tests.

Although DL—especially CNNs—is preferred for the decision between ML and DL is contingent upon individual issues, the accessibility of data, and the available processing power. The purpose of this work is to provide future researchers with an update on the efficacies and outcomes of different methods for identifying and categorizing crop or plant leaf diseases. [8]. Xin Jin et.al [9], The goal of this paper is to improve the Squeeze-and-Excitation (SE) blocks, for increasing the accuracy of deep architectures. It suggests a two-stage spatial pooling technique that includes information fusion and rich descriptor extraction, with a focus on the squeeze operation within SE blocks. The technique integrates many global and local descriptors to produce enhanced channel re-weighting accuracy with low additional expenses. Convolutional neural networks (CNNs) for image classification [10–14], image detection [15,16], segmentation [17], real-life [18–21]. In this paper, the Multiscale Dynamic Spatial Gating Squeeze and Excitation (MDSG-SE) is proposed. Section 2 summarizes the Materials used. The proposed classification method is discussed in Section 3. Section 4 explains the Deep Learning Model with the proposed method. Section 5 discussed about the Results and Section 6 provides conclusions.

II. MATERIALS USED

Leaf spot are found on Corn Leaves. The dataset includes 4188 images of four different classes with healthy samples of Corn crops. The Fig.1 shows the corn leaf diseases. The Fig.2 shows the images of each kind of potato leaf diseases. The dataset includes 4188 images of six different classes. The Fig.3 shows the images of each kind of cotton leaf diseases. Leaf Diseases such as Apple Rot, Leaf Blotch and Scab leaves are found on Apple Leaves. The dataset includes 419 images of four different classes. The Fig.4 shows the images of Apple leaf diseases. Includes 400 images of five different classes in plant village. The Fig.5 shows the images of each kind of chilli leaf diseases.

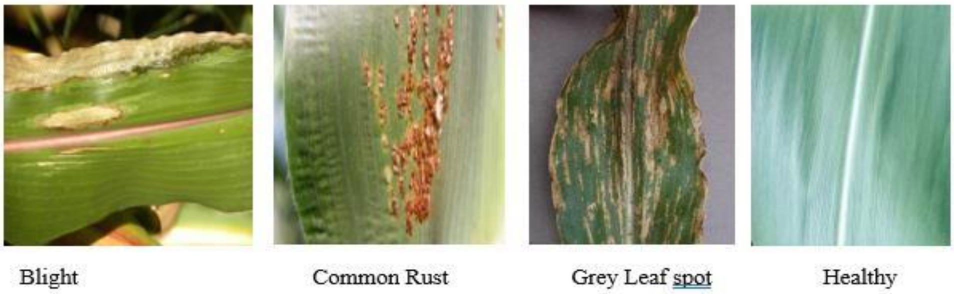

Fig.1: Corn Leaf Diseases

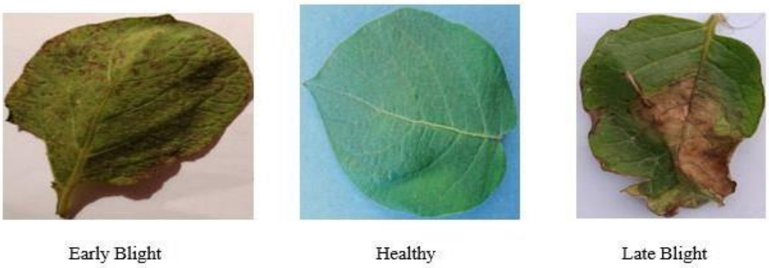

Fig.2: Potato Leaf Diseases

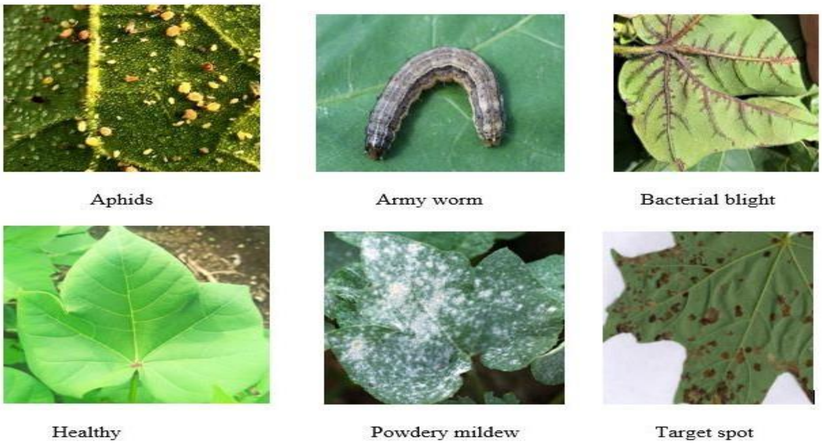

Fig.3: Cotton Leaf Diseases

Fig.4: Apple Leaf Diseases

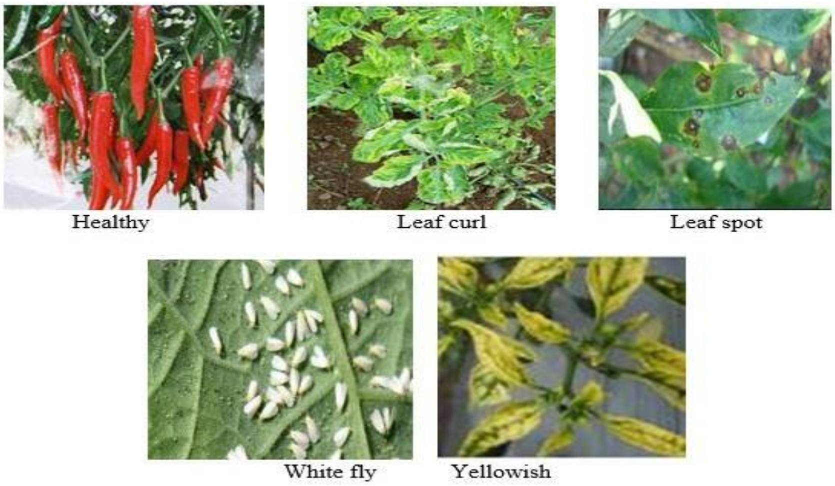

Fig.5: Chilli Leaf Diseases

III. Techniques Used

The following algorithm outlines a step-by-step approach for the proposed process of Image Recognition and Segmentation:

1. Image Acquisition: In this first phase, an image is taken using a digital camera or another appropriate imaging instrument.

2. Image pre-processing: The next step after acquiring an image is to improve its quality and get rid of any undesirable aberrations.

3. Pre-processing Techniques: Gaussian filtering is one of the methods used in the pre-processing stage to refine the image.

4. Segmentation Processes: Segmentation Processes includes used here are K-Means Filtering Technique.

5. Classification Processes: For classification, the MDSG-SE is proposed. The Fig.6 shows the Performance Analysis procedures

IV. Proposed Deep Learning (DL) Classification Techniques

Define the custom layers and blocks, such as a simpler ShuffleNet block and the SE block, in order to construct a custom image classification model. These are essential elements for improving the efficiency of the model and feature extraction. Gaussian blur and K-means segmentation are used in a custom data generator to pre- process photos, enhancing the dataset for improved generalization. The model architecture is MobileNetV2, whose weights have been set for avoiding further training. SE and ShuffleNet-like blocks are added to the underlying model to improve feature representation and encourage the interchange of spatial information. The custom data generator is used to create the training data, giving pre-processing instructions and augmentation parameters.

Lastly, a visualization of the accuracy and training loss over epochs provide light on the learning dynamics of the model. In order to improve classification performance while preserving the simplicity and efficacy of the model, this all- encompassing strategy combines sophisticated methods for picture pre-processing, attention mechanisms, and effective feature extraction.

The Fig.7 shows the architecture of the proposed MDSG-SE. It shows three parallel branches that process the input image data through convolutional layers, followed by normalization and activation layer. After these initial layers, the data is split into two branches: Branch 1 and Branch 2.

Branch 1: This branch processes the data through a 3x3 convolution layer followed by an SE block. SE blocks are a type of squeeze-and-excitation block, which is a channel attention mechanism that can improve the performance of CNNs. Branch 2: This branch processes the data through a 5x5 convolution layer followed by an SE block. The data from both branches is then concatenated together. Concatenation is an operation that joins two tensors together along a specific dimension.

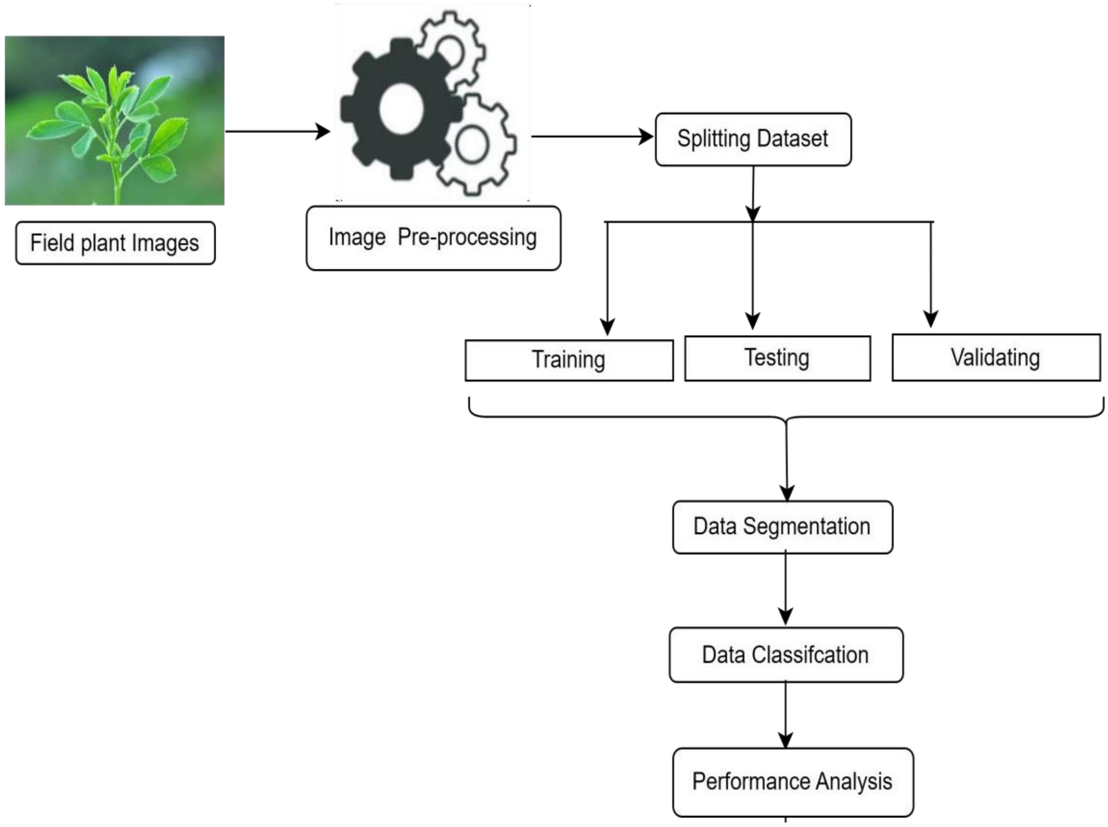

Fig.6: Performance Analysis procedures

In this case, the tensors are likely concatenated along the channel dimension, which would result in a tensor with a larger number of channels than either of the original tensors. After concatenation, the data is processed through a series of additional convolutional layers, a dynamic channel gating module, and a global pooling layer. Dynamic channel gating is a technique that can be used to improve the efficiency of CNNs by selectively gating out channels. Overall, the convolutional neural network architecture depicted in the block diagram is a complex system that can be used to learn complex features from image data.

V. DEEP LEARNING MODEL: SHUFFLENET

The ShuffleNet is designed to reduce computation complexity while maintaining performance in convolutional neural networks (CNNs). ShuffleNet achieves by utilizing group convolutions and channel shuffling techniques. Here's an explanation of the components of the ShuffleNet-like block:

A. Depthwise Convolution with Grouped Convolutions:

In the ShuffleNet-like block, depthwise convolution is used with the DepthwiseConv2D layer from TensorFlow Keras. This helps reduce computation complexity. In this block, the groups parameter controls the number of groups. After depthwise convolution, batch normalization and ReLU activation are applied. Pointwise convolution (also known as 1x1 convolution) is applied after depthwise convolution. In the ShuffleNet-like block, a Conv2D layer and kernel. Overall, the ShuffleNet-like block reduces computational complexity by using grouped convolutions and pointwise convolutions.

VI. RESULTS

Crops like Corn (almost perfect accuracy), Potato, and Cotton have very high accuracy values across epochs. This suggests the model confidently distinguishes these crops from others in the dataset. The significant drop in loss values from epoch 10 to 30 further emphasizes this improvement. Apple samples have the highest accuracy compared to other crops. Corn has the next highest accuracy (almost perfect at both epochs). Looking across epochs (10 vs. 30), the accuracy generally improves for all crops. Overall, the table suggests that the classifier is effective in classifying the different crop types in the dataset, and its performance. The Tab.1 shows the Accuracies and losses of the various crop samples.

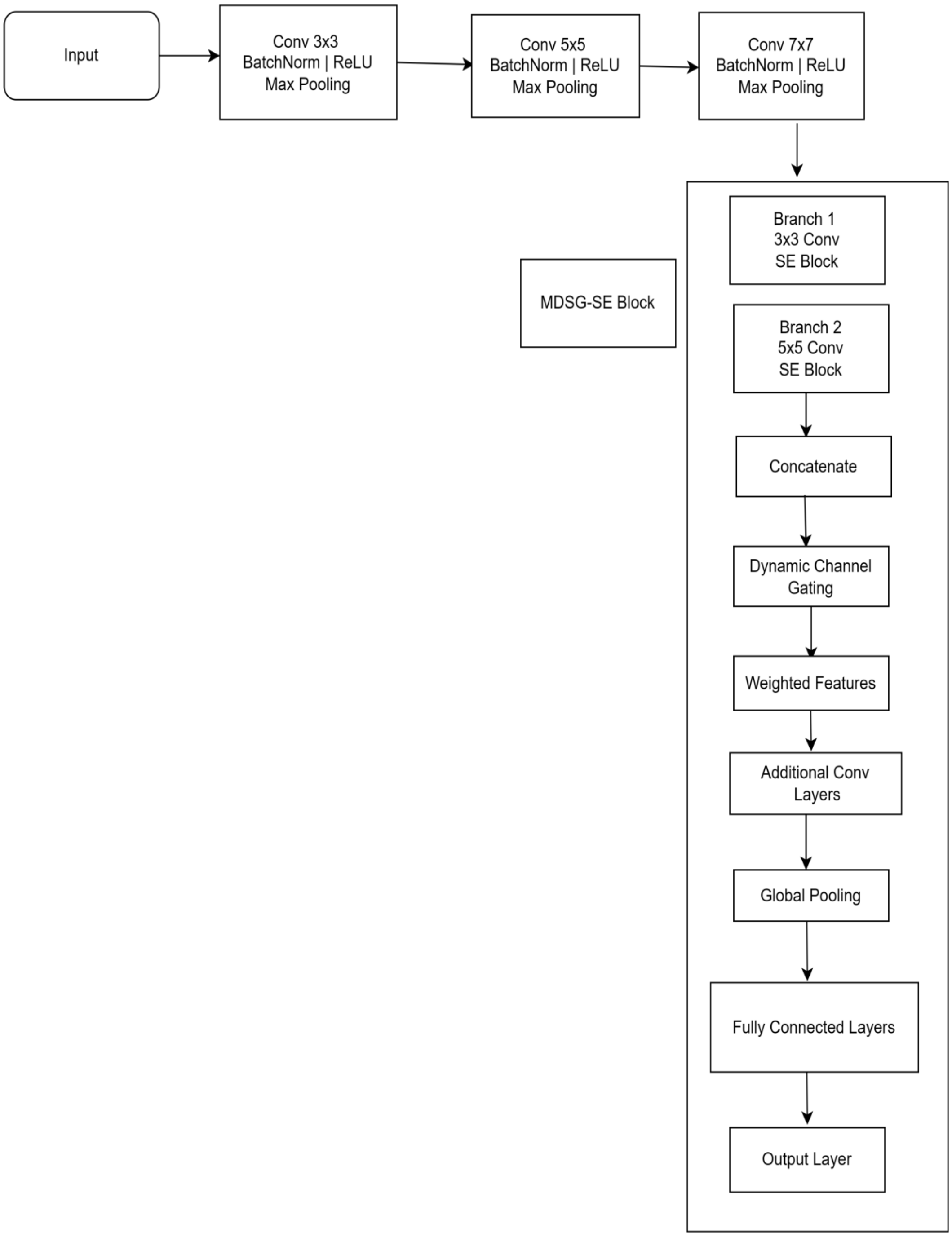

Fig.7: Architecture of MDSG-SE

Samples	Accuracies		Losses	
	10 Epochs	30 Epochs	10 Epochs	30 Epochs
Potato samples	0.9253	0.9470	0.2177	0.1311
Chilli Samples	0.9216	0.9608	0.5566	0.1873
Cotton Samples	0.9646	0.9852	0.1146	0.0425
Apple samples	0.7529	0.8648	0.7013	0.4263
Corn samples	0.9388	0.9674	0.1508	0.0857

Tab.1: Accuracies and Losses of various samples

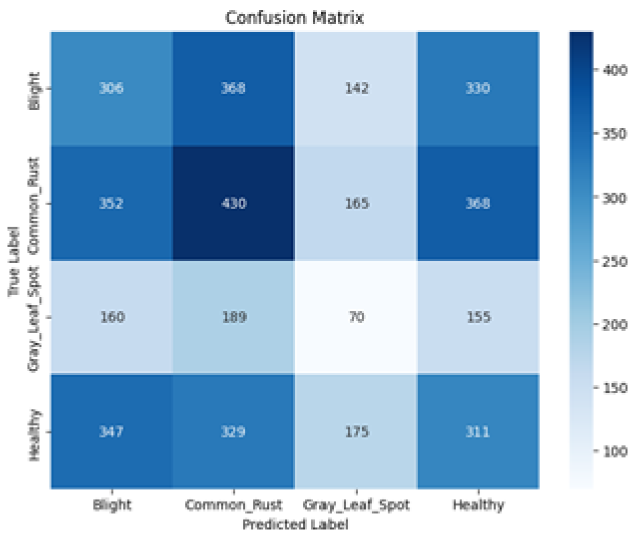

Fig.8 Confusion Matrix-Corn Leaf Diseases (10 Epochs)

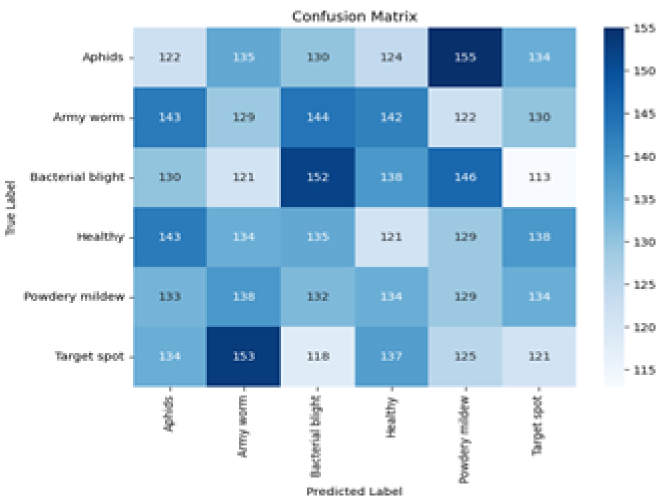

Fig.10 Confusion Matrix- Cotton Leaf Diseases (10 Epochs)

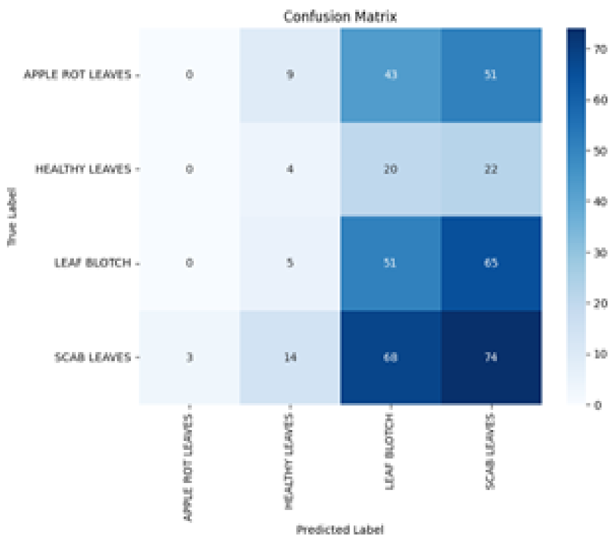

Fig.9 Confusion Matrix-Apple Leaf Diseases (10 Epochs)

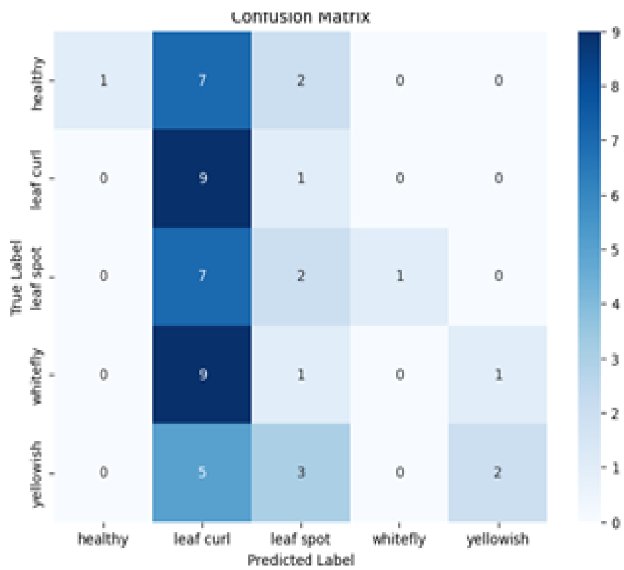

Fig.11 Confusion Matrix -Chilli Leaf Diseases (10 Epochs)

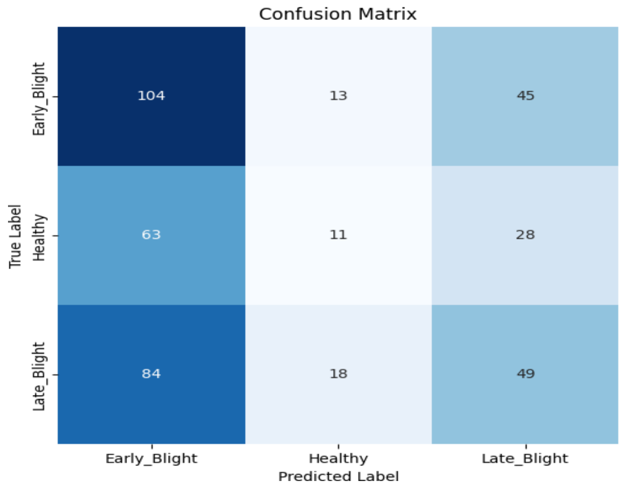

Fig.12 Confusion Matrix- Potato Leaf Diseases(10 Epochs)

From the Fig.8, In the matrix for 10 epochs of corn leaves, the examples in a predicted group are represented by each column, and the occurrences in a real class are represented by each row. The diagonal portion of the matrix displays the quantity of cases that were successfully classified. For 10 epochs, 306 leaves with blight were accurately identified as such, 430 leaves with common rust being common rust, and so forth. The amount of cases that are incorrectly classified is displayed by the matrix's off-diagonal entries. Misclassifications of 142 blight leaves as gray leaf spot, 165 common rust leaves as healthy, and so on. the Fig.9 shows the confusion matrix of 10 epochs for the Apple Leaf Diseases.

The model did well in this particular confusion matrix in distinguishing between healthy and diseased leaves. 24 out of 24 scab leaves and 70 out of 70 healthy leaves properly. The model had more trouble with leaf blotch and apple rot. Only twenty of the fifty leaves with apple rot were accurately recognized by the model. In terms of leaf blotch, the model performed poorly as well, properly categorizing only 30 out of 45 leaves. The model most frequently mistook leaf blotch with scabby leaves (15) and apple rot with healthy leaves (20). The Fig.10 shows the confusion matrix of Cotton Leaves for 10 epochs.

For 10 epochs, 130 cases of Alphids were successfully classified, as indicated by the cell. The number of examples that the model misclassified is indicated by the white boxes.The matrix's second row or third column's cell indicates that 15 army worm cases were identified as bacterial blight. The model did well on certain classes in this matrix of confusion, but not so well on others. All 147 instances of healthy plants were accurately classified by the model. However, out of the 255 occurrences of powdery mildew, only 125 were accurately categorized by the model.

From the Fig.11, the matrix for 10 epochs of chilli leaves has been showed. In this Nine out of nine healthy leaves were accurately categorized. by the model. Next for Leaf curl out of three leaves, the model accurately identified two as having leaf curl. One leaf curl was mistakenly identified as yellowish.

In the Leaf spot, Three of the four leaves with spots on them were accurately categorized by the model. One leaf speck was mistakenly identified as yellowish.

For Whitefly, the model accurately classified all three leaves, demonstrating good performance. Finally, Yellowish, Two of the four leaves were properly categorized by the model as yellowish. One yellowish leaf was misclassified as healthy and one as having a leaf spot. Fig.12 shows the Confusion matrix for the potato leaves for 10 epochs. For Healthy, the model correctly classified 100 out of 100 healthy potato leaves. In Early Bligh, the model correctly classified 104 out of 114 leaves with early blight.

It incorrectly classified 10 leaves as healthy and 45 leaves as late blight. Late Blight: The model correctly classified 20 out of 60 leaves with late blight. It incorrectly classified 11 leaves as healthy and 29 leaves as early blight. chilli samples show a similar decreasing trend in loss as Potato and Cotton, but the loss values are generally slightly higher across epochs. This suggests the model is learning well for Chilli, but it might be slightly less accurate compared to Potato and Cotton. Apple samples have the highest loss values among all crops throughout the epochs.

The Fig.13 showing the accuracy of a classifier for different sample types trained over multiple epochs. X-axis: Epochs - This represents the number of times the classifier has been trained. Y-axis: Accuracy - This represents the proportion of samples the classifier correctly classified. A value closer to 1 signifies better performance. Lines: Each line represents a specific crop type (Potato, Chilli, Cotton, Apple, Corn) in the dataset. Potato samples show a steady increase in accuracy, reaching nearly 0.94 at 30 epochs.

Chilli samples also see a rise in accuracy, but to a slightly higher extent compared to Potato samples. Cotton samples have a similar trend to Potato samples, achieving the highest accuracy at 30 epochs. Apple samples have the lowest accuracy throughout the epochs. While it improves slightly with more epochs, it remains the lowest among all crops. Corn samples show a significant increase in accuracy, reaching near perfect classification (almost 0.96) at 30 epochs. Corn and potato classifications were the most accurate, while apple samples were the most challenging. The Fig.14 shows the loss of various samples. Potato, cotton and corn crops have consistently low loss values throughout the epochs, dropping significantly from epoch 10 & 30.

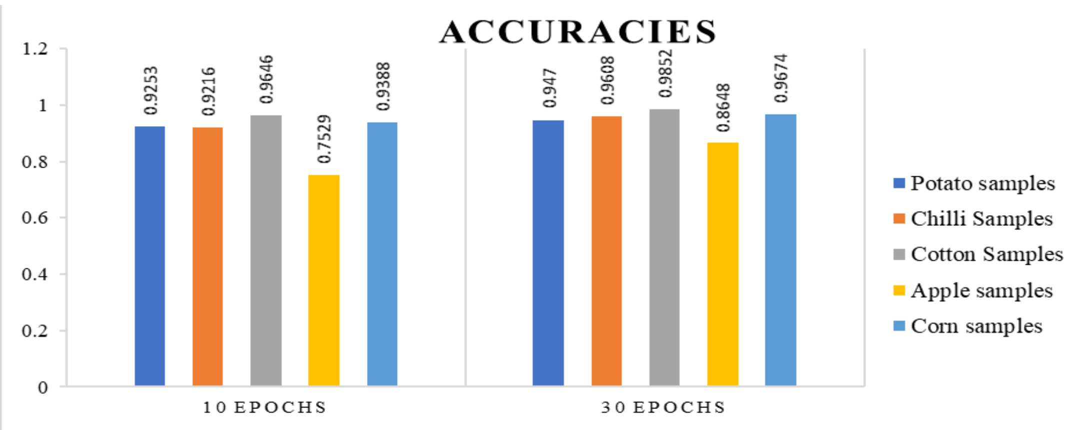

Fig.13: Accuracy of various samples of proposed work

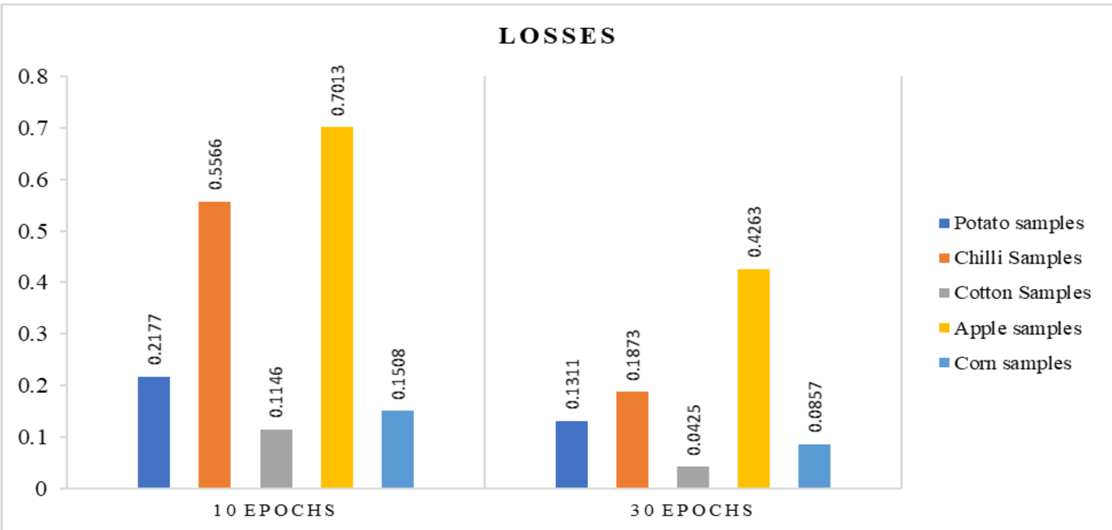

Fig.14: Loss of various samples of proposed work

VII. CONCLUSION AND FUTURE DISCUSSSION

The study proposed a novel deep learning classification model, MDSG-SE. The model leverages multi-scale dynamic spatial gating and Squeeze-and-Excitation (SE) blocks to effectively capture spatial information and adaptively recalibrate feature responses. The proposed MDSG-SE model achieves superior performance for various plant diseases. The integration of ShuffleNet-like blocks contributes to the model's efficiency by reducing computational complexity. From the above result, the Cotton leaf disease classification provides a better accuracy for 10 and 30 epochs of values 96% and 98% respectively. Overall, the research highlighted the potential of MDSG-SE in advancing automated plant disease diagnosis and promoting sustainable agricultural practices. Researchers can further refine the MDSG-SE model and enhance its impact on practical plant disease management in agriculture.

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