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Development of Smart Agriculture to detect the Arabica Coffee Leaf Disease using IAFSA based MSAB with Channel and Spatial Attention Network

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ABSTRACT- Plant diseases provide challenges for the agriculture sector, notably to produce Arabica coffee. Recognising issues on Arabica coffee leaves is a first step in avoiding and curing illnesses to prevent crop loss. With the extraordinary advancements achieved in convolutional neural networks (CNN) in recent years, Arabica coffee leaf damage can now be identified without the aid of a specialist. However, the local characteristics that convolutional layers in CNNs record are typically redundant and unable to make efficient use of global data to support the prediction process. The proposed Hybrid Attention UNet, also known as CMSAMB-UNet due to its feature extraction and global modelling capabilities, integrates both the Channel and Spatial Attention Module (CSAM) as well as the Multi-head Self-Attention Block (MSAB). In this study, CMSAMB-UNet is built on Resnet50 to extract multi-level features from plant picture data. Two shallow layers of feature maps are used with CSAM according to local attention. used throughout the feature extraction process to enrich the features and adaptively disregard unwanted features. In order to recreate the spatial feature connection of the input pictures using high-resolution feature maps, two global attention maps produced by MSAB are combined.

Keywords: Convolutional neural networks; Multi-head Self-Attention Block; Channel and Spatial Attention Module; Improved artificial fish swarm algorithm; Arabica coffee leaf.

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1. INTRODUCTION

Artificial intelligence (AI) is widely applied in smart agriculture, which uses the IoT (internet of things), big data, deep learning, and a number of other digital technologies [1]. To feed the expanding world population, there must be a significant rise in food production. The continuous and regular supply of high-quality food on a worldwide scale must be ensured by modern technology without endangering natural ecosystems [2]. A brand-new, cutting-edge method for data analysis and image processing is deep learning. It has shown positive outcomes, enormous potential, and has been successfully various industries, including agriculture, use it [3]. Smart agriculture solutions based on deep learning have lately achieved remarkable success. These systems use data acquired from diverse sources to handle various agricultural activities [4]. Different AI-based intelligent systems have varying degrees of ability to gather data, assess it, and assist farmers in making the best decisions possible. Any deep learning method may be used to assess data before imposing conclusions on operational areas using actuators [5]. IoT nodes (sensors) that are already installed can gather data. Automated computer control, worldwide satellite positioning, and remote sensing of geographic data are examples of contemporary technologies that assist the AI system in the real-time monitoring and administration of agricultural [6]. Additionally, AI-based smart agriculture may be used to plan the optimal distributions of resources like water, pesticides, and fertiliser, lowering pollution and operating expenses while boosting production [7]. Since AI may assist with early detection and prevention, less medicine would be required to control the development of plant diseases, significantly reducing environmental pollution [8]. Consistent use of agronomic inputs including water, nutrients, and fertilisers is crucial for maintaining plant health, growth, and yield [9]. This study looked at deep learning and AI use in agriculture and the future prospects for it. We also investigated the IoT-monitored agricultural variables and processed the data using deep learning algorithms [10].

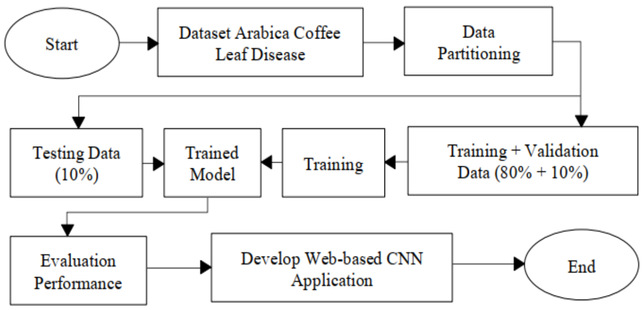

Figure 1: Research Stage Flowchart

With a 379,35 thousand tonne total export volume [11], Indonesian coffee growers produced a sizable amount of exports in 2020, demonstrating that coffee is one of the agricultural products with the highest demand on the world market. India finished third and Brazil first over the same time period [12]. Sumatra has the highest production, per the data. As a result, our research creates a method that can automatically categorise ailments in Arabica coffee leaves [13]. One of the many common problems that the continual advancement of digital image processing technology may help with is picture classification [14]. CNN was selected since it is that classifies pictures the most accurately, and one of its advantages is that it automatically extracts picture information, saving maybe both time and effort [15].

2. RELATED WORKS

Ramamurthy et al. [16] have created a trustworthy method for infestation detection with a low amount of computational complexity. Milke et al. [17] suggest a deep learning approach for the independent diagnosis of the condition causing coffee wilt. Utilising the ResNet50, MobileNetV2, InceptionResNetV4, and DensNet169 neural network architectures, Aufar et al.'s [18] objective is to enhance and increase the precision of the categorization of Arabica coffee leaf diseases. Additionally, this study shows off an interactive website connected to the Arabica coffee plant leaf disease forecasting system. Karthik et al. (19) have created a method based on deep learning for spotting diseases in coffee leaves. Raghavendra [20] proposes a color-based filtering technique to recognise diseases that emerge in coffee leaves. The image created from the dataset is pre-processed using top-hat transform-contrast limited adaptive histogram equalisation (THT-CLAHE), which enhances the visual attributes, before contrast enhancement.

3. RESEARCH MODEL

Figure 1 shows the evolution of this study. Next, change the picture resolutions in the dataset. The data partitioning stage will be followed by processing of the data grouping findings. When the model has been developed based on to evaluate the test results using the models and specified parameters, validation and training data as well as the test data will be used.

3.1 Dataset

The Mendeley data source's Arabica coffee leaf disease image collection is employed at first [21]. The collection contains 18985 photos of healthy coffee plant, 8337 photographs of diseased coffee leaves, 16979 images of diseased coffee leaves, 6572 images of diseased Phoma leaf spots, and 7682 images of diseased Cescospora leaf spots. For each of the dataset's five classes —healthy leaves, coffee corrosion, coffee leaf miner, phoma leaf spots disease, coffee corrosion, or cercospora leaf spot disease, *figure 2* displays the leaf state.

Figure 2: Sample images on each class

3.2 Data Partitioning

The dataset is first processed, such as by breaking it into separate pieces of data for training, testing, and validation, in the second step. While learned models are applied to test data to generate predictions about yet-to-be-observed data, model training requires training and validation data.

3.3 Background Knowledge about Attention Mechanisms

Recent years have seen an increase in the importance of attention processes in computer vision tasks. Depending on the significance of the information, the attention mechanism can dynamically pick representative aspects. It enables CNNs to focus on particular areas of the input picture and pick out valuable information from a sea of data.

$$Attention = f(g(x), x) \tag{1}$$

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If x is a picture, *g(x)* is an attention-generating process based on the image's representative sections, and *f(x)* is an attention-based image analysis technique that is based on attention *g(x)* created to obtain valuable information. The SoftMax function, which is defined as the distribution function often correlates to

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{n=1}^{n=N} e^{zn}} \quad (2)$$

where ez_i stands for the Natural Constant, and denotes the energy score. In order to produce weighted values, the attention weight and input data are multiplied.

The principle behind the attention processes described above is to assign various features varying weights. Alternatively put, the flexibility of the model is enabled by the attention mechanism use the input information's most pertinent portions.

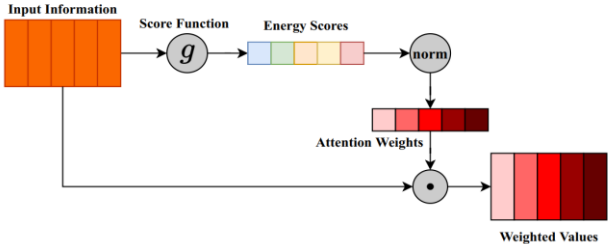

Figure 3: The typical attentional mechanism

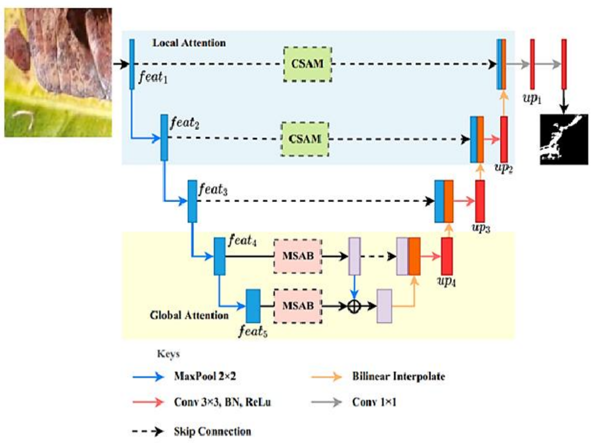

Figure 4: Model's overall architecture

4. METHODOLOGY

4.1 Overview

Given the intricacy of plant disease, a modified attention network based on CMSAMB-UNet is suggested to take use of both global and local aspects. Figure 4 shows the recommended extraction process's chain.

4.2 General Organisation of the Proposed CMSAMB-UNet

In recent years, unet and its variations have been employed extensively in the division of plant images. Convolution layers in Unet may capture redundant information, which might result in incorrect pixel categorization. Additionally, Unet's tiny convolution kernels' local receptive field is not well suited for leveraging global interaction.

4.2.1 Backbone

With regard to target detection and semantic segmentation, Resnet performs admirably in remote sensing images. The deep residual framework for learning is the core idea of Resnet, and a residual mapping is intended to fit within its stacked layers F(x) + x rather than an underlying mapping F(x) by using a quick connection and element-by-element augmentation. With the use of this framework's shortcut connection, Resnet may increase the network's depth and learn more detailed features without gradient deterioration [22].

Table 1: The Resnet50 structure that was utilised in this paper

Layer Name	Operator	Output Name	Output Size	Output Dimension
Conv1	7X7 Conv, stride=2, padding=3	$feat_1$	256X256	64
Conv2x	3x3 pool, stride=2 $\begin{bmatrix} 1X1\ Conv \\ 3X3\ Conc \\ 1X1\ Conv \end{bmatrix} \times 3$	$feat_2$	128X128	64
Conv3x	$\begin{bmatrix} 1X1\ Conv \\ 3X3\ Conc \\ 1X1\ Conv \end{bmatrix} \times 3$	$feat_3$	64X64	512
Conv4x	$\begin{bmatrix} 1X1\ Conv \\ 3X3\ Conc \\ 1X1\ Conv \end{bmatrix} \times 3$	$feat_4$	32X32	1024
Conv5x	$\begin{bmatrix} 1X1\ Conv \\ 3X3\ Conc \\ 1X1\ Conv \end{bmatrix} \times 3$	$feat_5$	16X16	2048

4.2.2 CSAM

For high accuracy segmentation, identifiable and representative feature representations are crucial. where y is the highlighted feature map, M_c and M_s denote, respectively, the channel attention and spatial attention-generated maps of activation after a sigmoid function, ⊗ depicts multiplication by elements, mlp denotes a convolution layer, and represents a multi-layer perceptron. Employing CSAM, the feature maps f eat1 and f eat2 flexibly raise salient portions of crucial water qualities in both the channel dimension as well as the spatial dimension, concentrating on water bodies while suppressing extraneous portions.

$$y = M_s(M_c(x) \otimes (M_x(x) \otimes x)) \quad (3)$$

$$M_c = sigmoid\left[mlp\left(x_{avgpool}\right) + mlp\left(x_{maxpool}\right)\right] \quad (4)$$

$$M_s = sigmoid\left[conv\left(concat\left(x_{avgpool}, x_{maxpool}\right)\right)\right] \quad (5)$$

4.2.3 MSAB

Assuming that x exemplifies the input feature, the MSAB a feature map of the output is provided

$$y = concat(y_1, y_2, \ldots, y_n) \tag{6}$$

and each self-attention head's specific calculating procedure is provided by

$$y_i = softmax\left(\frac{Q.K^T}{\sqrt{d_i}}\right).V \tag{7}$$

$$Q = W_q x, K = W_k x, V = W_v x \tag{8}$$

where *yi* represents the ith self-attention head's output feature map, *di* = *d*/*n* indicates the size of the head's self-attention. Q, K, and V, three distinct matrices produced by trainable 1 × 1 convolutions *Wq*, *Wk* and *Wv* represent queries, keys, and values times input x. The proposed optimisation (IAFSA) model generates the attention weights for each head of self-attention in *equation (8)*. the normalisation of attention mappings follows *pdi* and softmax function to obtain the global contextual information-containing attention ratings.

4.2.4 Weighting Selection of MSAB using Improved AFSA

The artificial intelligence programme known as the AFSA [24] was developed by mimicking the social behaviour of natural species. It uses artificial intelligence that is behavior-based and takes a bottom-up approach.

A) Better Prayer Habits

When praying, the fish's location and amount of food are noted with the labels f_m and F_m, respectively. Furthermore, an arbitrary location is chosen and tagged as being within the fish's field of perception f_n because of the food concentration F_n. When $F_n > F_m$, The pray behaviour update formula is written as follows:

$$f_{next} = \begin{cases} f_m + Rand.Step_k.\frac{f_n - f_m}{\|f_n - f_m\|} & F_n \geq F_m \\ Investigation\ Behavior & F_n < F_m \end{cases} \tag{9}$$

where Rand is an integer chosen at random from 0 to 1 and $\|f_n - f_m\|$ is the separation between f_n and f_m. f_{next} represents the fish's upcoming position.

B) Improved Swarm Behaviour

Within the fish's field of perception, there are swarms of n_f partners, whose central location is fc with a concentration of food F_c. $F_c/n_f > \delta Fm$ tells you that there is additional food available at f_c While there are no people around, the fish takes one step closer f_c. Otherwise, praying is a behaviour that is followed. The swarm behaviour updating formula is as follows:

$$f_{next} = \begin{cases} f_m + Rand.Step_k.\frac{f_c - f_m}{\|f_c - f_m\|} & \frac{F_C}{n_f} \geq \delta F_m \\ Pray\ Behavior & \frac{F_C}{n_f} < \delta F_m \end{cases} \tag{10}$$

where δ represents the component of crowdedness, and n_f is the fish companions.

C) Improved Follow Behaviour

A fish will follow the best mate when it has discovered that there is an abundance of food nearby $f_{\max}$ because of the food concentration $F_{\max}$ and advance towards fmax. If $F_{max}/n_f > \delta F_m m$, the fish moves closer to Fmax since there is more food concentrated there and its surrounds are not congested. If not, the desired behaviour is put into practise.

The update equation for the follow behaviours can be written as follows:

$$f_{next} = \begin{cases} f_m + Rand.Step_k.\frac{f_{max} - f_m}{\|f_{max} - f_m\|} & \frac{F_{max}}{n_f} \geq \delta F_m \\ Pray\ Behavior & \frac{F_{max}}{n_f} < \delta F_m \end{cases} \tag{11}$$

where f_{max} is the partner's ideal state partner's position coordinate.

D) Improved Investigation Behaviour

Therefore, the fish swarm is better equipped to leave its optimal location and stop the impending problem, as well as expedite convergence in the optimisation process.

E) Flow of the IAFSA

The following are the major processes for choosing a weight using the IAFSA:

Step 1: Entering the weight coordinate values from *eq. (8);*

Step 2: The initialization parameters are established, such as the most iterations possible K_{max}, The total population size N, the starting try number of repetitions, the initial try length Step1, the starting crowding factor d, the first stage length Step1, and the starting point for every fish (the coordinates value);

Step 3: Calculating each member of the fitness of beginning value of the fish swarm and recording it in the bulletin board's ideal fitness value;

Step 4: The adaptive $Visual_k$ and $Step_k$ is determined by the quantity of iterations;

Step 5: Based on the food concentration situation, The behaviours of swarm and follow are used, as well as the pray or exploration behaviours;

Step 6: In order to determine whether to change or keep the pray, follow, explore, and swarm behaviours, their fitness values are compared to those of the bulletin board;

Step 7: the iteration in light of K_{max} or the process of convergence is interrupted or repeated;

Step 8: The weight source's coordinates for position are output.

5. RESULTS AND DISCUSSION

0 is used to denote experimental outcomes less than 108. MATLAB 2018a, Windows 11, an Intel(R) Core (TM) i5-12500H @ 3.1 GHz CPU, and 16 GB of RAM were all employed in the experimental setup.

5.1 Performance Metrics

A range of performance metrics and execution time were used to evaluate our models. Among the performance measures were Cohen kappa, F1, and AUC values. As a method of evaluation, the k-fold cross-validation test was also used. The execution speed metrics were concentrated on the execution time, whilst the performance measures were determined using *equations (13–17)*:

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$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

$$Recall(True\ positive\ Rate) = \frac{TP}{TP+FN} \quad (15)$$

$$F1Score = \frac{2TP}{2TP+FP+FN} = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (16)$$

$$Cohen\ Kappa\ Score = \frac{Accuracy-P_{random}}{1-P_{random}} \quad (17)$$

In a TP (True Positive) circumstance, both the prediction and the target are true. Sometimes a forecast is accurate, but the goal is wrong. TN is the name for this. An FP (False Positive) is a forecast that is true but the target is false, while a FN (False Negative) is a prediction that is true but the target is false. The suggested model's confusion matrix is displayed in *figure 5*. The current models for disease detection employ a variety of datasets. As a result, our dataset is used to apply the current models, and the outcomes are averaged in *tables 2* and *3*.

Table 2: Analysis of the proposed model's validation without using IAFSA

Model	Accuracy	Precision	Recall	F1-score	Cohen Kappa score
MobileNet	89.29	0.871	0.87	0.89	0.7912
HS-MLPNN	90.29	0.89	0.89	0.90	0.8096
MHAM	91.76	0.91	0.90	0.91	0.8333
U-Net	92.23	0.92	0.921	0.93	0.8497
CMSAMB-UNet	94.76	0.94	0.942	0.94	0.8909

From *table 2* and *figure 6,7* and *8*, MobileNet has an accuracy rate of 89.29%, precision of 0.871%, recall of 0.87%, F1-Score of 0.89%, and Cohen Kappa score of 0.7912%. From *table 3* and *figure 6, 7 and 8*, MobileNet had accuracy rates of 90.07%, 0.92%, 0.90%, recall rates of 0.91%, F1-Scores of 0.91%, and Cohen Kappas of 0.829%.

Table 3: Analysis of Proposed Classifier with IAFSA

Model	Accuracy	Precision	Recall	F1-score	Cohen Kappa score
MobileNet	90.07	0.92	0.90	0.91	0.829
HS-MLPNN	91.94	0.91	0.91	0.92	0.851
MHAM	94.17	0.93	0.936	0.94	0.879
U-Net	95.01	0.95	0.951	0.95	0.885
CMSAMB-UNet	97.20	0.96	0.966	0.97	0.918

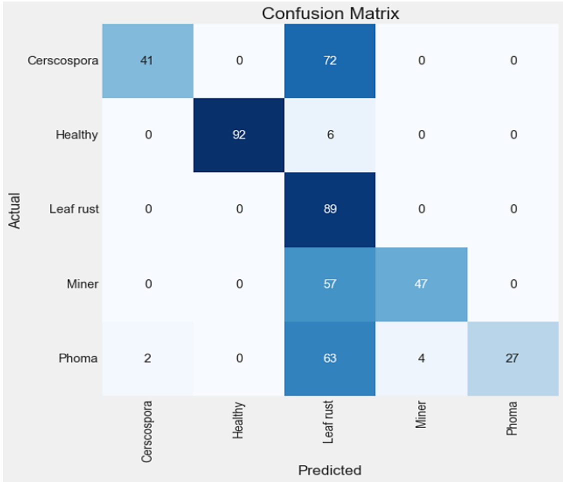

Figure 5: Matrix of confusion for the suggested model

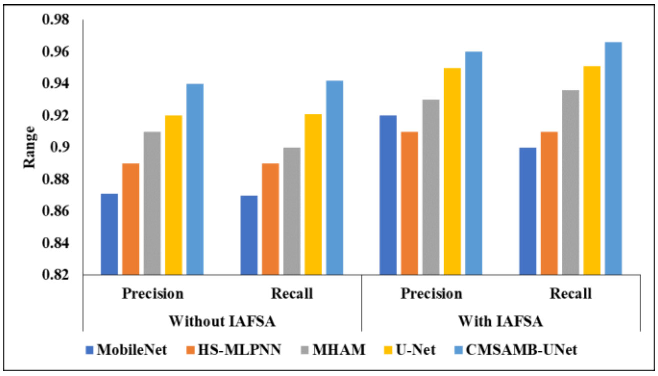

Figure 6: Analysis of different models in terms of two metrics

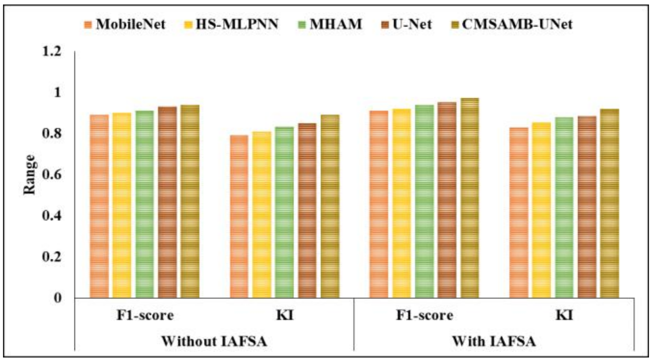

Figure 7: A visual comparison of different models

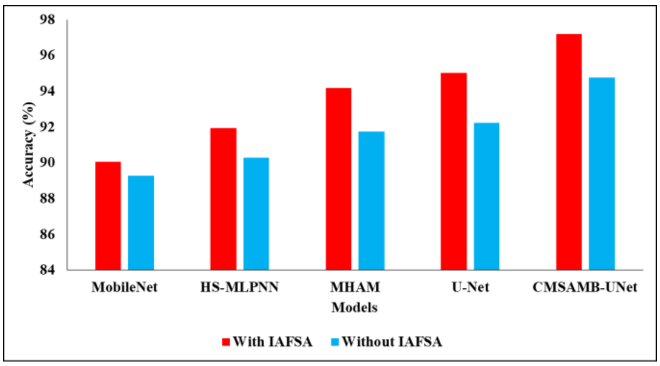

Figure 8: Accuracy analysis

6. CONCLUSION

In this study, CMSAMB-UNet, a hybrid attention-based algorithm, is proposed for disease prediction in coffee plant photos. Standard convolution layers' feature maps that include redundant features, At the beginning of the encoder, CSAM according to local attention is utilised to draw attention to attributes and screen out non-semantic qualities. In addition, MSAB is included to capture global data and long-range interactions of the input plant pictures at late stages of the encoder to balance out the typical convolution layer's insufficient global information gathering. The attribute maps for are also used to produce high-resolution feature maps. the encoder's final two stages in order to provide even deeper contextual interactions and geographical data. The IAFSA model chooses the MSAB's weight in the best possible way. The quantitative assessments and attention map visualisation outcomes both show that the suggested CMSAMB-UNet can accurately and successfully extract the illnesses. Therefore, the suggested technique has a lot of promise for image recognition of plant leaves.

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