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Integration of the Convolutional Block Attention Module to Enhance Malaria Detection in Microscopic Blood Cell Images

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ABSTRACT

Malaria is a life-threatening disease caused by Plasmodium parasites and transmitted through the bite of infected mosquitoes. Accurate and early detection is essential for effective treatment and control. In this study, we propose an enhanced deep learning approach using a Convolutional Neural Network (CNN) optimized with a Convolutional Block Attention Module (CBAM) to classify red blood cell images as malaria-infected or uninfected. The CBAM mechanism enables the model to focus more effectively on the most informative spatial and channel features, thereby improving its ability to detect subtle patterns in microscopic blood smear images. We compare the performance of the CBAM-optimized CNN against a baseline CNN using accuracy, precision, recall, and F1-score metrics. Experimental results show that integrating CBAM significantly improves classification performance, achieving higher detection accuracy and greater robustness against visual noise and variations. This study highlights the effectiveness of attention-based optimization in medical image classification tasks, particularly in resource-limited settings where reliable and automated diagnosis is highly needed.

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I. INTRODUCTION

Malaria is one of the deadliest infectious diseases in the world, particularly in tropical and subtropical regions. According to the World Health Organization (WHO) report, in 2022 there were more than 249 million malaria cases globally, with over 608,000 deaths, most of which occurred in developing countries with limited healthcare systems [1]. In Indonesia, based on data from the Ministry of Health in 2021, there were more than 330 thousand malaria cases, with the highest prevalence found in eastern regions such as Papua and East Nusa Tenggara. Early detection and accurate diagnosis are crucial to prevent complications and further transmission; however, conventional methods such as microscopic blood smear examination still face challenges related to time consumption, dependence on skilled experts, and the potential for diagnostic errors due to fatigue or subjectivity [2]-[3].

The advancement of Artificial Intelligence (AI) technology, particularly Deep Learning, has paved the way to overcome these limitations through automated detection based on digital imaging. One of the most prominent approaches is the use of Convolutional Neural Networks (CNNs), which have proven effective in medical image classification tasks [4]-[6]. Previous studies have demonstrated that CNNs can detect malaria parasites with high accuracy, even approaching the performance of professional laboratory analysts [7]-[9]. Nonetheless, challenges remain, particularly in extracting features from microscopic images that often have complex backgrounds, varying color intensities, and inconsistent image quality. In this context, additional strategies are required to enhance the model's sensitivity and focus in identifying important image features.

One emerging approach is the integration of an attention mechanism, which allows the model to selectively focus on the most critical regions of the input. A well-established and effective attention module is the Convolutional Block Attention Module (CBAM), which adaptively emphasizes relevant spatial and channel feature information, thereby strengthening the feature extraction process [10]. Several recent studies have shown that incorporating CBAM into CNN architectures can significantly improve accuracy and efficiency across various medical image classification tasks [11]-[13].

Based on this background and previous research, this study aims to develop and compare two CNN model architectures: a standard (baseline) CNN model and a CNN model integrated with CBAM, for detecting malaria infection in microscopic red blood cell images [14]. It is expected that the integration of CBAM into CNN will not only improve classification accuracy but also reduce detection errors and accelerate training convergence. This research contributes to the development of a more reliable and efficient automated malaria diagnosis system, particularly for application in remote areas with limited access to trained medical personnel.

A. Malaria Detection from Blood Cell Images

Malaria detection through microscopic blood cell images has become an increasingly popular diagnostic approach due to its visual accessibility and low cost [13]. Various methods have been developed, ranging from color-based and threshold-based segmentation [15] to the utilization of Mask-RCNN for red blood cell segmentation.The quality of detection is highly influenced by the segmentation technique and the extracted features, as malaria parasites exhibit complex variations in shape and color intensity [16] Several studies emphasize the importance of preprocessing and initial segmentation prior to classification. For instance, Nugroho and Nurfauzi [2] combined adaptive thresholding with a deep learning model to improve detection accuracy on the PlasmoID dataset. This technique demonstrates that segmentation and parasite detection processes must operate synergistically to ensure accurate infection identification.

B. Deep Learning for Image Classification

Deep learning has become the primary approach in medical image processing due to its ability to automatically extract and interpret complex features [17]. Unlike traditional learning methods that require manual feature extraction, deep learning enables an end-to-end process from input to output with minimal reliance on feature engineering. In malaria detection, this approach offers advantages in handling image variability, such as changes in lighting, contrast, and parasite morphology [18].

C. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is the most commonly used deep learning approach in medical image classification, including malaria detection. CNNs are capable of extracting spatial features from images through convolution and pooling layers, which are then classified by fully connected layers [19]. In the context of malaria, CNNs have been widely applied and have demonstrated promising performance, even on images with noise and low contrast. CNN models have also been modified to enhance accuracy through techniques such as dropout, batch normalization, and architectural explorations like ResNet or Inception [20]. Although CNNs are effective, they often do not explicitly focus on the most important regions in an image, opening opportunities for the integration of attention mechanisms. The basic operation in a CNN is convolution

$$\Psi(\iota + \varphi) = (\Xi * \Psi)(\iota + \varphi) = \sum_m \sum_n \Xi(\iota + \mu, \varphi + \nu) \square \Omega(\mu, \nu) \qquad (1)$$

D. Attention Mechanism

The attention mechanism in deep learning models helps networks focus on the most important parts of the input data, mimicking human attention by selectively concentrating on relevant regions of an image while ignoring irrelevant areas. This is particularly useful in tasks such as malaria detection, where specific image features such as the presence of red blood cells infected by parasites are more critical for accurate classification.

E. Convolutional Block Attention Module (CBAM)

The Convolutional Block Attention Module (CBAM) is a lightweight and efficient attention mechanism that can be integrated into CNNs to enhance classification performance. CBAM operates by applying both spatial and channel-wise attention, allowing the model to focus on the most relevant features for a given classification task. In a study by Siłka et al the integration of attention mechanisms demonstrated a significant improvement in malaria detection accuracy compared to standard CNN architectures [12].

The use of CBAM has also been shown to improve model interpretability, enabling analysis of which image regions contribute most to classification decisions. Channel Attention focuses on identifying which channels (feature maps) are most important, allowing the model to assign weights based on the relevance of different features at higher levels of abstraction. The channel attention is computed as:

$$F_c = \sigma(W_c [F_{avg}; F_{Max}] \qquad (2)$$

Spatial Attention focuses on determining which spatial locations (positions within the image) are most relevant. This allows the model to highlight specific regions where important features—such as red blood cells infected by parasites—are located. The spatial attention is computed as:

$$A_S = \sigma(W_s [F_{avg}; F_{max}]) \qquad (3)$$

F. Attention Mechanism in CNN

The attention mechanism in CNNs aims to direct the model's focus toward the most important parts of an image. In addition to CBAM, other methods such as saliency-based attention and parasite-attention approaches like YOLO-PAM have also been developed. This concept enhances the network's ability to detect small objects, such as malaria parasites scattered across blood smear images. The use of attention mechanisms is particularly relevant in scenarios with significant noise or irrelevant background elements, as it helps the model concentrate on diagnostically meaningful regions of the image

G. Loss Function and Model Evaluation

In the development of malaria classification models, the loss function and evaluation metrics play crucial roles in assessing model performance. A commonly used loss function is binary cross-entropy for binary classification and categorical cross-entropy for multi-class classification tasks [21]. The cross-entropy loss function is widely applied in classification problems, particularly in binary classification tasks such as malaria detection (infected vs. uninfected cells). The binary cross-entropy loss is defined as:

$$\Lambda = \sum_{i=1}^{n} y_i \lambda o\gamma(p_i) + (1 - y_i)\, \lambda o\gamma(1 - p_i) \qquad (4)$$

II. METHODOLOGY

A. Type and Research Approach

This study is a quantitative experimental research with a comparative approach. The objective is to evaluate the effectiveness of integrating the Convolutional Block Attention Module (CBAM) into the Convolutional Neural Network (CNN) architecture in improving image classification accuracy for malaria detection in blood cell images. The baseline CNN model is compared with the CBAM-enhanced model to identify performance improvements in spatial and channel feature extraction (spatial and channel attention).

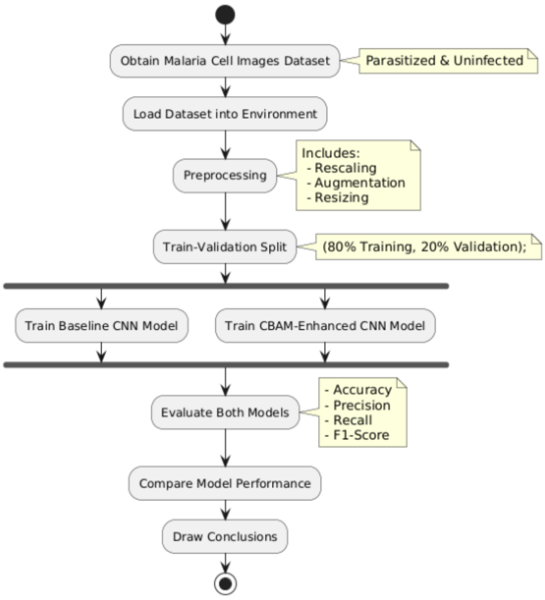

Fig. 1. Flowchart of the malaria detection process using the baseline CNN model and the CNN model enhanced with CBAM. This diagram illustrates the steps of dataset preparation, preprocessing, model training, evaluation, and performance comparison.

B. Research Method

The method used in this study is a computational experiment conducted in several stages: data acquisition, data preprocessing, model construction and training for both the baseline CNN model and the CNN model integrated with CBAM, followed by performance evaluation using classification metrics. The research was carried out in a Python programming environment utilizing the TensorFlow and Keras libraries.

The dataset used is the “Malaria Cell Images Dataset” by Arunava, obtained from the Kaggle platform, containing a total of 27,558 images evenly divided into two classes: Parasitized (malaria-infected) and Uninfected (uninfected). For the purpose of this study, a subset of 10,010 images was used.

C. Data Collection Technique

The data used in this study were obtained from an open-access online repository (Kaggle) and represent secondary data that are already available in a structured format. Each image in the dataset was visually classified by laboratory experts, ensuring that the dataset includes ground truth labels suitable for direct use in supervised learning.

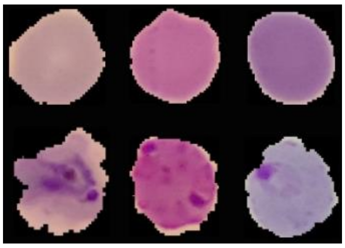

Fig. 2. Example images of red blood cells from the dataset: the top row shows healthy cells, while the bottom row shows malaria-infected cells.

The dataset used in this study is the Malaria Cell Images Dataset obtained from Kaggle. This dataset contains microscopic images of human blood cells that have been categorized by laboratory experts into two classes: Parasitized (blood cells showing the presence of malaria parasites) and Uninfected (blood cells not infected). The images are organized into two separate directories according to their respective labels. A total of 10,010 images were used in this study, consisting of a balanced combination of both classes.

III. RESULT AND DISCUSSION

A. Preprocessing

The initial step carried out was image normalization, performed by dividing each pixel value in every image by 255 so that all pixel values fall within the range of 0 to 1. This process helps stabilize and accelerate the training phase by standardizing the input scale, enabling the model to learn more efficiently. In addition to normalization, data augmentation techniques were applied, such as horizontal flipping and random zooming up to 20%. These augmentation techniques increase the diversity of training images without physically adding new data and help reduce the risk of overfitting by exposing the model to a broader range of image variations. This step is particularly important for medical datasets, which are often limited in both quantity and variability. The next step was resizing all images to a uniform dimension of 64×64 pixels, in accordance with the input layer requirements of the CNN architecture. Finally, the dataset was divided into two parts with an 80:20 ratio using the ImageDataGenerator technique for training and validation purposes. The preprocessing results showed that all images were successfully loaded and processed without any technical errors, and the class distribution remained balanced. Through this process, the malaria image data were properly prepared and ready for use in the classification model training.

B. *CNN Model Development and Training*

After the data were prepared, two CNN models were built and trained: a baseline CNN model and a CNN + CBAM model.

Baseline CNN Model

This model consists of two convolutional blocks, max-pooling layers, and fully connected layers. Training was conducted for 10 epochs. Table 1 below shows the training results of the baseline CNN model for each epoch, including accuracy, loss, and learning rate:

TABLE I. TRAINING RESULTS OF THE BASIC CNN MODEL.

Epoch	Time	Accuracy	Loss	Val Accuracy	Val Loss	Learning Rate
1	1439s	0.5839	0.6696	0.5939	0.7120	0.0010
2	49s	0.8034	0.4727	0.7782	0.5494	0.0010
3	82s	0.8948	0.2951	0.8037	0.4550	0.0010
4	48s	0.9104	0.2573	0.8287	0.3604	0.0010
5	48s	0.9171	0.2413	0.8641	0.3659	0.0010
6	48s	0.9221	0.2260	0.8596	0.3175	0.0010
7	48s	0.9308	0.2082	0.8876	0.2973	0.0010
8	49s	0.9352	0.1925	0.9036	0.2904	0.0010
9	51s	0.9352	0.1958	0.8671	0.3162	0.0010
10	79s	0.9387	0.1864	0.8861	0.2909	0.0010

From Table 1, it can be seen that the training accuracy increased from 58.39% in the first epoch to 93.87% in the tenth epoch. However, the validation accuracy only reached 88.61% at the end. The relatively high validation loss value (0.2909) indicates potential overfitting, meaning that the model learned very well on the training data but performed less effectively on the validation data. The following figure also shows the training and validation accuracy curves for the basic CNN model:

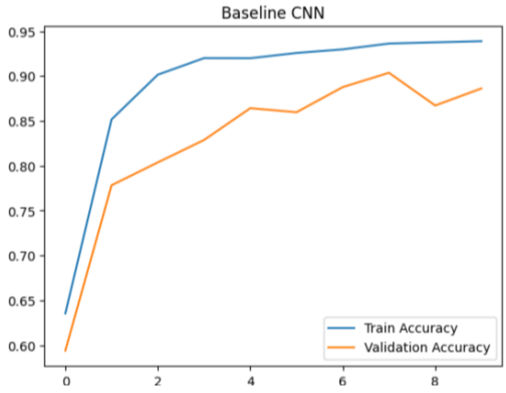

Fig. 3. ccuracy Curve of the Basic Convolutional Neural Network (CNN) Model

In Figure 3, it can be observed that the gap between the training accuracy curve and the validation accuracy curve begins to widen significantly after the 5th epoch. The training accuracy continues to increase and approaches its maximum value, while the validation accuracy becomes stagnant and even slightly decreases at certain points. This pattern indicates that the model is overfitting to the training data, failing to maintain similar performance on unseen validation data. The considerable difference between the two curves serves as a strong indicator of overfitting, a condition in which the model loses its ability to generalize to new data.

CNN Model with CBAM

The second model was built using the same architecture, but with the Convolutional Block Attention Module (CBAM) inserted after the second convolutional layer. Training was conducted over 7 epochs. Table 2 below presents the training results of the CBAM-enhanced model:

TABLE II. TRAINING RESULTS OF THE CNN MODEL OPTIMIZED WITH CBAM

Epoch	Time	Accuracy	Loss	Val Accuracy	Val Loss	Learning Rate
1	1678s	0.5831	0.6640	0.7682	0.5496	0.0010
2	134s	0.9303	0.2217	0.9336	0.1975	0.0010
3	144s	0.9476	0.1748	0.9416	0.1808	0.0010
4	104s	0.9446	0.1722	0.9486	0.1438	0.0010
5	103s	0.9481	0.1615	0.9316	0.1895	0.0010
6	104s	0.9524	0.1550	0.9505	0.1475	0.0010
7	106s	0.9519	0.1449	0.9481	0.1619	0.0005

From Table 2, it can be seen that this model achieved a validation accuracy of 93.36% as early as the 2nd epoch and reached its peak at 95.05% in the 6th epoch. The validation loss also decreased significantly to 0.1475, indicating better generalization compared to the baseline model. In addition, the learning rate was reduced in the final epoch (0.0005) to stabilize the training process.

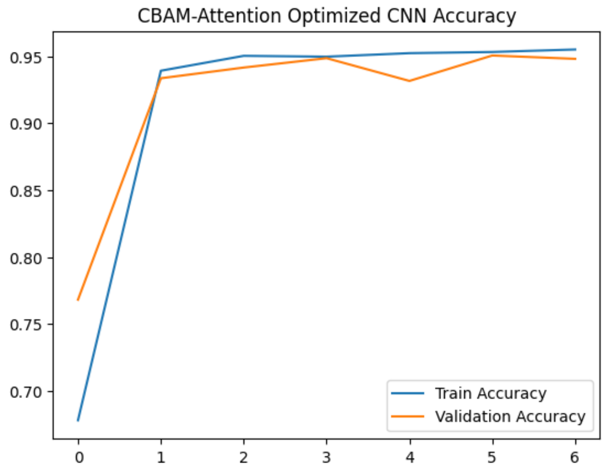

Fig. 4. Accuracy Curve of the CNN Model Optimized with CBAM-Attention

In Figure 4, it can be seen that the gap between the training accuracy curve and the validation accuracy curve is very small, even from the beginning of training. Both curves increase in parallel and remain stable, with accuracy values that are very close to each other until the final epoch. This indicates that the model has a strong generalization ability toward unseen data. The absence of a significant difference between the two curves also suggests that the model did not experience overfitting, and that the learning process proceeded efficiently and consistently. The integration of the CBAM module into the CNN architecture appears to contribute to this training stability by helping the model focus attention on the most important features

C. Testing

The model was tested using validation data with the evaluation metrics Accuracy, Precision, Recall, and F1-Score. The results are summarized in Table 3 below:

TABLE III. COMPARISON OF PERFORMANCE METRICS BETWEEN THE BASIC CNN MODEL AND THE CNN MODEL WITH CBAM.

Metric	CBAM-Attention Optimized CNN	Baseline CNN
Accuracy	0.9451	0.8996
Precision	0.9458	0.9013
Recall	0.9451	0.8996
F1 Score	0.9450	0.8995

The evaluation results show that the CNN model optimized with the Convolutional Block Attention Module (CBAM) consistently outperforms the basic CNN model in the task of classifying red blood cell images. The accuracy of the CBAM model reached 0.9451, higher than 0.8996 achieved by the baseline model. This improvement reflects the CBAM model's ability to classify images more accurately, with fewer errors overall.

In addition, the precision value also increased significantly to 0.9458, compared to 0.9013 in the baseline model. This indicates that the CBAM-enhanced model is more accurate in identifying positive cases and effectively reduces the number of false positives, or instances where healthy cells are incorrectly classified as infected. Furthermore, the recall value of 0.9451 demonstrates that the CBAM model is highly effective at detecting all relevant positive cases—cells that are truly infected with malaria. This means that almost all positive instances were successfully recognized without being missed. Equally important, the F1-score of the CBAM model reached a high value of 0.9450. The F1-score, which combines precision and recall, represents a balance between the model's ability to avoid false positives and its ability to capture all true positives. The high F1-score confirms that the CBAM model performs reliably and consistently across multiple evaluation aspects. In summary, these overall improvements in accuracy, precision, recall, and F1-score clearly demonstrate that the integration of CBAM significantly enhances the classification quality improving accuracy, reliability, and the model's generalization capability.

IV. CONCLUSION

Based on the results of the research and evaluation conducted, the integration of the Convolutional Block Attention Module (CBAM) into the Convolutional Neural Network (CNN) architecture has proven effective in enhancing performance in the task of red blood cell image classification for malaria detection. The CNN model optimized with CBAM achieved a final accuracy of 94.51%, surpassing the 89.96% achieved by the baseline CNN model. Furthermore, improvements were also observed across other evaluation metrics, including precision (94.58% vs. 90.13%), recall (94.51% vs. 89.96%), and F1-score (94.50% vs. 89.95%). These results indicate that the integration of CBAM not only enhances the model's accuracy in image classification but also strengthens the balance between its ability to detect positive cases and to avoid misclassifications. In terms of the training process, the CBAM-optimized model demonstrated faster convergence and greater stability, as evidenced by the consistent validation accuracy curve from the early stages of training. This suggests that the attention mechanism provided by CBAM helps the model to better focus on relevant spatial and channel features within medical images, thereby improving generalization. In conclusion, this study makes a significant contribution to the development of image-based malaria detection methods by demonstrating that CBAM integration can serve as an effective approach to improving CNN model performance in medical image classification applications..

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