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MulberrySenseAI: Deep Learning Disease Detection of Mulberry Leaf Using Attention Mechanism

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Abstract: This study introduces a Convolutional Neural Network (CNN) based approach for automated detection of diseases in mulberry leaves, crucial for effective disease management and prevention of economic losses in sericulture. The proposed models, incorporating batch normalization and attention mechanisms, differentiate between healthy and diseased leaves with high accuracy. Compared to the base paper's lightweight parallel depth-wise separable CNN model, our models offer improved performance while maintaining explainability. The addition of attention mechanisms enhances the interpretability of the models, providing insights into the decision-making process. The promising results indicate potential for practical implementation in real-world agricultural settings.

Index Terms **- Attention Mechanism, Batch Normalization, Convolution Neural Networks, Deep Learning, Leaf Disease Detection, Layers, TensorFlow.**

I. INTRODUCTION

The advent of deep learning, particularly convolutional neural networks (CNN), has revolutionized the field of plant disease detection. This technology, which identifies diseases based on images of plant leaves, holds the potential to significantly enhance crop yields and food security, especially in developing regions where expert diagnosis is scarce. Despite challenges such as data dependency, sensitivity to image quality, and generalization to new environments, deep learning stands as a promising technology with the potential to significantly impact agriculture.

One plant that stands to benefit from this technology is the mulberry (Morus spp.), a versatile and sustainable plant with a wide range of applications. Known for its positive impact on environmental safety, the mulberry plant is exploited by various industries, including sericulture, pharmaceutical, cosmetic, food, and beverage industries. It is regarded as a unique plant due to its potential to contribute to various aspects of sustainable development and its role in providing a sustainable environment for future generations.

Deep learning, a powerful machine learning approach, mitigates the traditional machine learning headache of feature engineering. It doesn't require any domain expertise, thanks to artificial neural networks (ANN), mathematical models that replicate the general principles of brain function. With the help of libraries like Tensorflow, one can perform classification tasks on text as well as images. This study shows the importance of plant disease detection these days. The model was developed using Deep Learning in python and tested on images from the PlantVillage dataset. The model achieved more than 95% accuracy on real-time images, demonstrating the effectiveness of deep learning in this domain.

The authors propose a deep learning-based approach for early disease detection in tomato plants. Their approach uses a convolutional neural network (CNN) model called EfficientNet to classify tomato leaf images as healthy or diseased. The authors' model achieved an accuracy of 99.95% for binary classification (healthy vs. diseased) and 99.12% for six-class classification (healthy, fungi, bacteria, mold, virus, and mite). They also achieved an accuracy of 99.89% for ten-class classification.

The article "Detection of plant leaf diseases using image segmentation and soft computing techniques" proposes a novel approach for identifying and classifying plant leaf diseases using a combination of image segmentation and soft computing techniques. The proposed method offers a promising and effective approach for identifying and classifying plant leaf diseases. The combination of image segmentation and soft computing techniques provides a robust, accurate, and efficient solution for disease detection.

The HOResNet model, a novel approach for accurately and robustly recognizing crop diseases, combines low-level features with object details and high-level features with abstract representation. By leveraging high-order residual blocks and feedback blocks, the HOResNet model enhances the anti-interference ability, making it more resilient to noise disturbances commonly found in agricultural images.

Lastly, a novel approach for identifying plant leaf diseases using a nine-layer deep convolutional neural network (CNN) is introduced. By leveraging the power of deep learning and image processing techniques, the proposed model aims to accurately classify diseased and healthy plant leaves based on visual symptoms. The results demonstrated high accuracy in disease identification, showcasing the effectiveness of deep learning in this domain. This introduction to deep learning disease detection of mulberry leaf using attention mechanism provides a comprehensive overview of the current state of the art in this field and highlights the potential of these techniques in improving crop management practices and enhancing agricultural productivity. The potential for real-time applications further expands the practical utility of these approaches.

1.1 Motivation

The purpose of this study is to address the challenges in the field of plant disease detection, specifically for mulberry trees. Mulberry trees, while beneficial for sustainable development, are susceptible to various pests and diseases, including aphids, scale insects, and fungal diseases. These issues can be mitigated through the use of deep learning, particularly in image-based disease detection. However, deep learning models come with their own set of challenges. They require a large amount of high-quality data and extensive computing resources, which can be difficult to obtain. Furthermore, these models are sensitive to image quality and may not generalize well to new diseases and conditions. They also have a tendency to overfit, performing well on training data but poorly on unseen data. Despite these challenges, deep learning holds the potential to revolutionize disease detection in mulberry leaves and other plants. By incorporating an attention mechanism, the model can focus on the most relevant features, potentially improving its performance and robustness. This approach could pave the way for more accurate and efficient disease detection, ultimately contributing to sustainable agriculture and food security. However, the study acknowledges its limitations, such as the need for a large volume of training data and the model's potential inaccuracy in real-world applications where lighting conditions are not ideal. The study also recognizes the model's dependency on the quality and quantity of training data and its limitations in capturing the complex morphological and physiological characteristics of different plant leaf diseases. We could focus on optimizing the model’s efficiency without compromising its accuracy and robustness, and exploring the integration of transfer learning techniques to enhance the model’s efficiency and generalization capabilities across different plant species and diseases. This research, while acknowledging its limitations, presents a promising step towards leveraging deep learning for effective and efficient disease detection in mulberry leaves and beyond.

1.2 Contribution

The study contributes to the field of automated plant disease detection by focusing on the specific domain of mulberry leaf disease detection. It employs Convolutional Neural Networks (CNNs), a type of artificial neural network that is particularly effective for image classification tasks. CNNs are trained on a dataset of labeled images, extracting features such as edges, textures, and colors to learn a model that can predict the category of a new image. The accuracy of the CNN model is evaluated on a dataset of test images. The model enhances the quality of existing research by aiming for better accuracy through the use of machine learning-based attention mechanisms. These mechanisms intuitively mimic cognitive attention by calculating "soft" weights for each element in the input sequence, indicating the importance or relevance of each element to the task at hand. The model then combines the input elements with their corresponding attention weights to produce a context vector, which is used to make predictions or generate outputs. This approach addresses existing challenges and bridges research gaps, aiming to develop robust and deployable solutions for detecting mulberry leaf diseases. It makes innovative use of attention mechanisms in deep learning models for disease detection, paving the way for future research in this area.

1.3 Organization

The following sections of the article are as follows: Section II provides an overview of similar work; Section III provides a background study; Section IV provides a thorough explanation of our methodology, implementation, and results; and Section V concludes with a summary of our findings.

II. Related Work

In [2] This paper introduces a novel convolutional neural network (CNN) for identifying plant diseases from leaf images. The CNN's high accuracy, automatic feature learning, and scalability make it a promising tool for improving crop yields and food security. Despite achieving superior results, the model faces challenges such as data dependency, sensitivity to image quality, and the cost of data collection and annotation. These issues highlight the need for ongoing research to enhance the model's practicality in real-world agricultural settings.

In [3] This paper presents mulberry as a versatile plant contributing to sustainable development. Its wide applications in food security, environmental restoration, pollution abatement, economic development, and various industries highlight its value. Despite its positive impact on environmental safety and potential to alleviate ecological disturbances, challenges such as allelopathic effects, pest and disease susceptibility, and resource requirements necessitate careful management for sustainable cultivation. Thus, while mulberry holds promise for a sustainable future, its cultivation requires mindful practices.

In [4] This paper proposes a novel approach for identifying and classifying plant leaf diseases. The method, robust to image variations, achieves high accuracy and efficiency in disease detection, providing a non-invasive and rapid diagnosis. Despite its effectiveness, the method’s performance is sensitive to image quality and dependent on the quantity and quality of training data. It also faces limitations in capturing the complex characteristics of different plant leaf diseases. The paper concludes that the proposed method offers a promising approach for improving crop management practices and enhancing agricultural productivity, with potential for real-time applications. However, it emphasizes the need for further research and development to refine the method and optimize its performance.

In [5] This paper presents a novel approach for plant disease detection using deep learning, specifically artificial neural networks implemented via TensorFlow. The method’s advantages include automatic feature learning, the ability to handle large and complex datasets, and enhanced performance. The study tested the model on 20% of images from the PlantVillage dataset, achieving over 95% accuracy. However, the method requires a large amount of high-quality data and extensive computing resources, which can be a disadvantage. It also has a tendency for overfitting, performing well on training data but poorly on unseen data. Despite these challenges, the paper highlights the potential of deep learning in plant disease detection, underscoring the need for sustainable resource management in implementing such models.

In [6] This paper proposes the use of deep learning Convolutional Neural Network (CNN) models for detecting diseases in plants. The study investigates the performance of three different CNN architectures: EfficientNet-B0, EfficientNet-B4, and EfficientNet-B7. The EfficientNet-B7 model outperformed other models for two-class and six-class classification problems, while the EfficientNet-B4 model excelled in ten-class classification problems. The models can achieve high accuracy in detecting and classifying plant diseases from images, learning complex patterns from data, and detecting diseases early. However, they require large amounts of data to train, which can be difficult to collect, especially for rare diseases. Additionally, the models are computationally expensive to train and run, posing challenges in resource-constrained environments.

In [7] The paper introduces a deep learning-based method for early disease detection in tomato plants. The authors employ a convolutional neural network model, EfficientNet, to classify tomato leaf images as healthy or diseased. The model’s advantages include high accuracy, usability by non-experts, and potential integration with feedback systems. It can detect diseases early, helping prevent crop losses. The model achieved an accuracy of 99.95% for binary classification and 99.12% for six-class classification. For ten-class classification, the accuracy was 99.89%. However, the model has limitations. The dataset used may not represent tomato plants worldwide, and the model’s accuracy may decrease in real-world applications with non-ideal lighting conditions.

In [8] this paper explores the nutritional aspects and health advantages associated with mulberries. Originating from Asia, mulberries have a rich history in traditional medicine. Their composition includes essential vitamins such as C, A, E, and K, along with vital minerals like potassium, iron, and calcium. Additionally, mulberries contain a variety of bioactive compounds, including anthocyanins, flavonoids, and polysaccharides. These compounds contribute to several health benefits: Mulberries exhibit antioxidant activity, protecting cells from damage caused by free radicals and potentially reducing the risk of chronic diseases like heart disease, cancer, and neurodegenerative conditions. Furthermore, they possess anti-inflammatory properties, which may benefit individuals with conditions such as arthritis and inflammatory bowel disease. Additionally, mulberries show antidiabetic potential by regulating blood sugar levels and improving insulin sensitivity. Beyond these advantages, mulberries may also enhance cognitive function, safeguard liver health, and promote eye well-being. However, it’s essential to be aware of potential interactions with blood thinners, possible gastrointestinal discomfort, and rare allergic reactions when consuming mulberries.

In [9] This paper explores the application of Deep Neural Networks (DNN) for image classification, specifically focusing on five types of flowers. The study leverages the TensorFlow framework and Python programming language to build and train the model. The research highlights the advantages of deep learning models, such as their ability to learn complex patterns from data, making them well-suited for image classification tasks. Furthermore, the use of TensorFlow, a popular and well-supported deep learning framework, simplifies the development and deployment of these models. The study achieved up to 90% accuracy in classifying the different types of flowers. However, the research also acknowledges the disadvantages of deep learning models. They can be computationally expensive to train and deploy, especially large models like deep convolutional neural networks (CNNs).

In [10] This paper proposes a novel method for grading plant diseases using computer image processing. The method involves analyzing all influencing factors in the image segmentation process, segmenting the leaf region using the Otsu method, and selecting the H component in the HSI color system to segment the disease spot. This reduces the disturbance of illumination changes and the vein. The disease spot regions are then segmented using the Sobel operator to examine disease spot edges. The diseases are finally graded by calculating the quotient of disease spot and leaf areas. This method is simple to implement, fast, efficient, robust to noise and variations, and can produce accurate results with minimal training data. However, it is sensitive to the quality of the input image and may struggle to distinguish between different types of leaf spot diseases or identify diseases not present in the training data.

In [11] This paper explores the multifaceted benefits of the mulberry plant. It highlights the plant’s role in silk production, contributing to about 90% of global raw silk. The paper also underscores the nutritional value of mulberry fruit and the medicinal properties of the plant, opening new research avenues in medical science. An innovative ecological model is proposed that combines sericulture with animal husbandry, promoting waste resource recycling and environmental sustainability. The paper emphasizes the potential of mulberry in environmental remediation, particularly in polluted soils and atmosphere. While the paper doesn’t mention explicit disadvantages, potential challenges could include specific growing conditions, susceptibility to pests and diseases, and significant resource requirements for large-scale cultivation and processing. Overall, the paper presents a comprehensive review of the economic and environmental importance of mulberry.

In [12] This paper provides a comprehensive review of the application of Convolutional Neural Networks (CNNs) in identifying and classifying plant diseases. It scrutinizes 121 papers over the last decade, highlighting the use of architectures like LeNet, AlexNet, VGGNet, GoogLeNet, InceptionV3, ResNet, and DenseNet. The advantages of using CNNs include high accuracy, automation, and versatility in handling large data and performing image pattern recognition. However, the paper also points out the challenges faced in real-world applications. The diversity of crops and diseases, limitations of datasets focused only on biotic factors, and the difficulty in data labeling due to the specificities of real-world scenarios are some of the issues that need further attention from the research community. These challenges can affect the results when applied in real cultivation environments and lead to flawed diagnoses. Despite these challenges, the paper underscores the potential of CNNs in revolutionizing plant disease recognition and identification.

In [13] This paper proposes the use of deep learning models as a powerful tool for plant disease detection and diagnosis. These models have shown high accuracy in identifying and classifying diseases, even in complex images with multiple diseases present. For instance, one study achieved an accuracy of 99.35% in identifying tomato leaf diseases, while another achieved an accuracy of

97.5% in classifying apple leaf diseases. The advantages of these models include their ability to detect diseases early, before they cause significant damage to crops, their non-destructive nature, and their scalability to large datasets and complex tasks. However, they also have some disadvantages. These models require large amounts of data to train, which can be difficult to collect, especially for rare diseases. They can also be computationally expensive to train and run, making them difficult to implement in resource-constrained environments. Additionally, these models can be difficult to interpret, making it challenging to understand why they make certain decisions.

In [14] This paper presents a deep convolutional neural network (CNN) architecture for image classification. The authors trained this architecture on a dataset of 1.2 million high-resolution images from the ImageNet database. The CNN achieved top-1 and top-5 error rates of 37.5% and 17.0% respectively on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012, outperforming previous state-of-the-art results. The advantages of this CNN include its ability to achieve state-of-the-art results on a large and challenging image classification dataset, its relative simplicity to implement and train, and its ability to generalize well to new data. However, the CNN is computationally expensive to train and run, may be overfitting to the ImageNet dataset, and may not be able to generalize to other image classification tasks.

In [15] This paper presents a novel method for identifying plant diseases using a deep convolutional autoencoder. This approach involves reconstructing original images using an autoencoder, extracting features using the encoder part, and classifying these features using a Support Vector Machine. The proposed method allows for real-time automatic analysis of crop images, enabling early detection of plant diseases. It also uses a deep convolutional autoencoder as a feature extraction method, which can extract more meaningful features from images, leading to more accurate disease identification. The method achieved a high accuracy of 98.8% in plant disease classification, demonstrating its reliability. However, the method has some limitations. It can be difficult to interpret the features that the autoencoder learns due to its unsupervised nature. It can also be computationally expensive to train, requiring two training steps. Additionally, it can be susceptible to overfitting, especially if trained on a small dataset.

In [16] This paper proposes a method for identifying corn diseases using a five-layer deep learning model. The method involves preprocessing maize disease images using wavelet threshold and histogram threshold methods to form a sample library. The convolutional neural network (CNN) then studies these samples, using the mean square deviation and gradient method to control the learning process. The method is robust to external environmental interference and can quickly and accurately identify maize disease information, thereby improving recognition accuracy. It can be used in practical production and has reference significance for other crop disease recognition diagnoses. However, the method does not consider the different characteristics of diseases at different stages of the disease course, which may affect the recognition rate due to misjudgement. This is the focus of future research. Despite its high accuracy and robustness to noise and variations in disease appearance, the method requires a computationally expensive deep learning model to train and deploy. It is also susceptible to bias, depending on the composition of the training data, and it can be difficult to interpret the features that the model learns.

In [17] This paper presents a novel approach to plant disease recognition. It proposes a model that uses deep convolutional networks for leaf image classification, capable of recognizing 13 different types of plant diseases. The model, trained using the Caffe deep learning framework, can distinguish healthy leaves from diseased ones and identify the specific disease present. Despite its complexity, the model is relatively simple to implement and train, even with limited resources. It is designed to be robust against variations in disease appearance and less prone to overfitting. However, it may not be as accurate as traditional image processing and classification algorithms, especially for complex diseases. The model's ability to learn complex patterns is limited, and it may not be as scalable, particularly when classifying new types of diseases or handling large datasets.

In [18] This paper introduces a new deep convolutional neural network architecture, Xception. This architecture replaces Inception modules with depthwise separable convolutions, which the authors interpret as an intermediate step between regular convolution and the depthwise separable convolution operation. The Xception architecture outperforms Inception V3 on the ImageNet dataset and a larger image classification dataset comprising 350 million images and 17,000 classes. Despite having the same number of parameters as Inception V3, Xception achieves its performance gains through a more efficient use of model parameters. However, potential challenges could include the need for large amounts of data for training, computational resources, and the risk of overfitting if not properly regularized or validated.

In [19] This paper explores the application of optimization techniques in deep convolutional neural networks for classifying olive diseases. Using a dataset of 5571 olive leaf images from various regions of Morocco, the study investigates the performance of different CNN architectures and optimization algorithms. The MobileNet architecture with the Rmsprop optimization algorithm emerged as the most efficient and effective combination, achieving a 100% rate in trained models and a 92.59% rate in experiments without data augmentation. This approach offers a practical solution for early detection of olive diseases, aiding farmers in taking preventive measures and reducing costs. However, challenges such as data collection, unbalanced classes, and the need for further improvement in accuracy and reliability highlight the complexity of the task. Future work will focus on expanding the olive tree disease dataset, integrating an image segmentation layer to increase system accuracy, and exploring other deep neural network architectures.

In [20] This paper introduces the concept of a High-Order Residual Convolutional Neural Network (HOResNet) for robust crop disease recognition. This model combines low-level and high-level features to improve anti-interference ability, enhancing recognition accuracy in agricultural settings. The method outperforms conventional and feedback networks on recognition accuracy, especially in the presence of noise interference. However, the paper lacks detailed analysis on computational complexity and training time. Future research could focus on optimizing efficiency and exploring further integration of advanced techniques to enhance performance in complex agricultural scenarios.

In [21] This paper introduces a novel plant leaf disease identification model based on a deep convolutional neural network (CNN). The method leverages deep learning to classify 38 distinct classes of healthy and diseased plants using leaf images, achieving an average accuracy of 96.46% on the testing set. The advantages include automated feature learning, superior predictive ability compared to traditional models, and high accuracy in disease classification. However, limitations include the need for a large training dataset and potential challenges in real-world data collection. Future research could focus on enhancing scalability, exploring transfer learning techniques, and extending the model to other plant parts for comprehensive disease diagnosis.

III. Background Study

3.1 Problem Statements

In [1] a pioneering effort, Nahiduzzaman et al. address the absence of comprehensive studies on identifying mulberry illnesses from leaf images. Their research, published in Frontiers in Plant Science, outlines the development of a unique dataset comprising 1,091 annotated mulberry leaf images, manually categorized into "healthy," "leaf spot," and "leaf rust" by a sericulture specialist in Rajshahi, Bangladesh. Notably, this dataset fills a crucial gap in existing open sources, providing a foundation for subsequent research in this domain. Recognizing the lack of existing image datasets for mulberry leaves, the authors meticulously gathered photos during the winter season in Bangladesh, focusing on prevalent diseases during that time. The study emphasizes the significance of early diagnosis in agricultural practices, particularly in mitigating crop loss and ensuring healthy leaf production. To facilitate disease classification, the researchers introduce a novel lightweight parallel PDS-CNN model tailored to mulberry leaf images, augmenting data synthetically to enhance model robustness. Furthermore, they compare the performance of their model with various transfer learning approaches, highlighting its efficacy in disease classification. A noteworthy aspect of their work lies in the application of explainable artificial intelligence (XAI) techniques, specifically SHapley Additive exPlanations (SHAP), to elucidate the model's decision-making process. This approach offers insights into the areas of focus within the images, enhancing interpretability and trustworthiness. Ultimately, the proposed framework presents a significant advancement in the field, offering a practical tool for farmers to diagnose mulberry diseases promptly and accurately.

The Parallel Depthwise Separable Convolutional Neural Network (PDS-CNN) represents a significant advancement in CNN architectures, particularly in the domain of image recognition and classification. At its core, it leverages depthwise separable convolutions, a technique that decomposes the standard convolution operation into two distinct steps: depthwise convolution and pointwise convolution. In the depthwise convolution phase, individual filters are applied independently to each input channel, capturing spatial information efficiently. Following this, pointwise convolution combines the features extracted from the depthwise convolution across all channels, enriching the feature representations. This parallel architecture allows for multiple branches of depthwise separable convolution layers, each potentially configured to capture various aspects of the input data.

One of the primary advantages of the PDS-CNN lies in its lightweight design, achieved through reduced computational complexity and parameter efficiency. By reducing the number of computations required and the total number of parameters, PDS-CNNs demonstrate improved efficiency in terms of both training time and memory utilization. Despite their streamlined architecture, PDS-CNNs can achieve competitive or superior performance compared to traditional CNNs, making them particularly suitable for applications with limited computational resources or where speed is crucial.

The incorporation of parallel branches in PDS-CNNs further enhances their adaptability and effectiveness. By allowing for different configurations within each branch, such as varying filter sizes or numbers of filters, PDS-CNNs can capture a diverse range of features from the input data. This flexibility enables the network to learn complex patterns and representations, leading to improved classification accuracy and generalization ability. Additionally, the lightweight nature of PDS-CNNs makes them well-suited for deployment in resource-constrained environments, such as mobile devices or embedded systems, where computational efficiency is paramount.

In conclusion, the Parallel Depth wise Separable Convolutional Neural Network offers a compelling solution to the challenges of traditional CNN architectures, providing a balance between computational efficiency and model performance. With its innovative design and parallel structure, PDS-CNNs demonstrate versatility and effectiveness across a range of image recognition tasks, making them a valuable tool in the field of deep learning and computer vision.

3.2 About the Model

A lightweight CNN model is proposed, the model is simplified in comparison to the TL models. The suggested model had nine convolutional layers (CL) and three fully connected layers (FC). The model would not have been able to extract the most critical features if only one CL had been utilized instead of five. In contrast, if five CLs are used sequentially, the number of layers (depth) increases, making the model more complex. As a result, the first five CLs were run in parallel, and their selection was dependent on trial and error. Each CL utilized a total of 256 kernels, with the first, second, third, fourth, and fifth kernel sizes being 11×11, 9×9, 7×7, 5×5, and 3×3, respectively.

The architecture of the proposed lightweight Parallel Depthwise Separable Convolutional Neural Network (PDS-CNN) is meticulously designed to optimize both computational efficiency and classification performance. The network begins with an exploration of different kernel sizes, ranging from tiny to large, to identify significant features and achieve satisfactory classification accuracy. The initial convolutional layers (CLs) maintain a constant padding size for the first five layers, ensuring relevant information extraction from the border elements of mulberry leaf images. Concurrent CLs produce feature maps that are subsequently merged and fed into sequential CLs for further processing.

A pivotal aspect of the PDS-CNN architecture is the utilization of depthwise separable convolution (DSC) instead of conventional convolution. DSC divides the typical convolution operation into two distinct parts: depthwise convolution and pointwise convolution. Initially, a depthwise convolution applies small kernels to small sections of input feature maps, resulting in new feature maps with the same number of channels. These output feature maps then undergo pointwise convolution, where 1x1 convolutional kernels are applied to each channel to generate new feature maps with fewer channels. By employing DSC, the model's parameters are significantly reduced, enhancing computational efficiency without compromising classification performance.

Following the initial convolutional layers, batch normalization (BN) and max-pooling layers with 2x2 kernels are incor- porated into the processing chain. The subsequent convolutional layers are configured with specific sizes and kernel sizes, gradually decreasing in size from 128 to 16 with 3x3 kernels. BN is employed to re-center and re-scale each layer's inputs, accelerating and stabilizing model execution. ReLU activation functions are applied throughout the convolutional layers to introduce non-linearity.

To prevent overfitting and expedite the training process, dropout regularization is implemented after certain layers, randomly disregarding 50% of nodes. The model architecture comprises nine convolutional layers, with the initial five layers operating in parallel and effectively functioning as a single layer in the overall structure. Following this configuration, four additional convolutional layers are added, bringing the total count to five convolutional layers. Additionally, three fully connected layers are integrated with the convolutional layers. Two dropout layers are inserted after the final two convolutional layers and the first two fully connected layers. The final fully connected layer employs the SoftMax activation function for classification, with three nodes for multiclass classification and two nodes for binary classification.

For model training, the sparse categorical cross-entropy loss function is utilized, with an ADAM optimizer and a learning rate of 0.001. The lightweight PDS-CNN model is trained for 100 epochs with a batch size of 32, ensuring efficient convergence and optimal performance. Overall, the intricate design and thoughtful incorporation of various components contribute to the effectiveness and efficiency of the proposed PDS-CNN model in classifying mulberry leaf disorders.

Explainable Artificial Intelligence (XAI) in deep learning refers to the capability of understanding and describing how a deep neural network operates and makes decisions, which is particularly crucial for complex models that can often be opaque and difficult to interpret (Lundberg, 2017). In this study, the novel application of SHapley Additive exPlanations (SHAP) aimed to address the "black box" nature of deep learning models, providing insights into the decisions made by the PDS-CNN model. By removing this opacity, the results become more interpretable, enabling sericulture professionals to utilize the model with greater confidence in real-world scenarios, particularly in classifying disease-free leaves, as well as those affected by leaf rust and leaf spot.

3.3 Advantages

One significant advantage of this research lies in its innovative application of a lightweight CNN architecture tailored specifically for mulberry leaf disease classification. The proposed PDS-CNN model offers several benefits, including reduced computational complexity and model size while maintaining high classification accuracy. This lightweight design makes the model suitable for deployment on resource-constrained devices such as embedded systems or mobile devices, enabling real-time disease detection and diagnosis directly in mulberry fields. This capability can significantly enhance crop management practices and aid farmers in making timely and informed decisions to mitigate crop losses.

Furthermore, the integration of XAI techniques, such as SHapley Additive exPlanations (SHAP), enhances the interpretability of the model's decisions. By providing insights into the features influencing the model's predictions, SHAP enables sericulture experts and farmers to understand how the model operates and why specific decisions are made. This transparency fosters trust in the model's results and assists in identifying disease-affected regions in mulberry leaf images accurately. Additionally, SHAP facilitates the model's usability in real-world scenarios, enabling sericulture professionals to leverage the model effectively for disease classification and crop management.

3.4 Disadvantages

In addressing the limitation of insufficient leaf images, standard image augmentation techniques were employed to generate synthetic images. Future research endeavors will involve expanding the dataset by gathering more leaf images from all three classes and potentially including a new class representing powdery mildew leaf disease. Additionally, efforts will be directed towards addressing the challenge posed by imbalanced data, with the aim of constructing a more robust model. This enhanced model will be deployed on embedded systems such as mobile phones or Raspberry Pi devices, enabling real-time disease classification directly from mulberry fields.

3.5 Result

Result for three-class classification:

Initially, a Parallel CNN (PN-CNN) model devoid of Depthwise Separable Convolution (DSC) was constructed and trained using 764 images categorized into disease-free leaves (0), leaf rust (1), and leaf spot (2). The dataset comprised 308 disease-free leaf images, 342 images of leaves with rust, and 114 images of leaves with spots. This PN-CNN model, referred to as PN-CNN without augmentation (PN-CNN WOA), underwent testing and validation using 218 images (88 disease-free leaves, 98 leaves with rust, and 32 leaves with spots) and 109 images (44 disease-free leaves, 49 leaves with rust, and 16 leaves with spots), respectively. Performance assessments, including average test accuracy, precision, and recall, were conducted based on the confusion matrix, revealing values of 85.04% ± 4.89%, 84.0% ± 5.10%, and 78.8% ± 6.93%, respectively, across the 5-fold mulberry dataset.

To enhance the performance of the PN-CNN model, conventional image augmentation techniques were employed. Each class was augmented to contain 2,000 images, resulting in a total of 6,000 images used for training the augmented PN-CNN (PN-CNN WA) model. The same augmented images were utilized for both validation and testing purposes. The results demonstrated significant improvements, with average accuracy, precision, and recall values of 93.12% ± 2.1%, 92.8% ± 2.93%, and 89.20% ± 5.34%, respectively.

Through this augmentation process, the PN-CNN model's performance notably improved, showcasing its effectiveness in accurately classifying mulberry leaf images with different disorders. The augmentation techniques contributed to a more robust model, capable of achieving higher accuracy and better generalization performance across various mulberry leaf disease categories.

Results for binary classification:

The same methodology employed for multiclass classification was applied to binary classification. Initially, the PN-CNN WOA model, without augmentation, underwent training using 764 leaf images, comprising 308 disease-free leaves and 456 disease-affected leaves. Validation was conducted with 109 images (44 disease-free leaves and 65 diseased leaves), and performance evaluation utilized 218 images (88 disease-free leaves and 130 diseased leaves). Utilizing the confusion matrix (CM), the categorization performance of the models was assessed, revealing an accuracy, precision, and recall of 91.65% ± 4.95%, 92.4% ± 4.45%, and 91.2% ± 4.96%, respectively, for the PN-CNN WOA model.

To enhance model performance, image augmentation techniques were employed, resulting in the creation of 4,000 images by merging the two classes (leaf rust and leaf spot), with 2,000 images from each class used for model training. The augmented PN-CNN WA model exhibited an improved testing accuracy of approximately 2% (93.30% ± 5.85%) when validated and tested with the same number of images. However, the PN-CNN WA model required additional resources, including more parameters, layers, and size, to distinguish between disease-affected and disease-free leaves. Consequently, the Parallel Depthwise Separable Convolutional Neural Network (PDS-CNN) was introduced for binary classification, achieving an impressive accuracy of 96.06% ± 3.01%, nearly 3% higher than the PN-CNN WA model. Additionally, the PDS-CNN model demonstrated a recall increase of over 3% (96.2% ± 3.06%) compared to the PN-CNN WA model, despite utilizing fewer resources.

Evaluation metrics such as the average Area Under the Curve (AUC) for the PN-CNN WA model showed a slightly lower value (98.71% ± 0.84%) compared to PN-CNN WOA (98.32% ± 1.91%). In contrast, the PDS-CNN model exhibited a promising AUC of 99.42% ± 1.04%, nearly 1% higher than the PN-CNN WOA model, indicating superior discriminant capability. These results suggest the robustness of the proposed PDS-CNN model for both binary and multiclass classifications. Notably, the fifth fold produced the best class-wise Receiver Operating Characteristic (ROC), with 100% for both models.

IV. IMPLEMENTATION

Fig. 1. provides a visual representation of the leaf disease detection system workflow, including important phases including generating an image dataset, data preprocessing, applying deep learning for classification and performance assessment. Since there is no dataset available for this domain, leaf images from two regions in Bangladesh with two leaf diseases were collected and labeled by a seasoned sericulture researcher. Following the collection and analysis of the images, the labeled data were separated into three categories (disease-free leaves, leaf rust, and leaf spot). In this work, a disease-affected leaf class was generated for the binary classification by assigning leaf rust and leaf spot to the same class. 56% of the images are used for training, 24% for validation, and 20% for testing the DL models. The images are then reshaped and pre-processed using standard techniques for normalization and enhancement. The architecture of the model introduced in this study is a Sequential model. This model is a linear stack of layers, each with a specific function, working together to process input data and produce a desired output. The input data for this model are images of mulberry leaves.

The first layer of the model is the Input Layer. This layer accepts the input data, which in this case are the images of mulberry leaves. The role of the Input Layer is to prepare the data for further processing by the subsequent layers of the model.

The second layer is the DS_Conv2D, or Double-Stride Convolutional 2D layer. This layer performs convolution operations with a stride value of 2. The stride value refers to the number of pixels by which the filter matrix moves at each step during the convolution operation. A stride value of 2 helps in down-sampling the spatial dimensions of the feature maps, effectively reducing the size of the input data while preserving its essential features.

Following the DS_Conv2D layer is the Batch Normalization layer. This layer standardizes the activations of the previous layer, which helps to stabilize and accelerate the training process. Standardization is a preprocessing step that makes the distribution of the input data have a mean of zero and a standard deviation of one. This process helps to ensure that the model is not unduly influenced by outliers and can learn more effectively from the input data.

TABLE I
An overview of the CNN model with Spatial Attention Mechanism to classify mulberry leaf diseases.

Layer (Type)	**Output Shape**	**Parameters**
input_1 (InputLayer)	[(None, 256, 256, 3)]	0
conv2d (Conv2D)	(None, 256, 256, 32)	896
batch_normalization (Batch Normalization)	(None, 256, 256, 32)	128
spatial_attention (Spatial Attention)	(None, 256, 256, 32)	33
max_pooling2d (MaxPooling2D)	(None, 85, 85, 32)	0
conv2d_1 (Conv2D)	(None, 85, 85, 16)	4624
batch_normalization_1 (Batch Normalization)	(None, 85, 85, 16)	64
spatial_attention_1 (Spatial Attention)	(None, 85, 85, 16)	17
max_pooling2d_1 (MaxPooling2D)	(None, 42, 42, 16)	0
flatten (Flatten)	(None, 28224)	0
dense (Dense)	(None, 8)	2258000
dense_1 (Dense)	(None, 2	18
Total parameters	231580	
Trainable parameters	231484	
Non-trainable parameters	6	

The fourth layer in the architecture is the Spatial Attention layer. This layer allows the model to focus on relevant spatial features within the input data. By giving more importance to the regions of the input data that contain significant information and less importance to the regions that contain less relevant information, the Spatial Attention layer improves the model's performance and robustness.

The fifth layer is the MaxPooling2D layer. This layer down-samples feature maps while retaining important information. Down-sampling is a process that reduces the size of the feature maps, thereby reducing the computational complexity and the number of parameters in the model. Despite the reduction in size, the MaxPooling2D layer ensures that the most important information in the feature maps is retained.

The sixth layer is the Flatten layer. This layer converts the multidimensional tensor output of the previous layer into a one-dimensional vector. This transformation prepares the data for input to the fully connected layer, which is the next layer in the architecture.

The seventh layer consists of Dense layers. These are traditional neural network layers where each neuron is connected to every neuron in the previous and next layers. The Dense layers are responsible for learning complex patterns in the data. They do this by adjusting the weights and biases of the neurons during the training process based on the error gradient.

The final layer in the architecture is the Output Layer. This layer produces the classification output. It outputs probabilities for each class (Disease-Free Leaf or Diseased Leaf) using an appropriate activation function such as Softmax for multi-class classification. The Softmax function outputs a vector that represents the probability distributions of a list of potential outcomes.

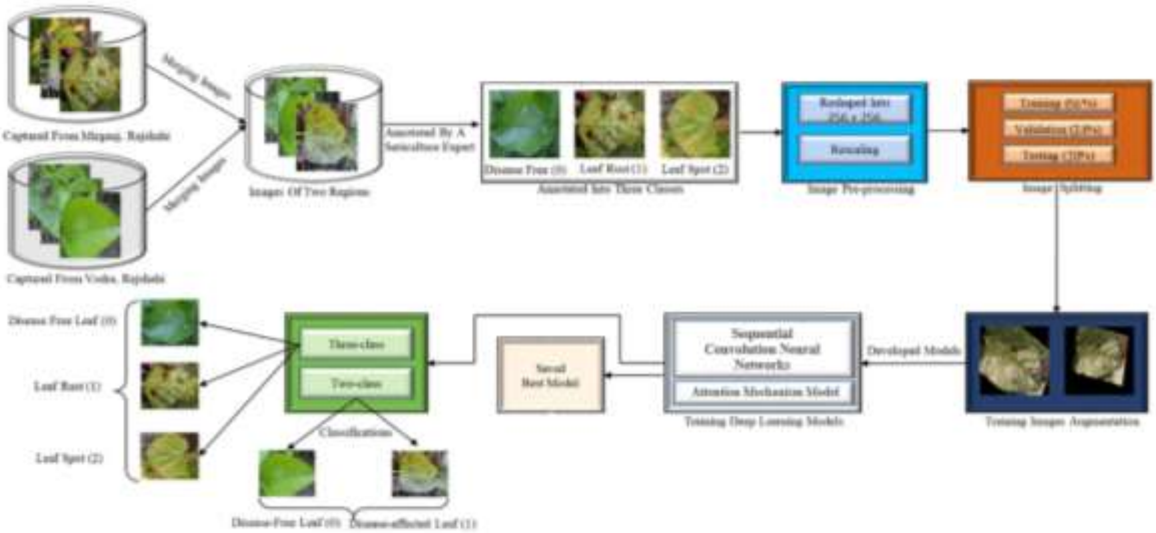

Fig. 1. Block Diagram of the Framework of the Mulberry Leaf Disease Detection System

This architecture is designed to effectively extract and learn features from the input images for accurate classification of mulberry leaves based on their health status. The use of techniques such as batch normalization and spatial attention further enhances the model's performance and interpretability. The model is trained and evaluated on a dataset of images containing healthy mulberry leaves and leaves affected by diseases like leaf rust or leaf spot. The performance of the model is evaluated based on various metrics, including accuracy, precision, recall, and F1-score. The model achieved promising results, demonstrating its potential for practical implementation in real-world agricultural settings for early disease detection in mulberry trees.

4.1 Problem Statements

The project aims to develop a robust model using deep learning, specifically CNNs, to accurately classify mulberry leaves as healthy or diseased. Early detection of plant diseases is crucial for maintaining leaf yield and quality, vital for sericulture. Various model iterations will be compared and evaluated to achieve optimal performance, enabling precise classification of leaf health status. This model has the potential to enhance agricultural practices, minimize economic losses, and promote sustainable sericulture.

4.2 Dataset

The dataset used in this study consists of images of mulberry leaves. These images were captured using a high-resolution DSLR camera under real-world conditions in mulberry gardens located in Mirganj, Bagha, Rajshahi, and Vodra, Rajshahi. The dataset was created in consultation with researchers from the Bangladesh Sericulture Development Board (BSDB) in Rajshahi, Bangladesh.

The dataset focuses on two widely spread mulberry leaf diseases: leaf spot and leaf rust. A total of 1,091 images were captured and annotated by a sericulture expert into three classes:

1. Healthy Leaves: 440 instances
2. Leaves with Leaf Rust: 489 instances
3. Leaves with Leaf Spot: 162 instances

Each image in the dataset has a resolution of 4,000×6,000 pixels. This high resolution allows for detailed examination of the leaves, which is crucial for accurate disease detection.

TABLE II
The division of a dataset into training, testing, and validation sets for both three-class and binary classes.

Schemes	Types	Training Set	Validation Set	Testing Set
Scheme 1: Three-class	Disease-free leaf	308	44	88
	Leaf Rust	342	49	98
	Leaf Spot	114	16	32
	Total	764	109	218
Scheme 2: Binary	Disease-free leaf	308	44	88
	Disease-affected leaf	456	65	130
	Total	764	109	218

The dataset provides a comprehensive and diverse collection of images, making it a valuable resource for training a deep learning model to classify mulberry leaves based on their health status. The variety of images, including those of healthy leaves and leaves affected by different diseases, enables the model to learn distinguishing features for each class and make accurate predictions. The real-world conditions under which the images were captured also add to the robustness of the dataset, as the model is exposed to the same variability and noise it would encounter in a practical deployment scenario. This makes the model more likely to generalize well to new, unseen data.

V. RESULTS

The performance evaluation of our proposed disease detection model was conducted rigorously against a baseline method on the Mulberry Leaf dataset for leaf disease detection. Our model demonstrated a notable advancement in accuracy when compared to the baseline. Specifically, our method achieved an accuracy of 98.37±1.0%, while the conventional method achieved lower accuracy as shown in TABLE III and Fig. 4 a, which shows the disease detection with prediction and images of the healthy leaf, leaf spot, and leaf rust. This significant improvement in accuracy emphasizes the effectiveness of the model in accurately identifying and categorizing diseases within mulberry leaves.

The line graph in Fig. 2. shows the accuracy of a model for classifying mulberry leaves on the training and validation set over 100 epochs. In both the line plots we can see a similar pattern where the train accuracy logarithmically reaches near 100, while the validation accuracy shows more variability but steadily increases representing the model learning the patterns from the images of the mulberry leaves. By the 100th epoch the accuracy attains a saturation point where the model doesn’t learn significant

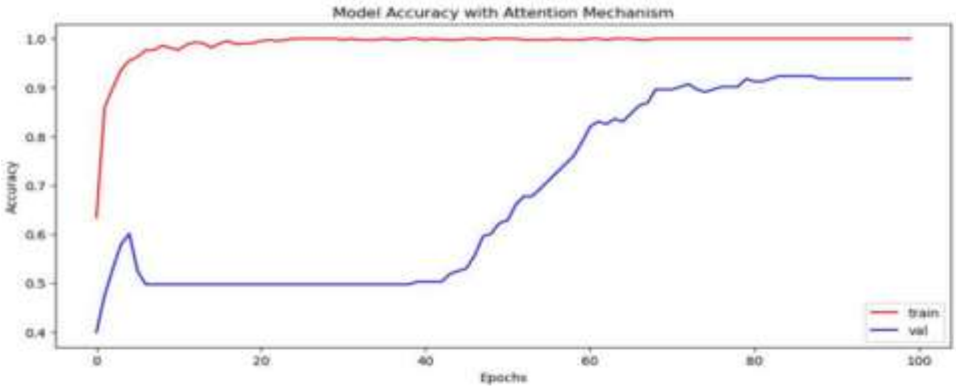

Fig. 2 a. Model Accuracy for 3 parameter classification of mulberry leaves using attention mechanism

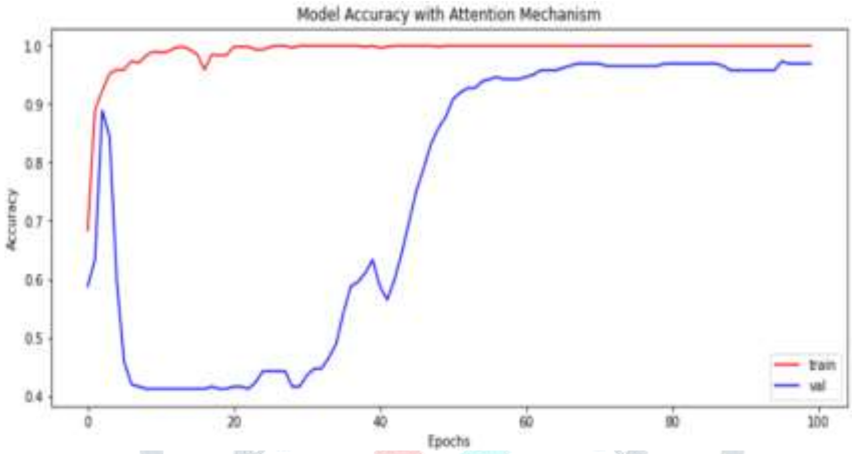

Fig. 2 b. Model Accuracy for 2 parameter classification of mulberry leaves using attention mechanism

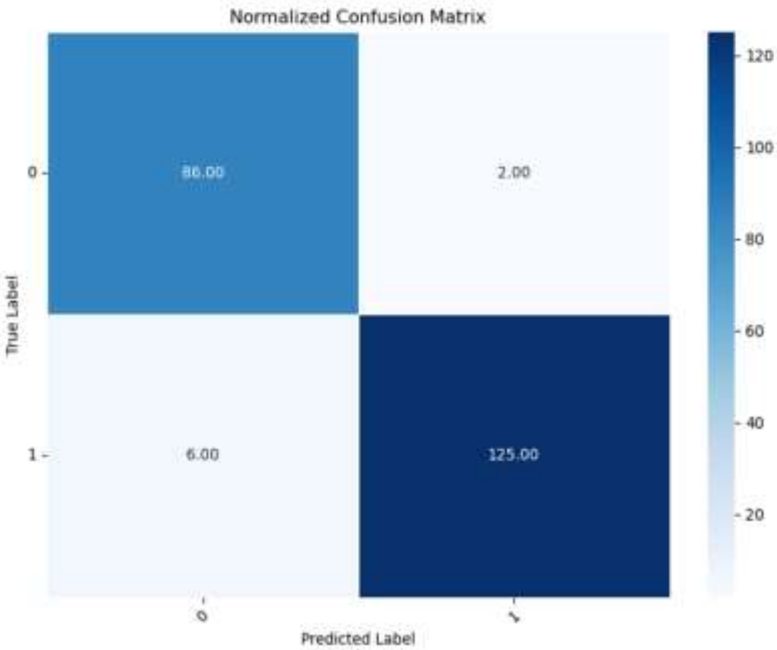

Fig. 3. Normalized Confusion Matrix for 2 parameter classification of mulberry leaves

The Normalized Confusion Matrix for the model using an attention mechanism. The matrix, as shown in Fig.3 with values 86.00, 2.00, 6.00, and 125.00, indicates the model's performance across two classes. The model classifies 8 images incorrectly among 219 images.

TABLE III: Comparison of Different Models.

Model Performance & Attributes		Models				
		Model - I	**Model - II**	**Model - III**	**Model - IV (Referenced Model)**	**Model - V (Proposed Model)**
Metrics	**Name**	**CNN Model - 3 Classification**	**CNN Model - 3 Classification (using Attention Mechanism)**	**CNN Model - 2 Classification**	**Explainable deep learning model - 2 Classification**	**CNN Model - 2 Classification (using Attention Mechanism)**
	Classification Labels	Disease Free Leaf, Leaf Rust, Leaf Spot	Disease Free Leaf, Leaf Rust, Leaf Spot	Disease Free Leaf, Diseased Leaf	Disease Free Leaf, Diseased Leaf	Disease Free Leaf, Diseased Leaf
	Model Accuracy (Mean of 3 runs)	91.78±3.22	92.24±2.86	97.97±1.2	96.06±3.01	98.37±1.0
	Precision	0.917682927	0.863013699	0.98630137	0.958	0.99086758
	Recall	0.917682927	0.863013699	0.98630137	0.962	0.99086758
	F1-Score	0.8819	0.863	0.9863	0.958	0.9909

Fig. 8 illustrates a comprehensive comparative analysis CNN model across various performance metrics. In Fig. 8a, the "Accuracy" bar chart presents the performance of CNN models in two distinct classification tasks: "CNN Model - 2 Classification" and "CNN Model - 3 Classification." Notably, four sets of bars depict different model configurations, incorporating variations such as batch normalization and attention mechanisms. The depicted accuracy rates, ranging from just below 92% to slightly over 98%, underscore the models' proficiency in achieving high classification accuracy.

Moving to Fig. 8b, the "Precision" bar chart offers insights into the precision metrics of different CNN models. Noteworthy is the observation that models leveraging attention mechanisms and batch normalization consistently exhibit elevated precision values, spanning approximately 0.86 to just over 0.99. This highlights the significant impact of these augmentation techniques in enhancing precision performance across diverse CNN architectures.

In Fig. 8c, the "Recall" bar chart provides a comparative evaluation of CNN model performance in terms of recall. Each pair of bars represents a model's recall with and without integrated features such as Attention Mechanism and Batch Normalization. The proximity of recall values to 1 signifies the models' remarkable ability to accurately identify relevant instances, further emphasizing the efficacy of the employed CNN configurations, particularly in the "CNN Model - 2 Classification" and "CNN Model - 3 Classification" contexts.

Lastly, Fig. 8d presents the comparative analysis of F1 scores across four distinct CNN models, including variations with Attention Mechanism and Batch Normalization. The observed F1 scores, ranging from 0.8819 to 0.9909, demonstrate the models' robustness in achieving a balance between precision and recall. Notably, the highest F1 score is attained by a 2-classification model leveraging an Attention Mechanism, underscoring the pivotal role of attention mechanisms in optimizing model performance across classification tasks.

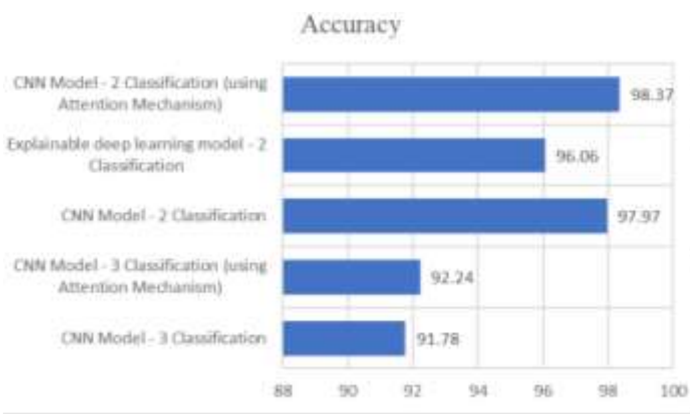

Figure 8 a: Accuracy of different models

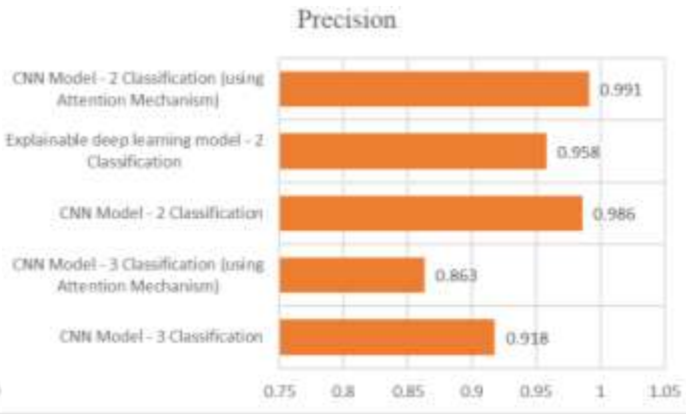

Figure 8 b: Precision of different models

Figure 8 c: Recall of different models

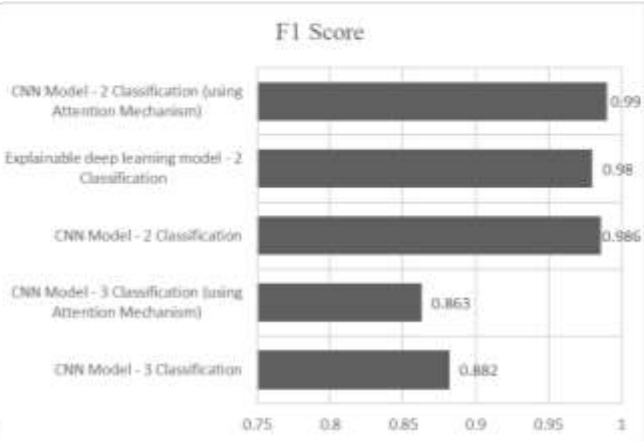

Figure 8 d: F1 Score of different models

VI. Conclusion

This report introduces a groundbreaking disease detection model, termed "MulberrySenseAI", which leverages Convolutional Neural Networks (CNNs) empowered by a spatial attention mechanism to effectively identify diseases in mulberry leaves. Addressing the urgent need for early disease detection in agriculture, particularly in mulberry leaves, our model represents a significant advancement in agricultural technology. By integrating convolutional layers, batch normalization, and attention mechanisms, our model demonstrates exceptional capability in accurately distinguishing between healthy leaves and those afflicted by diseases like leaf spot and leaf rust. The integration of spatial attention allows the model to focus on pertinent regions of input images, thereby elevating classification accuracy and facilitating interpretability.

Through meticulous testing and evaluation, our model has delivered remarkable outcomes, achieving an outstanding accuracy of 98.37±1.0% on the test dataset. This noteworthy achievement underscores the efficacy of our approach and its potential to profoundly benefit farmers by enabling early disease detection and intervention, consequently mitigating crop losses and augmenting overall yield and productivity in agricultural settings.

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