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An Attention-Based Dual-Optimized CNN Framework for Maize Leaf Disease Detection

Rohit Maheshwari[1], Arvind Kumar Sharma[2], Amit Sharma[3]
[1]Research Scholar, School of Engineering & Technology (Computer Science), Career Point University, Kota, India
[2]Professor, School of Engineering & Technology (Computer Science), Career Point University, Kota, India
[3]Associate Professor, Department of Computer Science and Engineering, Vivekananda Global University, Jaipur, India

***Abstract**: Leaf diseases of maize have contributed to the most significant loss in crop productivity and food insecurity across several regions, thus necessitating early and accurate disease identification as a critical need due to its application in precision agriculture. Traditional deep learning techniques sometimes have shortcomings because of growing disparities in the environmental conditions, improper extraction of features, and imperfect tuning of hyperparameters. To tackle these obstacles, this study proposes dual-optimized attention convolutional neural network which is based on convolution architecture optimization using particle swarm optimization in conjunction with hyperparameter tuning employing bayesian optimization. Moreover, a convolutional block attention module is included to improve the utilization of features learned from maize leaf images by emphasizing disease-relevant areas. The proposed framework is implemented on a publicly available maize leaf disease dataset of 4,887 images comprising four different disease categories. The experimental results demonstrate that DOA-CNN obtains a classification accuracy of 91.34%, which is also the state-of-the-art result among other models as well overfitting gap for the considered model with 0.01% margin. The results reveal that the dual-optimization frameworks together with attention mechanisms confer a large boost in classification accuracy and generalizability on smart agriculture applications.*
***Keywords**: Maize Leaf Disease, BO, PSO, Dual-Optimized Attention, CBAM, Precision Agriculture*

I. INTRODUCTION

Maize is one of the economically most valuable crops for modern agriculture; it serves as a staple food and contributes significantly to the economic development in both developed and developing countries. Maize is an important component of food supply chains and industrial production due to its high adaptability and wide range of industrial uses. Despite the broad adaptation of maize to a wide range of environmental conditions and its highest yield potential compared to other crops, large-scale maize production also poses significant threats from numerous biological threats, especially foliar diseases that devastate yields and threaten food security. A reduction in the production of maize would cause havoc all over the world because it destabilizes food supply systems and, consequently, forcibly impoverishes millions of smallholder farmers who work for their subsistence in agricultural jobs.

Foliar diseases, mainly common rust, grey leaf spot and leaf blight pose a vital risk to continuous maize yields in this regard.

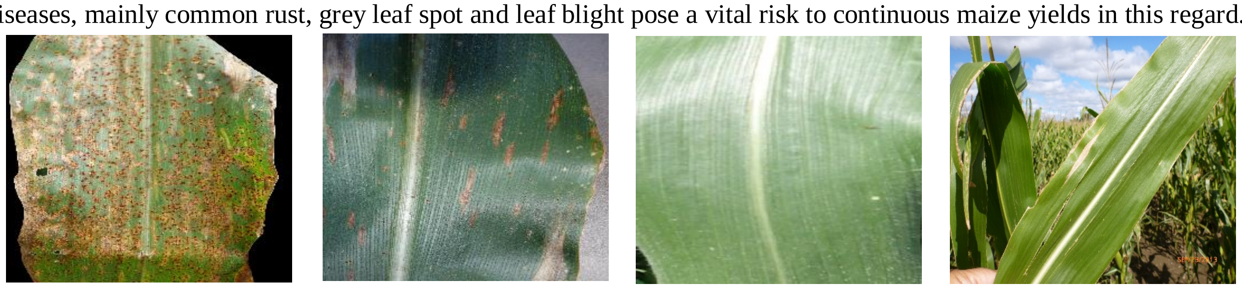

Figure 1: Representative sample images from the dataset (a) Common Rust, (b) Gray Leaf Spot, (c) Healthy, (d) Northern Leaf Blight.

These diseases not only spoil the aesthetic quality of plant tissue, but can drastically reduce photosynthetic ability and are responsible for 20-30% yield loss during severe epidemics. Identification of these diseases has traditionally relied on expert plant pathologists performing manual visual inspections. Although this approach may be true in a controlled environment, it tends to be unscalable, time-consuming, and subjective. Manual diagnostics can take several days and would allow uncontrolled spread of infection, cycles of financial desperation, and increased reliance on chemical control in the most pressured farming environments.

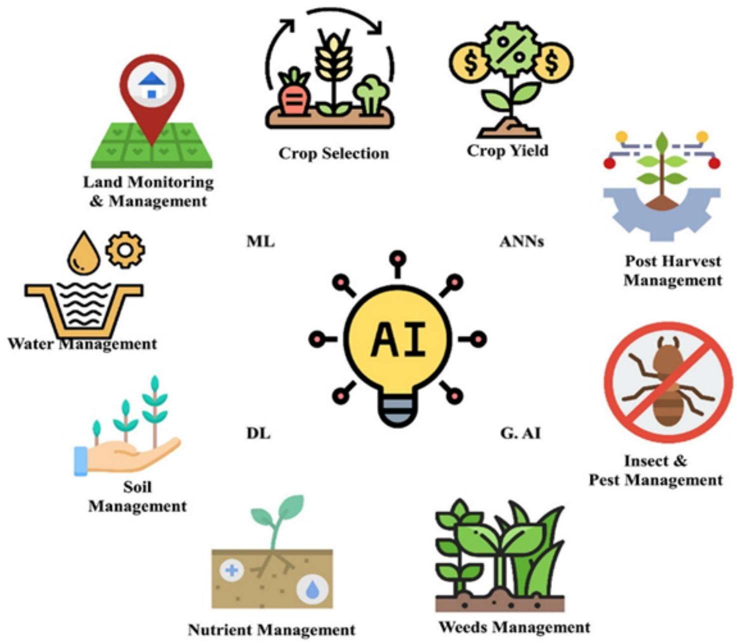

Figure 2: The process of machine learning and deep learning models in precision agriculture [17]

Precision agriculture has transformed traditional farming practices from intuition-based methods to data-driven decision-making systems. With advancements in artificial intelligence (AI), remote sensing, and data analytics, modern agricultural systems are now capable of monitoring crop health in near real time through automated technologies. Computer vision-based disease detection systems play a vital role in identifying crop diseases at an early stage, enabling timely intervention and reducing potential crop losses. Such technological advancements not only improve agricultural productivity but also support sustainable farming practices by optimizing resource utilization and minimizing unnecessary inputs. In this context, the development of intelligent disease classification systems has emerged as an important research area that bridges agricultural challenges with advanced technological solutions.

A. Computer Vision in Agricultural Technology

Rightly, the past few years have been revolutionary for machine learning in computer vision; access to large labelled datasets has allowed deep learning advances especially with regards to agriculture. Earlier versions of plant disease detection exclusively used traditional machine learning algorithms such as support vector machines and random forests. These techniques mostly used manually designed feature extraction methods such as colour histogram or texture descriptors and shape-based analysis. While these handcrafted features were informative, they generally did not generalize well across the highly variable and temporally changing pattern space conceptualized by plant diseases modulated by environmental conditions. The advent of convolutional neural networks (CNN) in rapid developments of deep learning represents a watershed moment for plant disease image classification. They can learn hierarchical feature representations directly from raw images, thus avoiding the necessity of manual feature extraction. They can capture spatial structures, textures and contextual information well resulting in significant improvements over plain classification performance. Numerous experiments proven the usage of CNNs to application in agriculture and most commonly used on leaf diseases detection and are repeatable achieving accuracy. Transfer Learning applied with these large-scale pre-trained architectures dramatically increased the competitiveness of CNN methods over state-of-the-art methods. Common feature extraction or fine-tuning models are transfer-learning pretrained models on large-scale datasets, commonly used in computer vision, such as ImageNet. Transfer learning reduces the training time and improves accuracy, though it does not address vulnerabilities specific to agricultural field environments. In datasets diagnosed with class imbalance, models more accurately predict majority classes while prediction of unwanted events that occur less frequently is worse. Environmental noise is also a key issue because field images are captured in uncontrolled lighting conditions, environmental artifacts can compete for attention with disease-related features. In addition, some hyperparameters of CNN, learning rate, number of convolutional filters and depth of the network are so sensitive that their variation will give a great impact in performance.

Tuning these hyperparameters manually is a slow process, and can lead to poor generalization such limitations further motivate the more comprehensive frameworks which improve in parallel both feature extraction and model architecture, while also systematically tuning hyperparameters for training procedures.

B. Theoretical Foundation

Deep learning-based disease classification often faces the challenge of manual hyperparameter tuning which is a major bottleneck. Traditional hyperparameter optimization methods exploit the grid search and random search which are very computationally expensive, tedious, and mostly impractical. The diversity and complexity of convolutional neural network architectures is rising rapidly and with it the corresponding number of hyperparameters grows combinatorially, so that manual tuning becomes impractical even for small datasets commonly found in real-world applications.

To overcome this problem, this work uses meta-heuristic optimization techniques which are recently emerged as a powerful solution for automating the architectural search process. Within these methods, particle swarm optimization (PSO) is one of the more simple and efficient methods. PSO is the second of the swarm-based optimization algorithms and it involves evaluating multiple candidate solutions referred to concept railed from collective behaviour observed in birds flocking or fish schooling. Each particle updates its position according to this local optimum and the global optimum. In the case of optimising CNNs, use PSO to search globally over architectural parameters. PSO performs global searches very well but is relatively poor at tuning parameters which can be adjusted in a near-optimal manner [4]. To bypass this limitation, one can reformulate the sequential optimization problem as a BO problem. BO is a stochastic global optimization algorithm for expensive black-box functions [1]. It using a surrogate model most commonly gaussian processes to construct an approximation of the objective function, and directs the search process towards areas where there is high expected improvement. BO captures the trade-off between exploration and exploitation which allows for finding the best hyperparameters like learning rate, dropout rate, or even number of neurons in dense layers it is therefore ideal to fine-tune deep learning models locally.

While discussing object recognition, another major limitation of conventional CNNs is their inability to adaptively focus on the most salient and disease-relevant regions within an input image. To address this limitation, attention mechanisms have been introduced in deep learning architectures. The Convolutional Block Attention Module (CBAM) [10] enhances feature representation by sequentially applying channel attention and spatial attention mechanisms. Channel attention emphasizes the most informative feature maps by assigning greater importance to discriminative channels, whereas spatial attention highlights important regions within the image to improve low-level and high-level feature learning [17]. This dual-attention mechanism is inspired by the human visual system, which naturally concentrates on regions of interest rather than processing the entire scene uniformly. Motivated by these advantages, this paper proposes a novel Dual-Optimized Attention Convolutional Neural Network (DOA-CNN) framework for maize leaf disease classification. The proposed framework integrates global architectural optimization using Particle Swarm Optimization (PSO), local hyperparameter fine-tuning through Bayesian Optimization (BO), and attention-based feature refinement using CBAM to effectively overcome the limitations of traditional CNN-based models.

C. Research Contributions

This work mainly addresses the important problem of designing a classification model that not only has good accuracy overall, but also generalizes well for different environment conditions. The key problem is that there is no integrated framework which can simultaneously optimize CNN architecture, tune hyperparameters and construct feature. The main contributions in this paper are as follows:

- A new attractive DOA-CNN framework for robust classification of maize leaf diseases.
- Hybrid optimization strategy using PSO for global architecture search and BO for local hyperparameter tuning.
- Implementation of CBAM for adaptive feature refine, providing the model to pay more attention to vital disease-specific areas.
- Mitigating overfitting with fine-tuning training regimes and attention mechanisms which leads to enhanced generalization performances.
- Show superior classification accuracy over the baseline models and single-optimization approaches on multiple evaluation metrics.

II. LITERATURE REVIEW

Based on research, the current trend is in CNN methods to determine plant diseases where some transfer learning models are varied architecture shows promising results.

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However, these approaches typically require cumbersome hyperparameter tuning and tend to have poor generalization power between environments. Existing maize disease detection approaches suffer from limited generalization, inadequate feature attention, and inefficient hyperparameter optimization. Most studies focus either on architectural improvements or optimization independently, whereas the proposed DOA-CNN integrates both PSO-based architectural search and BO-based hyperparameter tuning with CBAM attention for improved robustness.

A. Standard and Transfer Learning Approaches

Early-stage deep learning was focused on the accuracies of existing CNN architectures in classifying plant diseases standard CNNs are effective to classify corn leaf blight and leaf spot using datasets from Kaggle [2][3]. In a recent study compared performance of different architectures such as AlexNet, GoogLeNet, ResNet-50 and InceptionV3 across multiple crops at the same time and highlighted that transfer learning outperformed training from scratch [8]. In a recent work based on the analysis of corn leaf diseases [6], for the first time exploited SqueezeNet and variant architectures of ResNet to classify 4 different health states using images captured from field in Madura region, Indonesia [5].

B. Augmentation and Texture-Based Classification

For the problems of small or limited datasets, researchers have explored new data augmentation approaches and texture-based analytics methods. A strong classification framework with a ConvMixer based architecture along with the MixUp and CutMix augmentation methods for classifying corn leaf diseases was proposed [9]. Similarly, a combination of CNN features and traditional machine learning classifiers, where they computed texture-based features using pre-trained layers in CNNs [10]. In such an idea, it examines spatial texture information which plays a crucial role in recognizing the disease bark from plant trees.

C. Hybrid Models and Optimization Strategies

The integration of multiple algorithms has become a critical strategy for enhancing classification accuracy utilized an improved swarm algorithm for optimization, combined with a hybrid architecture of CNN and long short-term memory (LSTM) networks, to detect multiple diseases in mango crops [4]. Similarly integrated CNN and LSTM layers with self-attention mechanisms to diagnose diseases in rice leaves [6]. Expanding on this analytical approach, employed UAV-based multispectral and thermal imagery, along with an ensemble of RF, SVM and XGBoost algorithms [8].

D. Attention Mechanisms and Semantic Segmentation

Recent trends in the field focus on fine-grained segmentation and attention-driven feature extraction introduced the SE-Swin U-Net, a model that combines swan transformers with squeeze-and-excitation (SE) attention to enhance semantic segmentation of maize leaf diseases [14]. Additionally, conducted an analysis of 94 distinct CNN-based studies, concluding that the integration of attention mechanisms with optimized feature extraction is essential for the advancement of agricultural diagnostic tools [9]. However, despite these advancements, no existing studies have effectively combined PSO, BO and CBAM into a single, jointly optimized framework for classifying maize leaf diseases.

Table 1: Summary of Related Works on Plant Disease Detection Using Deep Learning

Author & year	Topic	Methodology	Dataset
Li & Tanone 2023	Corn leaf disease classification with augmentation	ConvMixer + MixUp & CutMix	Custom (Indonesia)
Ariska et al. 2024	CNN-based classification of corn leaf blight and spot	Standard CNN	Kaggle
Deputy et al. 2023	Multi-crop disease detection using DL architectures	AlexNet, GoogLeNet, ResNet-50, InceptionV3	PlantVillage
Deepa & Ruby 2022	Multi-disease detection on mango leaves and fruits	I-SSA + CNN-LSTM hybrid	Benchmark mango dataset

Bagga & Goyal 2024	Review of CNN evolution for plant disease detection	Analysis of 94 CNN studies	Multiple datasets
Rachmad et al. 2023	Corn leaf disease classification (4 classes)	SqueezeNet, AlexNet, ResNet-18/50/101	Madura region
Khan et al. 2023	Hybrid diagnosis of rice leaf diseases	CNN + LSTM + Self-Attention	Mendeley rice dataset
Yang et al. 2024	Semantic segmentation of maize leaf diseases	SE-Swin U-Net	PlantVillage (800 images)
Jia et al. 2023	UAV-based monitoring of maize southern leaf blight	Multispectral + thermal; RF/SVM/XGBoost	UAV imagery
Barburiceanu et al. 2021	Texture-based classification using CNN features	Pre-trained CNN + ML classifiers	Various plant datasets

III. METHODOLOGY

The methodology includes dataset acquisition, preprocessing, augmentation, class imbalance handling, model architecture design, and optimization strategies. The proposed framework integrates different modules to improve feature extraction and classification performance.

A. Data Acquisition and Preprocessing

The process of acquiring relevant datasets from reliable sources to train and test the proposed model. Data quality is important, so raw data undergoes rigorous examination to remove discrepancies, missing values and duplicates. The worth uses a pre-processing state of points like normalization, feature extraction, encoding, and validation of the data for efficient ML evaluation optimally.

1) Dataset Description

The center of any deep learning-based classification system is its training dataset and without noise free data with ample diversity the system fails. This paper, using a maize leaf disease dataset from Kaggle consist of 4188 images whereby an extra 699 of from agriculture university totaling to be 4,887 labelled images between four classes which are Common Rust, Gray Leaf spot and Northern Leaf Blight and Healthy Leaves. In preprocessing, the data was resized into all 128 × 128 pixel images, and therefore a dataset tensor of shape (4,887, 128, 128, 3). The dataset was further split into three parts: 3,420 images for training, 440 images for validation and 1,467 images for testing. The classes are however moderately imbalanced with a few disease categories containing far fewer samples than others. The model will be biased to predict the most classes, and you will need different training methods specifically.

2) Preprocessing and Augmentation

All input images were resized to 128 × 128 pixels while preserving the original RGB color space to maintain disease-related color patterns. Pixel intensity values were normalized by dividing them by 255, scaling them to the range [0,1]. This normalization stabilizes gradient updates and improves convergence during training. To improve model generalization and to avoid overfitting, the following augmentation methods were used during training:

- Random Rotation (±20°): Simulates different camera angles and leaf orientations.
- Zoom Transformation (scale factor 0.8–1.2): Mimics varying camera-to-leaf distances.
- Horizontal Flipping: Represents natural variations in leaf positioning.
- Width and Height Shifts: Introduces minor positional perturbations for spatial robustness.

3) Class Imbalance Handling

To address class imbalance, class weights were computed inversely proportional to class frequencies and incorporated during training. This ensures that minority classes contribute more significantly to the loss calculation. Additionally, focal loss was employed to emphasize difficult and misclassified samples while reducing the influence of easily classified instances. This approach improves the model's ability to learn representative features from minority disease categories and reduces prediction bias toward majority classes.

B. Proposed DOA-CNN Architecture

The proposed DOA-CNN framework is built on a CNN backbone enhanced with CBAM and optimized through a dual-stage process that combines PSO and BO. The architecture follows a hierarchical feature extraction pipeline:

- Conv2D layers with ReLU activation for hierarchical feature extraction.
- MaxPooling layers for spatial down sampling and noise suppression.
- Progressively increasing filter depth to capture increasingly abstract disease patterns.
- CBAM modules for selective channel and spatial attention.
- Global Average Pooling (GAP) before fully connected layers for dimensionality reduction.

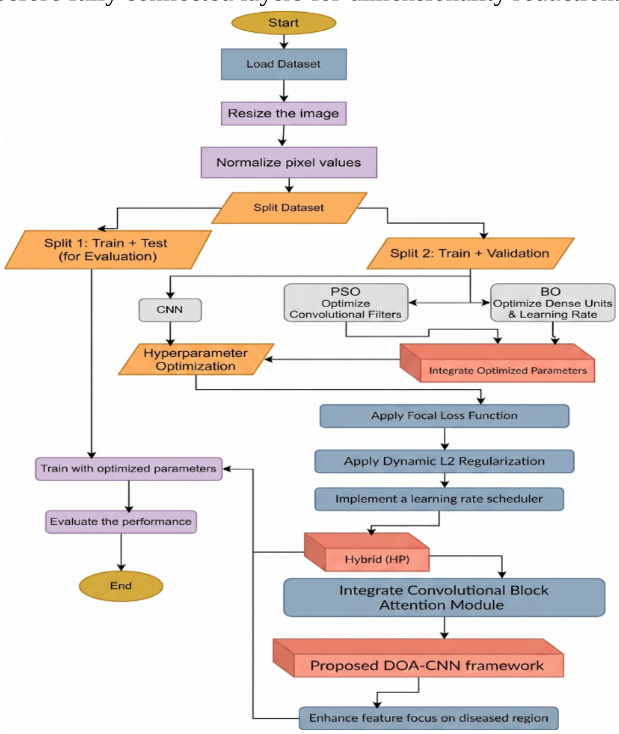

Figure 3: Proposed DOA-CNN framework flow diagram

1) Channel Attention

The channel attention module utilizes both global average pooling (GAP) and global max pooling (GMP) to produce channel descriptors, which are passed through a shared MLP to calculate channel-wise attention weights:

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \quad \text{….(1)}$$

where F: Input feature map, $AvgPool(F)$: Global average pooling, $MaxPool(F)$: Global max pooling, MLP: Multi-layer perceptron, $sigma$: Sigmoid activation

2) Spatial Attention

The spatial attention module applies average and maximum pooling along the channel axis, concatenates the results, and processes them through a 7 × 7 convolutional layers:

$$M_s(F) = \sigma(f^{7\times7}([AvgPool(F); MaxPool(F)])) \quad \text{….(2)}$$

where $f^{7\times7}$: Convolution with 7×7 kernel, $[\,;\,]$: Concatenation, Output = spatial attention map

3) Global Average Pooling

Instead of using traditional flattening, a GAP layer is employed before the fully connected layers. GAP reduces the dimensionality of feature maps by computing the average value of each feature channel. This significantly reduces the number of trainable parameters, thereby lowering the risk of overfitting and improving generalization performance.

$$G_k = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} F_k(i,j) \quad \text{….(3)}$$

where $F_k(i,j)$: Activation value at position (i, j) in the k^{th} feature map, H, W: Height and width of the feature map, G_k: Output value for the k^{th} channel after pooling

C. Dual-Optimization Framework

Bayesian optimization was employed to optimize important training hyperparameters, including the learning rate, dropout rate, and the number of neurons in the dense layer. In this approach, the objective function is approximated using a Gaussian Process surrogate model, while the search process is guided by an Expected Improvement acquisition function. As a probabilistic optimization technique, BO efficiently identifies near-optimal hyperparameter settings with a minimal number of function evaluations, thereby reducing computational cost and training complexity. It seen that particle swarm optimization was used to explore the architectural search space and determine the optimal arrangement of convolutional filter sizes within the CNN model. In PSO, each particle represents a candidate architecture, and its fitness is evaluated based on validation accuracy obtained after training on a subset of the dataset. During the optimization process, particles iteratively update their positions according to both their personal best solution (pbest) and the global best solution (gbest). This collaborative search mechanism enables the swarm to gradually converge toward an optimal network architecture with improved classification performance.

D. Training Protocol

To boost generalization and reduce overfitting, augmentation like rotation, zooming and horizontal flip were incorporated during training. The models were trained by Adam optimizer of an initial learning rate = 0.001, categorical cross-entropy was used as the loss function. All experiments were conducted with a batch size of 8 and for 20 training epochs.

$FL(p_t) = -\alpha(1-p_t)^{\gamma}\log(p_t)$ ….(4)

where p_t: predicted probability for true class, α: class balancing factor, γ: focusing parameter. Additional regularization techniques include reduce LR on plateau and early stopping to prevent overfitting and ensure stable convergence. Model generalization is further quantified by the Overfitting Gap (OG).

$OG = Accuracy_{train} - Accuracy_{val}$….(5)

IV. RESULTS AND DISCUSSION

In this work a combination of three factors: a) PSO explores the architectural search space efficiently, b) BO induces desirable training dynamics to avoid suboptimal convergence, and c) CBAM effectively encourages the model to selectively focus on spatial regions with disease relevance.

A. Performance Evaluation

The performance of the proposed DOA-CNN framework was evaluated and found superior classification performance across all evaluation metrics. The comparative analysis confirms that integrating PSO-based architectural optimization, BO-driven hyperparameter tuning, and CBAM attention significantly improves feature learning and classification capability.

Table 2: Comparative Performance test dataset of All Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline CNN	82.276755	82.591733	82.117314	82.285116
BO-CNN	90.115883	90.389279	90.184958	90.201983
PSO-CNN	90.184049	90.405656	90.304192	90.261383
Hybrid	90.388548	90.660769	90.474615	90.486854
Proposed	91.342877	91.554376	91.529080	91.400775

The experimental results show that the proposed DOA-CNN achieved the highest accuracy of 91.34%, outperforming Base CNN (82.27%), BO-CNN (90.11%), PSO-CNN (90.18%), and Hybrid CNN (90.38%). The improved performance is mainly attributed to the combined effect of architectural optimization, hyperparameter tuning, and attention-based feature enhancement.

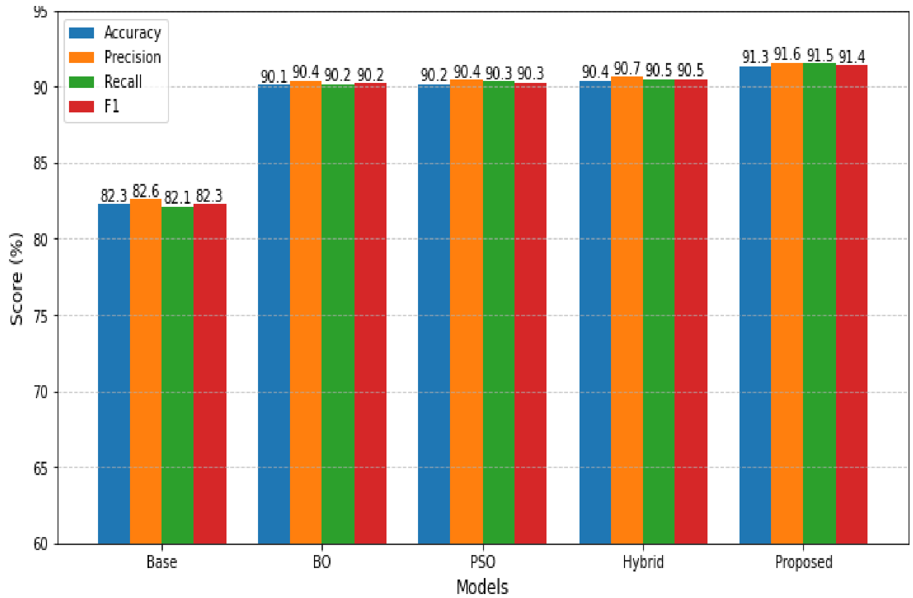

Figure 4: Comparative bar chart of all evaluated models

As shown in table 2 and fig 4, the proposed DOA-CNN achieved the highest values among all compared models. The baseline CNN exhibited the lowest performance across all metrics, confirming the substantial benefit of integrating optimization and attention mechanisms.

B. Error Rate Analysis

The error rate analysis indicates that the proposed DOA-CNN achieved the lowest classification error among all evaluated models. Lower error rates demonstrate improved robustness and reliability of the proposed framework for maize leaf disease classification under varying environmental conditions.

Table 3: Error Rate Comparison of All Models

Model	Accuracy (%)	Error Rate (%)	Interpretation
Baseline CNN	82.276755	17.723245	Indicating limited capability in extracting robust disease features
BO-CNN	90.115883	9.884117	Enabled better convergence and enhanced generalization performance
PSO-CNN	90.184049	9.815951	Effectively enhanced architectural design
Hybrid	90.388548	9.611452	Optimization and hyperparameter tuning produced a more balanced and efficient learning framework
Proposed	91.342877	8.657123	Incorporation of CBAM attention along with dual optimization strategies enabled superior feature representation and improved focus on disease-relevant regions.

C. Training Convergence

The fig 5 presents the training and validation loss and accuracy curves for the proposed DOA-CNN in which the close alignment between curves confirms and severe overfitting was effectively mitigated, with an overfitting gap of 0.01%.

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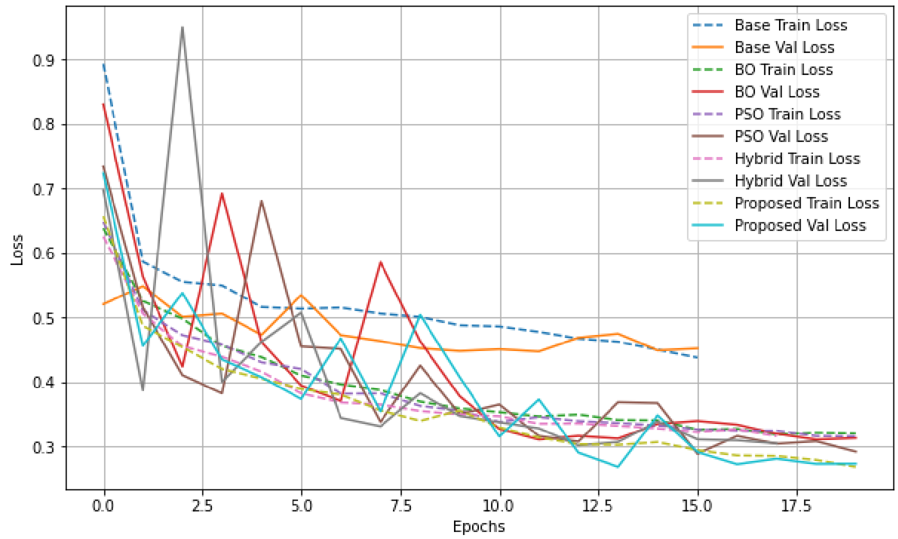

Figure 5: Training and validation loss/accuracy convergence curves

D. GAP Feature Activation Analysis

Figure 6 illustrates the global average pooling (GAP) feature activations extracted from the proposed DOA-CNN framework. The observed activation peaks indicate strongly learned semantic features corresponding to disease-discriminative patterns in maize leaf images. Lower activations represent suppressed non-informative features and background noise. The distribution confirms that the proposed attention-guided architecture effectively captures relevant visual characteristics necessary for robust disease classification.

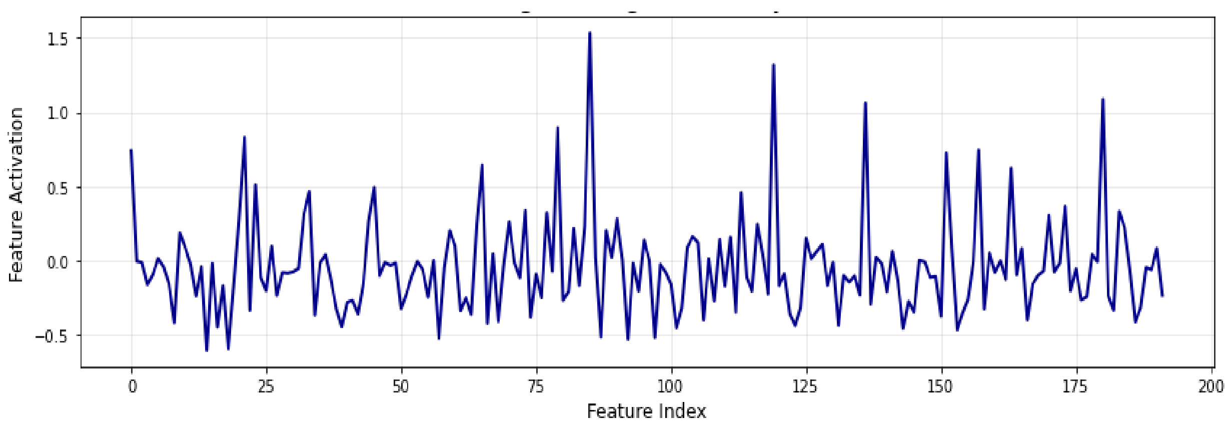

Figure 6: GAP feature activations of the proposed DOA-CNN model

V. CONCLUSION AND FUTURE WORK

This work, proposes a dual-optimized attention convolutional neural network framework for accurate and robust classification of maize leaf diseases. After using ML models, tackle some of the most substantial challenges associated in agricultural image analysis including environmental variation, inefficient feature extraction and sub-optimal hyperparameter tuning. This framework utilizes PSO to optimize the configurations of deep neural networks and BO for hyperparameter tuning to improve learning skills from data and prediction than standard CNN models. The CBAM also allows you to selectively emphasize relevant spatial regions related to diseases, enhancing its ability to extract features in a better way. In addition, the sequential channel and spatial attention strategies allow effective learning of subtle visual differences between disease categories to improve classification reliability and reduce misclassifications. The accuracy of the DOA-CNN model achieved 91.34%, precision of 91.55, recall of 91.53, and an F1-score of 91.40, which was better than other models. It had lowest error rate of 8.66 % and overfitting gap only 0.01% confirming its best in terms of generalization. A comparative analysis shows that the fusion of dual optimization strategies with attention-based feature enhancement provides major improvements to deep learning on agricultural image classification tasks.

Future work will include the design of lightweight model variants for online deployment on small heterogeneous IoT devices, integration with other IoT-aware smart farming systems, and testing on larger multispecies disease datasets. Additional improvements like transfer learning from domain-specific pre-trained models, federated learning for privacy-preserving distributed training or transformer-attention based architectures may also increase the scalability and generalization performance of models in precision agriculture.

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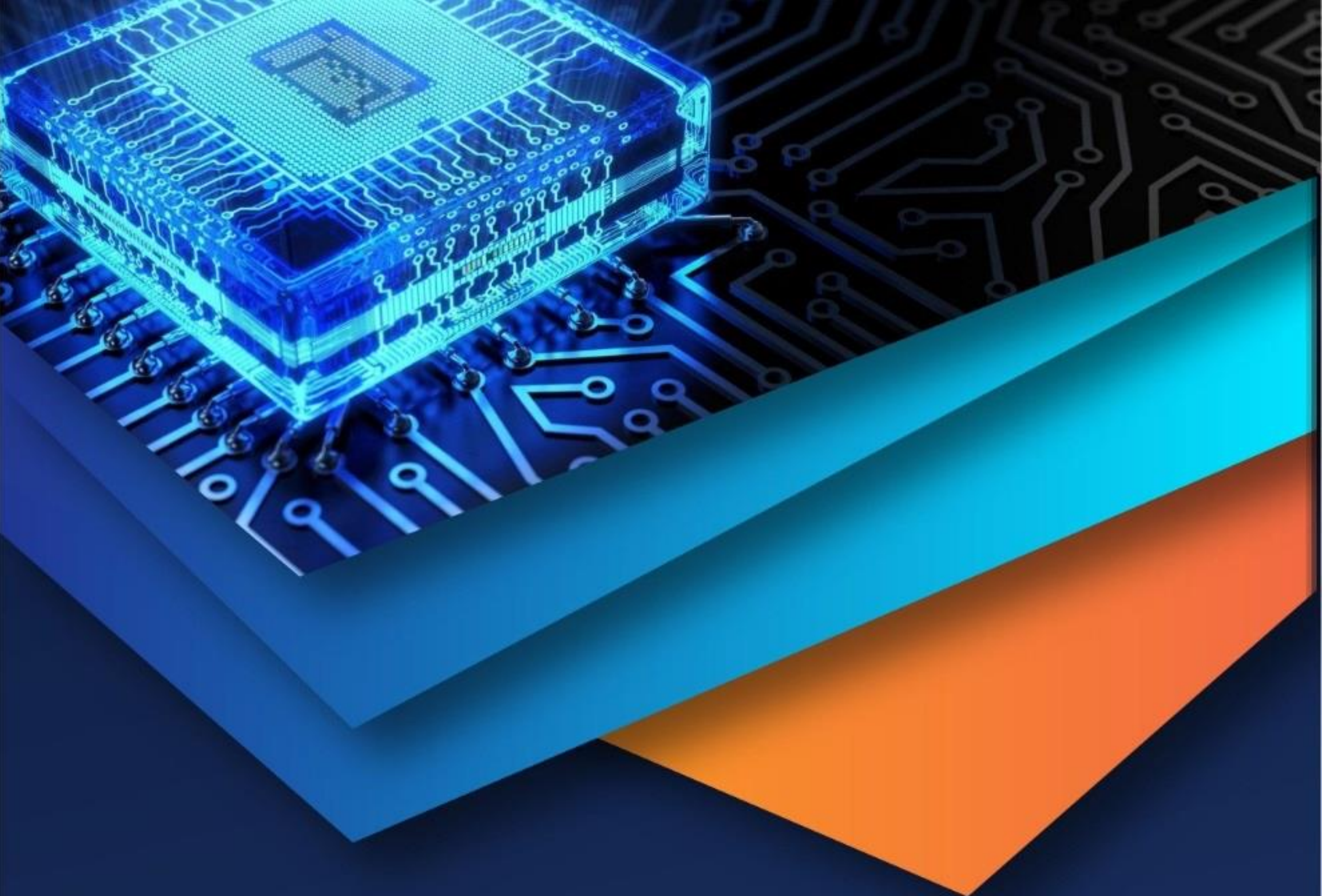

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