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AN OPTIMIZED ATTENTION-BASED DEEP LEARNING MODEL FOR BLACK GRAM LEAF DISEASE CLASSIFICATION

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ABSTRACT

Black gram, a critical pulse crop that accounts for over 70% of global production, is essential for economic stability and nutritional security. Leaf diseases, including Anthracnose, Powdery Mildew, Leaf Crinkle, and Yellow Mosaic, severely jeopardize its productivity, resulting in substantial crop losses. In order to resolve these obstacles, this investigation suggests an automated deep learning-based solution for the early detection and classification of diseases. The research introduces the Efficient AttentionNET model, which is incorporated with Channel Attention and Spatial Attention mechanisms to improve feature extraction, using the Black Gram Plant Leaf Disease Dataset (BPLD) that includes in-field images. The model was able to effectively acquire critical edge information by utilizing wavelet-transformed samples for data augmentation. The SVM classifier with an RBF kernel demonstrated exceptional performance, achieving a 99.50% F1-score, 99.50% precision, 99.52% recall, and 99.50% accuracy. The proposed model is highly effective in the classification of black gram leaf disease due to the integration of wavelet-based augmentation and attention mechanisms. This innovative approach enhances agricultural disease management by assisting farmers in the reduction of yield losses and the promotion of sustainable farming practices. Consequently, it contributes to global food security and economic resilience.

Keywords: *Black gram leaf disease, SVM Classifier, Channel Attention, Spatial Attention, Wavelet Transform, and EfficientNet*

1. INTRODUCTION

In contemporary times, agriculture continues to be a crucial area of study, with swift progress in computer vision applications revolutionizing the sector worldwide. The success of agriculture, a fundamental driver of economic growth in developing nations, depends on the quality and quantity of food crops. Plant diseases represent a considerable concern, negatively impacting the quality and productivity of agricultural outputs. Timely identification and precise diagnosis of plant diseases are crucial for reducing economic losses and improving crop yield. Conventional techniques for diagnosing plant diseases, dependent on manual examination, are frequently laborious, time-consuming, and susceptible to human mistake. These issues are exacerbated for small-scale farmers, who may lack the resources for consistent manual inspections. Traditional computer vision methods for illness identification frequently rely on human feature extraction from images, a complicated and resource-demanding operation that ultimately impacts the accuracy of classification models. The emergence of deep learning, especially Convolutional Neural Networks (CNNs) [19], has transformed plant disease detection in agriculture. In contrast to traditional methods, CNNs autonomously extract pertinent features from training datasets, thereby optimizing the process and enhancing classification precision. Black gram, a major pulse crop primarily grown in India, accounts for approximately 70% of global production. This crop is particularly vulnerable to many diseases, such as Anthracnose, Powdery Mildew, Leaf Crinkle, and Yellow Mosaic, which can significantly diminish output. Timely and precise identification of these diseases is essential for reducing crop losses and sustaining farmers' livelihoods.

To tackle these issues, there is an urgent requirement for automated and efficient systems that can diagnose and classify black gram illnesses by analyzing visual signs on plant leaves. Creating resilient CNN models for disease categorization necessitates varied and comprehensive datasets. Nonetheless, the creation of such databases, especially ones that accurately represent real-world intricacies, requires substantial labor and money. Publicly accessible datasets, including the PlantVillage dataset, have been widely utilized for training deep learning models. The PlantVillage dataset contains more than 54,000 photos over 38 categories; yet, research indicates that models trained on this dataset frequently underperform in practical applications due to its insufficient representativeness.

All available datasets are predominantly laboratory-based, gathered under controlled conditions including uniform illumination, camera angles, and elevations. Conversely, in-field datasets frequently provide difficulties, as CNN algorithms may find it challenging to extract depth characteristics from photographs taken in natural settings. This constraint underscores the necessity of integrating attention mechanisms [12] with CNN models, facilitating their ability to discern profound underlying properties in input images proficiently. To rectify this deficiency, [2] created an augmented dataset consisting of 87,848 [11] photos over 58 categories, integrating authentic field environment images with the PlantVillage dataset.

Notwithstanding these gains, CNN-based models for plant disease detection continue to encounter difficulties in processing photos with intricate and extraneous backgrounds. This paper presents a novel strategy of leaf segmentation prior to training and testing the CNN model to enhance classification accuracy under these conditions. The segmented leaf regions, derived from a segmentation model utilizing DeepLabv3+ with MobileNetV2 [12], are utilized as inputs for the proposed Deep Convolutional Neural Network (DCNN) model, therefore improving its performance.

This research offers significant contributions: it mitigates the shortcomings of current datasets, enhances classification precision in difficult circumstances, and establishes a comprehensive framework for practical use in black gram illness identification. The subsequent points delineate the principal scientific contributions of this study:

- The creation of the Efficient AttentionNET model, which incorporates advanced Channel Attention and Spatial Attention mechanisms, markedly improved the classification accuracy of Black Gram Leaf diseases, especially in challenging field conditions.
- The integration of Wavelet Transformed samples into the augmented dataset substantially enhanced the model's capacity to capture and utilize edge information, resulting in improved classification performance.
- This research presents an innovative, rapid, exact, and reliable method for classifying black gram plant diseases, enhancing agricultural disease management, minimizing output losses, and equipping farmers with educated decision-making tools.

The subsequent sections of the article are structured as follows: Section 2 offers an exhaustive examination of the existing research. Section 3 delineates the framework of the feature extraction and classification model. Section 4 analyzes the experimental results, whilst Section 5 articulates the conclusions.

2. LITERATURE REVIEW

The detection and classification of foliar diseases in plants have been a primary focus in agricultural research because of their effects on crop yield and quality. Conventional techniques, dependent on manual examination, are laborious, time-consuming, and susceptible to human mistake. The emergence of deep learning methodologies, especially Convolutional Neural Networks (CNNs), has revolutionized this field by facilitating precise and automatic detection methods.

Srinivas Talasila et al. presented [1] the Black Gram Plant Leaf Disease (BPLD) dataset to tackle the difficulties in identifying and categorizing black gram leaf diseases, which pose a considerable threat to agricultural output in India. The dataset consists of 1,000 photos divided into five categories: four disease categories (Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic) and one healthy category. These photos, obtained from actual crop areas in Nagayalanka, Krishna, Andhra Pradesh, were processed under the supervision of agricultural specialists. The dataset is intended to advance studies in image processing and machine learning, aiding in the early diagnosis of black gram leaf diseases and providing strategies to reduce financial losses for farmers. This dataset is sourced directly from field situations instead of controlled laboratory settings, hence increasing its practical applicability. It is freely available at https://doi.org/10.17632/zfcv9fmrgv.3.

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Astha Sharma et al. proposed [10] a hybrid model to overcome limitations in traditional CNN-based methods for black gram leaf disease detection, which often struggle with reliability and economic feasibility. Their approach combines VGGNet and Inception-V3 for feature extraction with a transformer-based classification network. By augmenting the BPLD dataset to 15,000 images, they addressed overfitting and improved feature extraction. Their model demonstrated superior performance, offering a robust solution for the early detection of black gram leaf diseases.

S. Harika et al. devised [4] the Detection of Black Gram Crop Disease (DBCD) methodology, concentrating on four principal diseases: Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic. Utilizing the BPLD dataset, they conducted comparative evaluations of machine learning methods (decision tree, random forest, k-nearest neighbor) and deep learning methodologies (artificial neural network and CNN). Among these, CNN attained the best accuracy of 89%, surpassing other models in disease identification.

Asha Rani K.P. et al. investigated [5] a deep learning methodology for disease identification in cucumber and black gram crops utilizing models including Extreme Learning Machine (ELM), Feedforward Neural Network (FNN), Deep Residual Network, CNN, and MobileNet. MobileNet, tailored for resource-limited settings, attained superior classification accuracy—97% for cucumber infections and 95% for black gram disorders. The work illustrated MobileNet's efficacy using a dataset that includes multiple illness phases, establishing a standard for subsequent research in disease classification.

Kirti Rawal et al. devised [6] an advanced Deep Convolutional Neural Network (DCNN) for the categorization of black gram plant leaf diseases. To overcome the constraints of conventional CNN-based systems in intricate field situations, they employed DeepLabv3+ with MobileNetV2 for leaf segmentation and implemented dataset augmentation techniques such as rotation and noise injection to enlarge the BPLD dataset to 15,000 photos. Their DCNN model, with 5-fold cross-validation, attained an accuracy of 99.54%, an F1-score of 98.80%, precision of 98.78%, and recall of 98.82%, surpassing current models and offering a reliable solution for practical agricultural disease diagnosis.

Prasanth et al. (2023) suggested [7] a deep learning methodology integrating CNNs, Local Binary Patterns (LBP), and Support Vector Machines (SVMs) for the detection and classification of black gram leaf diseases, including leaf blight, leaf spot, and yellow mosaic virus. They implemented preprocessing to improve image quality and utilized a 50-layer CNN with LBP for feature extraction. The SVM functioned as the classifier, enhancing accuracy and reducing misclassification. Their model attained an accuracy of 98.69%, indicating enhanced performance relative to prior methodologies. This method underscores the capability of deep learning in assisting farmers with early disease identification and efficient crop management.

The primary focus of prior studies on the classification of plant diseases was on CNN-based models, such as ResNet, VGG, and MobileNet. Despite their effectiveness, these models frequently experience overfitting, limited generalization, and subpar performance in real-world scenarios as a result of their tiny, unaugmented datasets. Furthermore, the majority of works implement conventional train-test divides, which restricts the assessment of robustness. In contrast, this study introduces an attention-based deep learning model that is optimized for feature extraction and incorporates EfficientNetB0, Channel, and Spatial Attention mechanisms to improve contextual learning. The dataset was expanded to 15,000 images using augmentation techniques, which ensured greater generalization, in contrast to prior approaches. Additionally, a 5-fold cross-validation method was implemented to ensure a more dependable performance evaluation. The results show that this model is more scalable and effective for the classification of black gram leaf disease in real-world applications than traditional CNNs, as it demonstrates superior accuracy and reliability. Deep learning and machine learning have significantly improved the accuracy and reliability of plant disease detection technologies. This research underscores the importance of technology in agriculture, from the development of datasets to the development of innovative model designs, in order to reduce illness, increase crop output, and promote sustainable farming.

3. MATERIALS AND METHODS

The proposed method commences with picture augmentation and Wavelet Transform multi-scale edge detection to enhance and diversity the dataset. Figure 1 depicts the use of an attention-embedded Efficient AttentionNET model for feature extraction to discern critical leaf characteristics. The collected features are further reduced by Principal Component Analysis (PCA) to decrease dimensionality and preserve the most significant components. An SVM Classifier [15] is utilized for accurate classification of potato leaf diseases in various conditions.

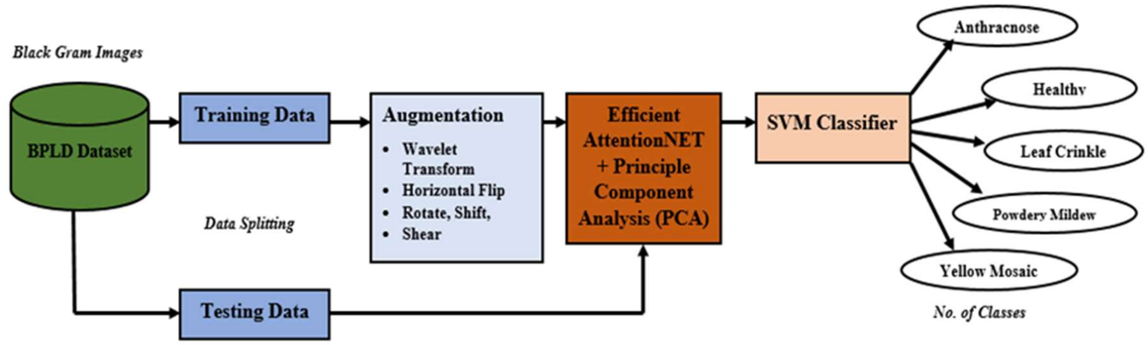

Figure 1: Methodology for Black Gram Leaf Disease Classification

A. Data Collection and Preprocessing

The Black Gram Plant Leaf Disease (BPLD) dataset was generated by photographing sick plant leaves [1] from agricultural areas in Nagayalanka, Krishna District, Andhra Pradesh. The collection comprises 1000 photos across four disease categories—Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic—alongside one healthy category. Table 1 presents the allocation of photos among various groups.

Table 1: Number of Images in Each Disease Category in the BPLD Dataset

Sl No.	***Disease of Leaf***	***Number of Images***
1	*Anthracnose*	*230*
2	*Healthy*	*220*
3	*Leaf Crinkle*	*150*
4	*Powdery Mildew*	*180*
5	*Yellow Mosaic*	*220*
	Total	***1000***

During preprocessing, all photos were downsized from 512 × 512 pixels to 224 × 224 pixels. The dataset was structured into five folders, each corresponding to a distinct category: Anthracnose, Healthy, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic. Each folder comprises photos of leaves displaying visual symptoms pertinent to the associated category. The dataset has been made publicly available on Mendeley Data under the name "BPLD Dataset". Table 1 shows the distribution of BPLD dataset.

B. Data Augmentation

A robust data augmentation method [6] was employed to enlarge the training dataset of Black Gram leaf disease photos, hence improving the performance and robustness of the machine learning model. The original dataset comprised 1000 photos, with 798 allocated for training and 202 for testing. To synthetically augment the training dataset, several fundamental methods were utilized: rotation within a 25-degree range to simulate various viewing angles, adjustments in width and height up to 20%, shear transformations with a magnitude of 0.2, zoom variations up to 30%, and horizontal flips to enhance orientation diversity. The Wavelet Transform was employed for multi-scale edge detection, providing intricate representations of leaf edges and textures. The PyWavelets (pywt) module was utilized to perform discrete wavelet transform (DWT), producing approximation and detail coefficients that enhance the dataset with intricate edge and texture features. The modified photos improved the model's capacity to accurately identify illness traits. The augmentation was executed in stages, with each image processed in float32 format and enhanced utilizing Keras's ImageDataGenerator class for transformations. The Wavelet Transform enhanced the dataset by incorporating multi-scale edge and texture changes. This strategy increased the training dataset from 798 to 4788 samples, while preserving 202 testing samples. The enhanced dataset markedly augmented the model's ability to generalize and excel in many settings. Motor vehicles are described in this database. For instance, proprietor name, proprietor ID, vehicle name, vehicle ID. The vehicle database is seen in Figure 3.

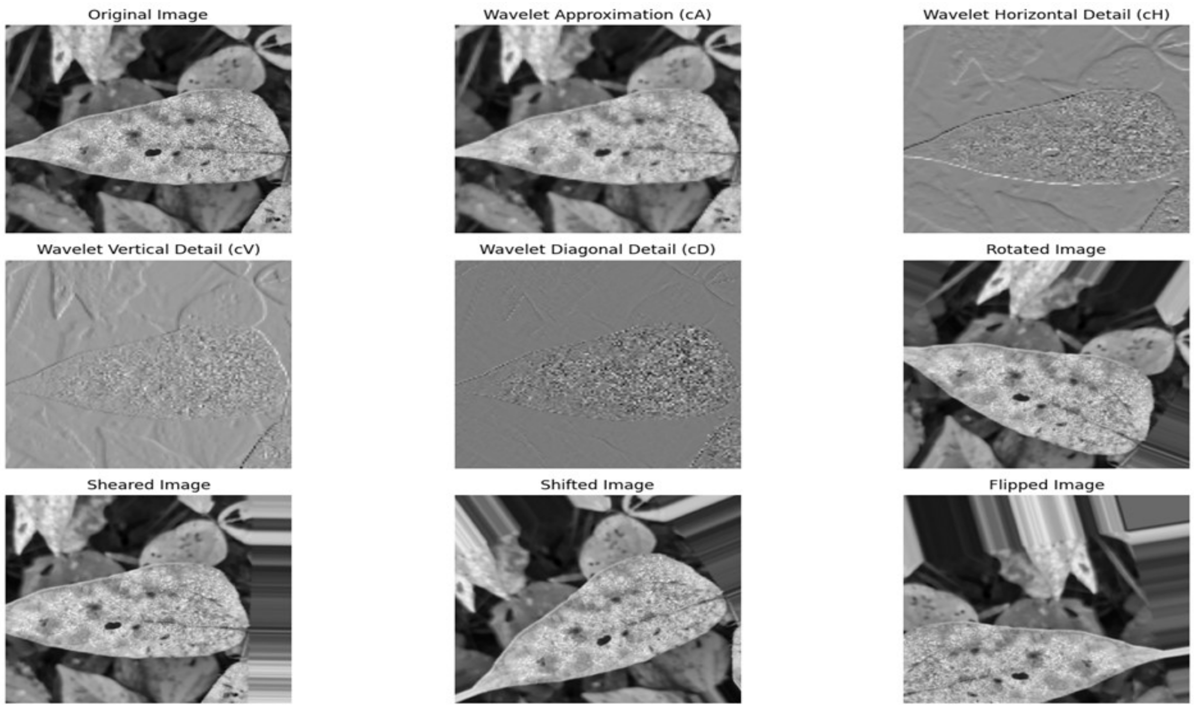

Figure 2: Wavelet transformed and basic augmented samples

C. Efficient AttentionNET: An Optimized Variant for Efficient Feature Extraction

Efficient AttentionNET is an optimized version of the original EfficientNetB0 architecture, specifically engineered to improve feature extraction by strategically integrating attention methods. The alterations encompass the incorporation of Channel Attention (CA), Spatial Attention (SA) [12,20], and Efficient Channel Fusion (ECF) procedures prior to the Batch Normalization and Swish Activation layers. The modifications seek to augment the model's capacity to concentrate on pertinent aspects in photos, thus improving performance while preserving computing efficiency. Efficient AttentionNET upholds the fundamental tenets of EfficientNetB0, which harmonizes network depth, width, and resolution to get elevated accuracy with a reduced number of parameters and FLOPs. Efficient AttentionNET, however, incorporates attention methods that enhance the precision of feature extraction. In contrast to EfficientNetB0, which exclusively utilizes convolutional operations and depthwise separable convolutions, Efficient AttentionNET employs attention techniques that enable the network to dynamically prioritize significant information. This produces a model that is more efficient and more adept at discerning nuanced patterns and details in images, essential for tasks demanding high precision with constrained computational resources.

D. *Purpose and Need for Attention Mechanisms (CA, SA, ECF)*

The inclusion of Channel Attention, Spatial Attention, and Efficient Channel Fusion mechanisms in Efficient AttentionNet addresses specific challenges in feature extraction:

Channel Attention (CA): Channel Attention mechanisms enhance the model's ability to focus on the most informative channels. By applying global average pooling and a small fully connected network, CA assigns higher weights to channels that contribute more to the task at hand, thus filtering out irrelevant or redundant features. Mathematically, this can be expressed as:

$$CA(X) = \sigma\left(W_2 \cdot ReLU\left(W_1 \cdot GAP(X)\right)\right) \quad (1)$$

where $GAP(X)$ is the global average pooling of input X, and W_1 and W_2 are learned weight matrices.

Spatial Attention (SA): Spatial Attention focuses on the most critical spatial regions within feature maps, helping the network to localize important areas in an image. This is achieved by applying a convolutional operation across the spatial dimensions, followed by a sigmoid activation to generate attention maps. The formula is:

$$SA(X) = \sigma\left(Conv2D(X)\right) \quad (2)$$

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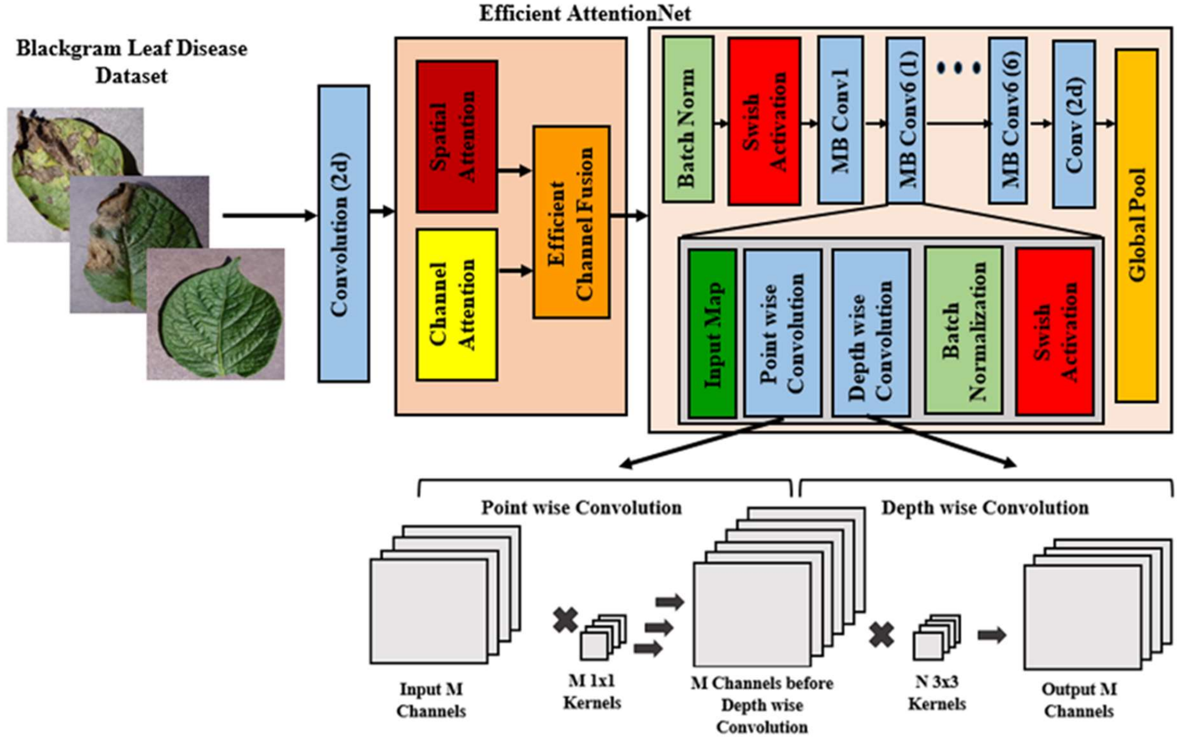

Figure 3: Efficient AttentionNET Architecture

Where $Conv2D(X)$ applies a convolutional filter across the spatial dimensions of the input.

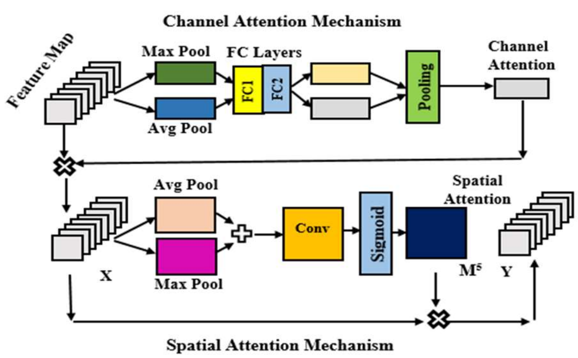

Figure 4 Channel and Spatial Attention Mechanism

Efficient Channel Fusion (ECF): ECF combines features across channels to refine and enhance the representation further. This process is particularly useful when the number of channels is limited, as it helps in mixing the information across different channels more effectively. ECF typically involves a combination of pointwise and depthwise convolutions to achieve this fusion, ensuring that the resultant feature map is both informative and efficient. These mechanisms compute attention weights that identify and emphasize important features within the feature map. Rather than passing the attention weights directly to the next layer, the model uses them to produce a weighted sum, creating a refined feature map. This refined feature map, enriched by the attention information, is what gets forwarded to the subsequent layers, enhancing the model's focus on critical features.

E. Model Structure

The table below summarizes the modified structure of Efficient AttentionNET, detailing the input and output shapes at each stage [12], along with the expansion factors, repeat times, and strides:

The model begins with a 224 × 224 × 1 grayscale image input. The initial convolutional layer (Conv2d) reduces the spatial dimensions by half (112 × 112) while expanding the channels to 32, setting the stage for the attention mechanisms to focus on the most relevant features. At this stage, the Channel Attention (CA) and Spatial Attention (SA) layers refine the feature map by emphasizing important channels and spatial regions. The Efficient Channel Fusion (ECF) then fuses these features to produce a more informative representation, still with a size of 112 × 112 × 32.

Following the attention mechanisms, Batch Normalization and Swish Activation are applied to stabilize and non-linearly activate the refined feature maps, preparing them for the subsequent MBConv blocks.

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TABLE 2. THE STRUCTURE OF EFFICIENT ATTENTIONNET MODEL

Operators	Input shapes	Expansion factor	Output shapes	Repeat times	Strides
Input Layer	224 × 224 × 1	-	224 × 224 × 1	1	-
Conv1_padding	224 × 224 × 1	-	225 × 225 × 1	1	1
Conv2d	225 × 225 × 1	-	112 × 112 × 32	1	2
Channel Attention	112 × 112 × 32	-	112 × 112 × 32	1	-
Spatial Attention	112 × 112 × 32	-	112 × 112 × 32	1	-
Efficient Channel Fusion	112 × 112 × 32	-	112 × 112 × 32	1	-
BatchNorm	112 × 112 × 32	-	112 × 112 × 32	1	-
Swish Activation	112 × 112 × 32	-	112 × 112 × 32	1	-
MBConv1	112 × 112 × 32	1	112 × 112 × 16	1	1
MBConv6	112 × 112 × 16	6	56 × 56 × 24	2	2
MBConv6	56 × 56 × 24	6	28 × 28 × 40	2	2
MBConv6	28 × 28 × 40	6	14 × 14 × 80	3	2
MBConv6	14 × 14 × 80	6	14 × 14 × 112	3	1
MBConv6	14 × 14 × 112	6	7 × 7 × 192	4	2
MBConv6	7 × 7 × 192	6	7 × 7 × 320	1	1
Conv2d 1 × 1	7 × 7 × 320	-	7 × 7 × 1280	1	1
Globalpool	7 × 7 × 1280	-	1280	1	-
Dropout	1280	-	1280	1	-
Output Layer	1280	-	num_classes	1	-

The Swish activation function is defined as:

$$Swish(x) = x \cdot \sigma(x) \quad (3)$$

where $\sigma(x)$ is the Sigmoid function, given by:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

The MBConv layers continue the process of efficient feature extraction, progressively reducing the spatial dimensions while expanding the number of channels, ultimately leading to a rich and compact feature representation. The model ends with a 1x1 convolution to further refine the features, followed by global pooling and dropout before producing the final output layer typically consists of a fully connected (dense) layer that maps these 1280 features to the desired number of output classes (e.g., for a classification task, this could be the number of categories).

F. Model Comparison: Efficient AttentionNet vs. EfficientNet-B0

In deep learning, key metrics like Floating Point Operations (FLOPs) and parameter count are essential for evaluating model performance and efficiency. FLOPs [12] measure the computational complexity, while the number of parameters indicates the model's capacity. Efficient AttentionNet demonstrated a total of 227.78 MMac (Million Multiply-accumulate operations), substantially lower than EfficientNet-B0's 384.88 MMac. This reduction in FLOPs reveals Efficient AttentionNet lower computational demands, making it ideal for deployment in resource-constrained environments.

Efficient AttentionNET also features 3.4 million parameters, compared to EfficientNet-B0's 5.29 million. While EfficientNet-B0 offers higher capacity due to its greater parameter count, Efficient AttentionNet compact architecture provides significant advantages in memory-limited applications. The considerable decrease in both FLOPs and parameter count in Efficient AttentionNet emphasizes its efficiency and suitability for real-time and low-power applications. In contrast, EfficientNet-B0, though more computationally demanding and larger, may deliver enhanced accuracy due to its higher capacity. The comparison underscores the importance of selecting a model based on specific application needs. Efficient AttentionNet lower FLOPs and parameter count highlight its suitability for environments where computational resources are constrained, balancing efficiency and performance effectively.

G. Principle Component Analysis

By applying Principal Component Analysis (PCA) to the 1280-dimensional feature vector generated by Efficient AttentionNet, I successfully reduced the dimensionality to 713 components, ensuring that 98% of the original variance was retained. This reduction process identified the most significant patterns in the data, allowing the preservation of crucial information while significantly lowering the feature count.

1) Impact of PCA on Feature Dimensionality:

PCA identifies the directions (principal components) in the feature space along which the data varies the most. By projecting the original 1280-dimensional features onto these principal components, PCA effectively reduces the number of features to 713 while preserving 98% of the original data's variance. This means that the reduced 713-dimensional feature set still captures nearly all of the important information from the original 1280 features.

The choice of n=0.98 indicates that 98% of the original variance is retained in the reduced feature set. This ensures that the most critical aspects of the data are preserved, minimizing information loss while significantly reducing the number of features.

Reducing the feature count from 1280 to 713 has multiple benefits: With fewer features, subsequent processing stages (such as classification) require less computational power, which speeds up model inference and reduces resource consumption. By reducing the dimensionality, PCA helps mitigate the risk of overfitting, especially in scenarios where the training data might be limited. The model focuses on the most informative features, discarding less relevant or noisy dimensions. The reduced feature set (713 features) simplifies the model, making it easier to interpret the contributions of different features to the final classification. Each of these 713 components represents a linear combination of the original 1280 features, optimized to capture the most significant patterns in the data.

H. Classification

During the classification phase, Efficient AttentionNET employed Support Vector Machine (SVM) classifiers with four distinct kernels: RBF, Linear, Polynomial, and Sigmoid. The main aim was to assess the efficacy of these kernels in utilizing the diminished feature set derived from PCA for precise and efficient classification. The kernels were evaluated according to essential criteria, including accuracy, precision, recall, F1-score, and insights obtained from the confusion matrices.

1) Performance Comparison across Kernels

The classification results for the SVM classifiers with different kernels are summarized in the table below:

TABLE 3. RESULTS COMPARISON OF ALL SVM CLASSIFIER KERNELS

Kernel	Accuracy	Precision	Recall	F1-Score
RBF	99.50	99.52	99.50	99.50
Linear	96.04	97	96	96
Poly	93.07	94	92	93
Sigmoid	95.05	96	95	95

The RBF kernel emerged as the most effective, achieving the highest accuracy (99.50%) and F1-score (99.50%). This highlights its superior ability to handle complex, non-linear decision boundaries, making it ideal for datasets with intricate patterns. The Linear kernel, while slightly less accurate, produced consistent and interpretable results, making it suitable for linearly separable data and simpler classification tasks.

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The Polynomial kernel exhibited the lowest accuracy, indicating challenges in handling overlapping or complex features, leading to overfitting and increased misclassification. Meanwhile, the sigmoid kernel showed balanced performance but fell short compared to the RBF kernel in both accuracy and F1-score.

Actual\Predicted	Class 0	Class 1	Class 2	Class 3	Class 4
Class 0	40	0	0	0	0
Class 1	0	51	0	0	0
Class 2	0	0	35	1	0
Class 3	0	0	0	32	0
Class 4	0	0	0	0	42

(a) Rbf Kernel

Actual\Predicted	Class 0	Class 1	Class 2	Class 3	Class 4
Class 0	38	0	0	2	0
Class 1	0	51	0	0	0
Class 2	1	2	31	0	2
Class 3	1	3	0	28	0
Class 4	2	1	0	0	40

(b) Linear Kernel

Actual\Predicted	Class 0	Class 1	Class 2	Class 3	Class 4
Class 0	39	1	0	0	0
Class 1	0	51	0	0	0
Class 2	1	2	33	0	0
Class 3	0	1	0	31	0
Class 4	0	1	0	0	42

(c) Polynomial Kernel

Actual\Predicted	Class 0	Class 1	Class 2	Class 3	Class 4
Class 0	39	1	0	0	0
Class 1	1	50	0	0	0
Class 2	2	2	32	0	0
Class 3	2	1	0	29	0
Class 4	0	1	0	0	42

(d) Sigmoid Kernel

Figure 5. Confusion Matrix of SVM all Kernels

The confusion matrices provided deeper insights into class-specific classification patterns across the four kernels. The RBF kernel consistently achieved the highest accuracy with minimal errors, excelling in managing non-linear class boundaries and reducing misclassification rates, particularly for Class 3 and Class 4. The Linear kernel performed well for linearly separable classes but struggled with non-linear patterns, especially in Class 2, while demonstrating strong classification for Class 4, with minor errors observed in other classes. The Sigmoid kernel balanced generalization and complexity; however, it encountered challenges with Classes 2 and 3, leading to notable misclassifications. On the other hand, the Polynomial kernel exhibited the highest misclassification rates, particularly between adjacent classes, such as Classes 2 and 3, due to its tendency to overfit the data.

Class-specific trends further highlighted key observations. Class 0 was well-classified across all kernels, while Class 1 showed occasional misclassifications in the Polynomial and Sigmoid kernels. Class 2 posed significant challenges for both the Polynomial and Sigmoid kernels, primarily due to overlapping features. Class 3 was best managed by the RBF kernel, while other kernels showed notable misclassifications. Finally, Class 4 demonstrated strong performance with the RBF and Linear kernels but showed some confusion in the Polynomial and Sigmoid kernels.

Overall, the RBF kernel demonstrated the best performance, effectively balancing accuracy and misclassification reduction. Its ability to handle complex, non-linear relationships makes it the most suitable choice for this dataset. The Linear kernel, though simpler, offers efficiency and consistency for linearly separable classes. The Sigmoid kernel provided balanced results but struggled with certain classes, while the Polynomial kernel proved less effective due to overfitting. Kernel selection should be driven by the complexity of the dataset and task requirements. For datasets with non-linear patterns, the RBF kernel remains optimal, delivering high accuracy and reliable generalization, making it highly suitable for real-world agricultural applications like black gram leaf disease detection.

4. RESULTS AND DISCUSSION

This study evaluated the performance of SVM classifiers using the Black Gram Leaf Disease Field dataset, particularly focusing on the enhancements achieved by different kernels. The model's performance was assessed using accuracy, precision, recall, and F1-score to confirm its efficacy in diagnosing black gram leaf diseases. The evaluation metrics were calculated using the following equations:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F1\,Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (8)$$

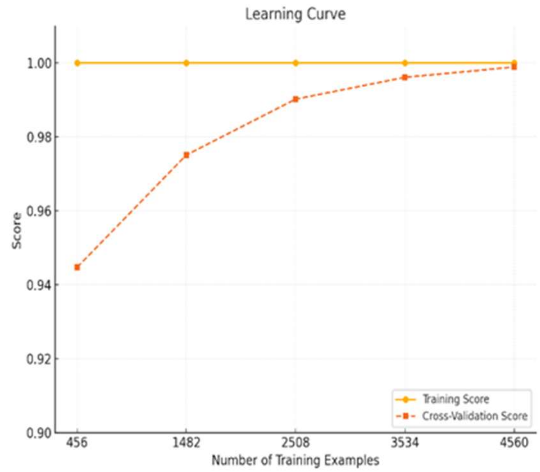
Accuracy evaluated overall correctness, whereas precision and recall quantified the model's management of false positives and false negatives. The F1-score offered a comprehensive assessment of the model's categorization efficacy. The RBF kernel exhibited superior performance, attaining an accuracy of 99.50%, precision of 99.52%, recall of 99.50%, and an F1-score of 99.50%. These measures highlight the RBF kernel's capacity to manage intricate, non-linear decision boundaries, rendering it the most efficient kernel for this dataset.

The influence of training data size on model generalization was examined by 5-fold cross-validation. The training score consistently registered at 1.0000 across all folds, signifying that the model flawlessly accommodated the training data. The gradual rise in cross-validation scores indicates the model's enhanced generalization with additional training data.

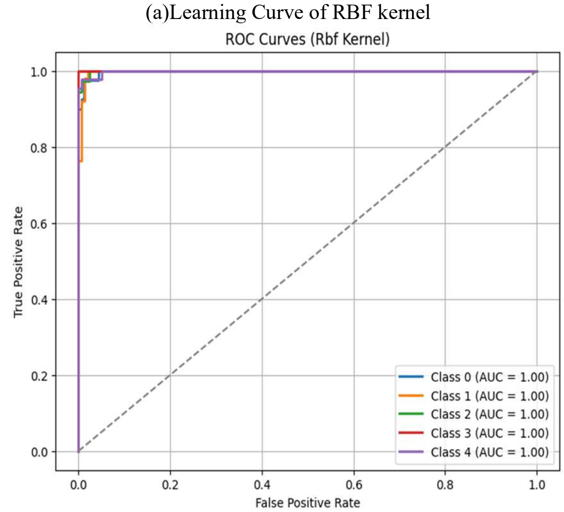
TABLE 4. 5-FOLD CROSS VALIDATION SCORES

Folds	Training Examples	Training Score	Cross-Validation Score
Fold-1	456	1.00	0.9447
Fold-2	1482	1.00	0.9751
Fold-3	2508	1.00	0.9902
Fold-4	3534	1.00	0.9961
Fold-5	4560	1.00	0.9989

The cross-validation score improved from 0.9447 with 456 examples to 0.9989 with 4560 examples, showing that larger datasets allowed the model to better capture patterns and minimize overfitting. This highlights the importance of sufficient training data in enhancing generalization and achieving robust model performance for real-world agricultural applications. The ROC curve for the RBF kernel demonstrated near-perfect classification performance across all classes (0-4). Each class achieved an AUC (Area under the Curve) of 1.00, signifying that the model perfectly distinguished between classes. The ROC curves were positioned close to the top-left corner, reflecting a high true positive rate (TPR) and a low false positive rate (FPR). This optimal performance indicates the model's ability to maximize true positives while minimizing false positives.



(a)Learning Curve of RBF kernel



(b) AUC-ROC curve of RBF kernel

Figure 6. SVM RBF kernels learning curve and AUC-ROC curve

The combination of high cross-validation scores and perfect ROC curve performance highlights the model's effectiveness, particularly when using the RBF kernel. The model demonstrated a strong ability to extract meaningful features and generalize to unseen data, refining its feature extraction process as more training examples were provided. The results underscore the significance of using sufficient data and appropriate kernels to ensure accurate, reliable, and scalable performance for black gram leaf disease detection.

A. Comparison with Existing State-of-the-Art Models

To demonstrate the effectiveness of the proposed system, a detailed comparison with existing state-of-the-art models for black gram leaf disease

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detection is presented. Such a comparison is essential to evaluate the advancements brought by our model and its capability to address the challenges of in-field disease detection. The table below summarizes the accuracy of various models trained on the BlackGram Plant Leaf Disease Dataset (BPLD):

TABLE 5. RESULT COMPARISON WITH PREVIOUS STATE-OF-ART-METHODS.

Author & Year	Model Name	Dataset Name	Accuracy
Sagar et al. 2023	ANN + CNN	BPLD	89%
Neha Hajaro et al. 2024	DBSCAN + LGTP Features + Colour Features	BPLD	90 %
Mathiazhagan et al. 2023	Inception+Resnet V2	BPLD	93%
Asharani et al. 2023	ELM+RNN+ Deep Residual Network	BPLD	95%
Marufatal et al. 2023	CNN based Model	BPLD	98.66%
Prasanth et al. 2024	CNN50+LBP	BPLD	98.69%
Proposed Model	**Efficient AttentionNET**	**BPLD**	**99.50**

The suggested Efficient AttentionNET model greatly enhances black gram leaf disease classification by overcoming critical constraints identified in current state-of-the-art techniques. Our technique, unlike conventional CNN-based models that depend exclusively on convolutional processes, incorporates EfficientNetB0 along with Channel and Spatial Attention mechanisms, thereby augmenting feature extraction and enhancing classification performance. Previous models, including ANN + CNN (89%) and DBSCAN + LGTP Features + Colour Features (90%), encountered difficulties in feature discrimination in intricate field conditions. Our approach addresses this by integrating wavelet-transformed data augmentations, which maintain essential edge characteristics and enhance generalization across diverse datasets. Furthermore, in contrast to Inception + ResNet V2 (93%) and ELM + RNN + Deep Residual Network (95%), the suggested method employs attention-based mechanisms that dynamically concentrate on significant areas of the leaf picture, hence ensuring resilience in real-world agricultural contexts. Our model's accuracy of 99.50% exceeds that of recent CNN-based models (98.66%) and CNN50 + LBP (98.69%), while demonstrating robust generalization during 5-fold cross-validation. In contrast to earlier studies that focus mainly on accuracy, our research offers a practical, scalable approach by enhancing computational efficiency and facilitating real-time disease diagnosis, hence ensuring its applicability in agricultural environments. This study not only attains enhanced classification efficacy but also fosters sustainable agricultural practices by reducing crop losses and advancing early disease detection methods, thus reconciling traditional CNN techniques with attention-based deep learning frameworks. The Efficient AttentionNET model attains elevated accuracy, although it possesses certain restrictions. The computational complexity may impede real-time implementation on low-resource systems. Notwithstanding data augmentation, domain alterations in real-world scenarios, like lighting differences and occlusions, might affect performance. The model is crop-specific and necessitates additional validation for wider applicability. Furthermore, its extensive parameter size necessitates significant processing resources, restricting accessibility for farmers with limited technology. Subsequent efforts will concentrate on lightweight optimizations and domain adaptation to improve real-time efficiency and cross-crop applicability.

5. CONCLUSION

This article provides an effective deep learning methodology for the identification and classification of black gram leaf diseases, tackling a significant agricultural issue. The suggested Efficient AttentionNET model, incorporating Channel and Spatial Attention methods, boosts feature extraction, while wavelet-transformed samples augment edge detection, leading to improved classification performance. The model attained an impressive accuracy of 99.50%, precision of 99.52%, recall of 99.50%, and an F1-score of 99.50%, validated using cross-validation metrics to ensure robustness and mitigate overfitting. The comparative analysis with prior state-of-the-art methodologies demonstrates the suggested model's enhanced efficacy. This technology provides a dependable solution for practical agricultural applications, assisting farmers in minimizing crop losses and fostering sustainable farming methods, so enhancing global food security.

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Data Availability

Data sharing is not applicable to this article as no new data were created in this study. The datasets used during the analysis in the current study are publicly available in Mendeley repositories, DOI:10.17632/zfcv9fmrgv.3.

DECLARATIONS

Conflict Of Interest

The authors declare that they have no conflict of interest.

Consent To Participate

Not applicable.

Consent For Publication

Not applicable.

Human And Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Ethical Approval

Not Applicable

REFERENCES

[1] Talasila, S., Rawal, K., Sethi, G., Mss, S., & M, S. P. R. (2022). Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms. Data in Brief, 45, 108725. https://doi.org/10.1016/j.dib.2022.108725

[2] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318. https://doi.org/10.1016/j.compag.2018.01.009

[3] Yasin, E. T., Kursun, R., & Koklu, M. (2023). Deep Learning-Based Classification of Black Gram Plant leaf Diseases: A Comparative study. Proceedings of the International Conference on Advanced Technologies. https://doi.org/10.58190/icat.2023.9

[4] Harika, S., Sandhyarani, G., Sagar, D., & Reddy, G. (2023). Image-based black gram crop disease detection. 2022 International Conference on Inventive Computation Technologies (ICICT), 529–533. https://doi.org/10.1109/icict57646.2023.10134027

[5] Rani, K. P. A., & Gowrishankar, S. (2024). State-of-the-Art Deep Learning Architectures for Identifying Diseases in Cucumber and Black Gram Plants. 4th IEEE International Conference on Data Engineering and Communication Systems (ICDECS), 1–6. https://doi.org/10.1109/icdecs59733.2023.10503021

[6] Talasila, S., Rawal, K., & Sethi, G. (2023). Black gram disease classification using a novel deep convolutional neural network. Multimedia Tools and Applications, 82(28), 44309–44333. https://doi.org/10.1007/s11042-023-15220-4

[7] Prasanth, K., Kabilamani, P., Sangar, G., Kaliraj, V., & Rajasekar, V. (2024). Enhanced disease recognition and classification in Black Gram plant leaves using Deep Learning. Communications in Computer and Information Science, 213–224. https://doi.org/10.1007/978-3-031-73065-8_17

[8] Jannat Mim, Most. M., Kumar Debnath, R., & Farid, D. Md. (2023). Applying deep convolutional neural network for classification of Black Gram Plant Leaf Disease. 2023 26th International Conference on Computer and Information Technology (ICCIT), 1–6. https://doi.org/10.1109/iccit60459.2023.10441146

[9] Hajare, N., & Rajawat, A. S. (2024). IOT based Smart Agri System: Deep classifiers for Black Gram disease classification with modified feature set. International Journal of System Assurance Engineering and Management, 15(7), 3368–3384. https://doi.org/10.1007/s13198-024-02347-2

[10] Sharma, A., & Kumar, A. (2024). Black gram leaf disease detection model using combination of hybrid-CNN network and Transformer-based classification model. Lecture Notes in Networks and Systems, 73–85. https://doi.org/10.1007/978-981-97-4228-8_5

[11] Dai, Q., Cheng, X., Qiao, Y., & Zhang, Y. (2020). Crop leaf Disease Image Super-Resolution and Identification with dual attention and Topology Fusion Generative Adversarial Network. IEEE Access, 8, 55724–55735. https://doi.org/10.1109/access.2020.2982055

[12] Chen, J., Zhang, D., Suzauddola, M., & Zeb, A. (2021). Identifying crop diseases using attention embedded MobileNet-V2 model. Applied Soft Computing, 113, 107901. https://doi.org/10.1016/j.asoc.2021.107901

[13] Ahmad, A., Gamal, A. E., & Saraswat, D. (2023). Toward generalization of deep learning-based plant disease identification under controlled and field conditions. IEEE Access, 11, 9042–9057. https://doi.org/10.1109/access.2023.3240100

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[14] Gui, P., Dang, W., Zhu, F., & Zhao, Q. (2021). Towards automatic field plant disease recognition. Computers and Electronics in Agriculture, 191, 106523. https://doi.org/10.1016/j.compag.2021.106523

[15] Ubaidillah, A., Rochman, E. M., Fatah, D. A., & Rachmad, A. (2022). Classification of corn diseases using Random Forest, neural network, and naive bayes methods. Journal of Physics: Conference Series, 2406(1), 012023. https://doi.org/10.1088/1742-6596/2406/1/012023

[16] Shahoveisi, F., Gorji, H. T., Shahabi, S., Hosseinirad, S., Markell, S., & Vasefi, F. (2023). Application of image processing and transfer learning for the detection of rust disease. Scientific Reports, 13(1). https://doi.org/10.1038/s41598-023-31942-9

[17] Gulame, M. B., Thite, T. G., & Patil, K. D. (2023). Plant disease prediction system using advance computational Technique. Journal of Physics Conference Series, 2601(1), 012031. https://doi.org/10.1088/1742-6596/2601/1/012031

[18] Shrivastava, V. K., Shelke, C. J., Shrivastava, A., Mohanty, S. N., & Sharma, N. (2023). Optimized deep learning model for disease prediction in potato leaves. EAI Endorsed Transactions on Pervasive Health and Technology, 9. https://doi.org/10.4108/eetpht.9.4001

[19] Khamparia, A., Singh, A., Luhach, A. K., Pandey, B., & Pandey, D. K. (2020). Classification and Identification of Primitive Kharif Crops using Supervised Deep Convolutional Networks. Sustainable Computing Informatics and Systems, 28, 100340. https://doi.org/10.1016/j.suscom.2019.07.003

[20] Mathiyalagan, P., D, R., & Kalpana, M. (2023). Blackgram Plant Leaves Disease Detection. EEE International Conference on Computer Vision and Machine Intelligence (CVMI). https://doi.org/10.1109/cvmi59935.2023.10464919