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Computer-Assisted Disease Diagnosis Application for Malaria Early Diagnosis Based on Modified CNN Algorithm

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Abstract: Since its emergence in the early 20th century, Malaria has been confirmed as a deadly disease that has spread throughout the world with very high mortality and morbidity. This is in accordance with the WHO report in 2018 which stated that worldwide there have been more than 220 million cases of malaria with a death rate of nearly 500 thousand cases. However, Malaria is actually a disease that can be cured and prevented if treatment initiatives are implemented early and effectively. Unfortunately, this disease is often ignored because it is considered the common cold and is only diagnosed when it has reached a critical phase. This research is expected to be an alternative for early diagnosis of malaria. Hence, confirming the presence of the malaria parasite earlier will make the treatment of this disease more effective in reducing mortality. This research is expected to produce website-based computer-assisted disease diagnosis (CAD) software enriched with deep learning algorithms to become an alternative for early diagnosis of malaria. This CAD system has the potential to provide fast and reliable malaria diagnosis and avoid detection errors by experts due to human error. This research uses various pre-trained CNN architectures that have been proven to have the best performance in extracting features and recognizing image patterns such as MobileNetV2, EfficientNetBO, RestNet50, InceptionV3 and Xception. This architecture was then modified by adding several additional layers to improve its performance. To be concluded, this research succeeded in exceeding previous studies by obtaining an accuracy value above 97%. Moreover, this developed CAD software is also equipped with various features to make it easier to use.

Keywords: Computer-assisted disease diagnosis (CAD), Convolutional Neural Network (CNN), Malaria, Pre-trained CNN, Thin Blood Images, Website

1. Introduction

Malaria is a type of disease that has a long history in human life whose existence has been recorded since the sixth century BC [1]. Malaria is caused by the bite of a female Anopheles mosquito infected with the protozoan Plasmodium parasite which is then transmitted through the circulation of red blood cells. As the main cause of malaria, the first known plasmodium parasite was *P. falciparum*. *P. falciparum* infection first discovered in Southeast Asia, Oceania, and South America in the late 1950s and early 1960s. Meanwhile, *P. vivax* malaria was first discovered in 1989 in Australian citizens traveling to Papua New Guinea. The disease has been identified in Southeast Asia, Ethiopia, and Madagascar.

Since it was found, Malaria has been confirmed as a fatal disease that has spread throughout the world with very high mortality and morbidity rates. This was confirmed by a report published by WHO in 2018. In this report WHO stated that worldwide there have been more than 220 million cases of malaria with a death rate of nearly 500 thousand cases [2]. Although based on this report it can be concluded that there has been a decrease in the death rate from 585,000 cases to 405,000 during the 2010 to 2018 period, until now malaria is still categorized as one of the biggest problems in world health. This is based on the very high prevalence of malaria where almost half of the world's population is at risk of contracting malaria. To date, malaria has infected more than 87 countries around the world with the highest risk levels being in Africa, Southeast Asia, the West Pacific, South America, and the Eastern Mediterranean [3]. Apart from that, in terms of the susceptibility of sufferers, it is known that malaria is very easy to infect children under five. It is recorded that more than half of malaria cases occur in this segment. Moreover, the mortality rate for this segment is alarming with an average death for one affected child occurring every two minutes. In addition, the elderly segment and people with health problems such

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as pregnant women also experience a high vulnerability to malaria infection.

However, this disease can actually be cured if treatment initiatives are implemented early and effectively [4]. It has been agreed that early identification of the presence of malaria will make treatment more effective and at the same time reduce patient mortality [5]. Early and accurate identification of the infecting Plasmodium genus will enable patients to receive appropriate and effective treatment. Thus, the ability to make an accurate early diagnosis plays an important role in the fight against malaria. Unfortunately, malaria is often detected late because the symptoms are difficult to identify at an early stage due to the symptoms are practically indistinguishable to the common cold. [6]. The symptoms that are often found in sufferers of malaria are high fever, gastritis, enteritis, nausea, vomiting, and chills. [7]. Due to the similarity of these symptoms, malaria is often ignored because it is considered the common cold and only treated when it reaches a critical phase.

Until now, microscopic examination of thick and thin stained blood smears is the gold standard for the diagnosis of malaria due to its low cost and wide availability. Even though various new methods have emerged, sometimes these new methods require special tools that are not suitable for use in underdeveloped areas and have a higher cost, of course. However, behind the advantages of practical use and low cost, microscopy examination has several fatal weaknesses because the procedure is very time-consuming [8]. In addition, the effectiveness of this examination is highly dependent on the skill of the parasitologist in analyzing the red blood cell images [9] [10] [11]. Therefore this procedure sometimes cannot be applied effectively in third countries which have relatively limited resources of parasitologists. Hence this causes inaccurate diagnostic results and which leads to inappropriate treatment as well. This study aims to be an alternative for early diagnosis of malaria by utilizing the reliability of deep learning algorithms. Hence, it is hoped that this research can be used to reduce malaria mortality

2. Related Work

Along with the changes in human life that increasingly rely on the presence of technology, this has triggered many initiatives to take advantage of the reliability of technology to assist in the diagnosis of malaria and overcome obstacles in the conventional diagnosis of malaria. One of the most popular efforts is to develop a technology known as Computer-Assisted Disease Diagnosis (CAD). This CAD system has the potential to provide a fast, inexpensive and reliable diagnosis of malaria, avoiding the detection errors that usually occur with manual examinations. CAD is considered to have great potential in assisting efforts to detect early malaria because of the nature of computers that can work continuously without tired. In addition, CAD can be easily duplicated to be used in areas that have limited medical expertise. Therefore, CAD can be used by medical experts as early detection tool to be able to detect and recognize various life-threatening diseases more quickly and increasing efficiency in decision making. Thus far, many CAD applications have been developed that are enriched with computer vision to assist early diagnosis of a disease. Recent research trends reveal that deep learning algorithm have become one of the main foundations of CAD application development. Table I below shows various Deep Learning algorithms used in CAD development for early malaria diagnosis in the last 5 years.

Based on the Table I above, it can be seen that there are various deep learning algorithms that have been used to help diagnose malaria. In the last 5 years, there have been 68 studies that tried to discuss the development of CAD for the diagnosis of malaria. Unfortunately from the large number of these studies, only a few studies have tried to make ready-to-use applications that can be used directly to diagnose malaria. A summary of the research that developed ready-to-use CAD applications can be seen in Table II below.

Based on information from Table II , it is found that the majority of research is limited to efforts to develop deep learning models with the best performance. It can be concluded that CAD application development research is still under discussed and become one of the research gap that must be resolved. Therefore, this research is expected to bridge the research gap by developing a ready-to-use CAD application that can be a tool for early detection of malaria. As a benchmark for measuring the success of CAD applications, an accuracy performance standard of 97% is used as a minimum standard for research success. This accuracy standard is obtained from the best performance obtained by previous studies as shown in Table II .

A. Research Gap and Contribution

As previously explained, the use of Deep Learning algorithms in CAD development has achieved quite promising performance to help diagnose malaria. However, based on the literature study described in the previous section, it was found that there are at least 2 research gaps that must be resolved in order to contribute to assisting the early diagnosis of malaria. The first problem that is concluded as a research gap in the use of CAD for early detection of malaria is that existing studies tend to use deep learning algorithms with direct pre-trained architecture. The majority of related studies do not attempt to modify the pre-trained architecture to improve the performance of the CAD being developed. The second problem that arises is related research that focuses too much on its discussion in the development of deep learning models. Research that discusses the use of deep learning models in making ready-to-use CAD software is still very rare as previously stated.

In order to contribute to addressing these two issues, this research is expected to provide 3 main contributions as illustrated in figure 1 below. As shown in the figure, this study proposes 3 main contributions in relation to efforts to resolve research gaps. The first contribution made was

TABLE I. Research Trend of Deep Learning Algorithm Implementation for Malaria Early Diagnosis

No	Method		Reference
1	Novel Algorithm		[9] [12] [13]
2	CNN	Normal CNN	[14] [15] [16] [6] [10] [17] [18] [19] [20] [21] [22] [23] [24] [25] [11] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [8] [38] [39] [40] [41] [42] [43] [44] [45] [46] [47] [48] [49] [50] [51] [52] [53] [54] [55] [56] [57] [58] [59] [60] [61] [62] [63] [64] [65]
		Mask R-CNN	[66] [67]
		faster R-CNN	[68] [69] [70] [71] [72]
3	CapsNet		[73] [29] [74]
4	Hand Crafted Deep Learning		[75]
5	YOLO		[76][77]
6	Ensemble Learning		[78]

TABLE II. Summary of Ready-to-use CAD Applications for Malaria Early Diagnosis

Ref	Number of Data	Method	Architecture	Result
[68]	643	Faster R-CNN	ResNet101 ResNet50 InceptionV2	P = 0.7791; R = 0.8981 P = 0.7461; R = 0.9062 P = 0.7229; R = 0.9303
[11]	1,819	CNN	Customized network	Acc = 93.46; Prec = 94.25
[34]	27,558	CNN	custom CNN model	Acc = 97.30
[70]	903	Faster R-CNN	SSD MobileNet	mAP@0.5 = 0.6292
[41]	201	CNN	Mosquito-Net	Acc = 0.966
[71]	643	Faster R-CNN	Customized	Avg prec = 0.9306
[72]	2,967	Faster R-CNN	Customized	Acc = 96
[47]	2,967	CNN	Proposed IGMS & custom CNN	Acc = 0.97

the modification of the Pre-trained CNN architecture to improve deep learning algorithm performance. The next contribution that is expected is a deep learning model for image recognition of malaria red blood cells with better performance. This deep learning model can be used by other researchers for ready-to-use software development. As a final contribution, this research produces web-based ready-to-use CAD software as an alternative to early malaria diagnosis.

3. Methodology

In order to achieve the research objective of developing CAD for early detection of malaria, this research was conducted in stages in four main phases. The first stage in this study was the collection of malaria image data followed by image pre-processing. The third advanced stage is the application of the CNN architecture for the development of the Deep Learning model. As a final step, this research was closed by developing a website-based CAD software for an alternative diagnosis of malaria. The overall phases of the research work are described in Figure 2 below.

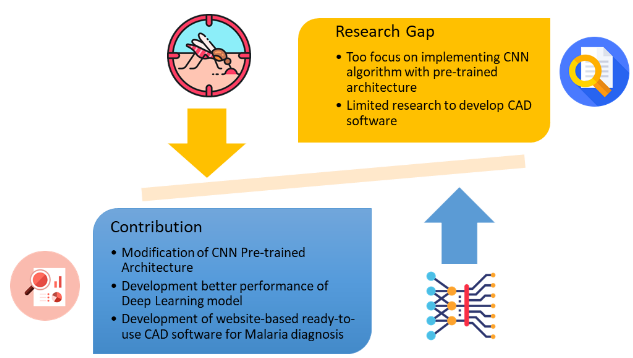

Figure 1. Summary of Research Gap and Research Contribution

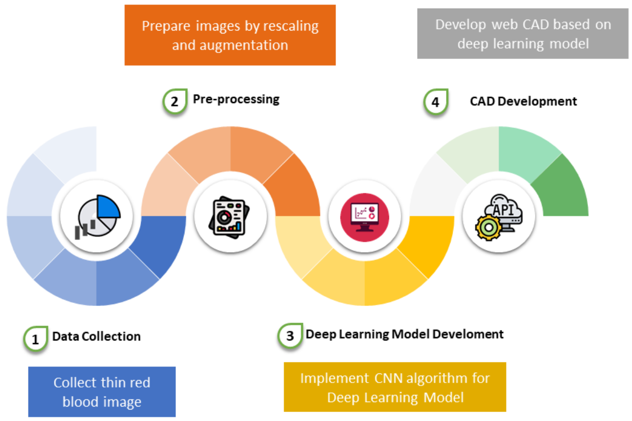

Figure 2. Research Framework for Development of Malaria CAD Software

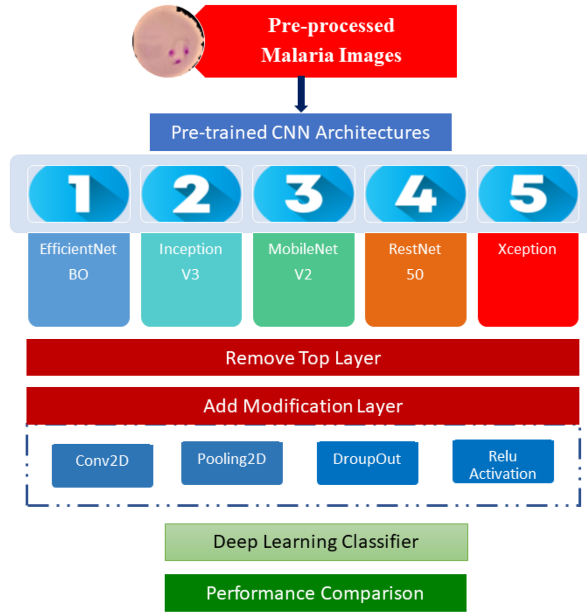

Figure 3. Pre-trained CNN Modification

A. Data Collection and Pre-processings Stage

In the case of a diagnosis of malaria, a sample of malaria sufferers will be examined using the red blood cells of the patient. There are two types of red blood cells used, namely Thin and Thick. Furthermore, these red blood cells will be stained in the process of detecting the presence of malaria parasites in the red blood cells. There are several staining techniques used in the detection of malaria parasites namely Giemsa, Leishman, Leishman-Methylene blue, Combination of DNA and RNA fluorescent, Wright, Fluorochrome, Romanowsky, Acridine orange (AO), DAPI/Mitotracker, Toluidine blue and Unstained.

Taking into account its various advantages, the image of malaria used in this study is the image of thin blood using the Giemsa staining technique. The thin blood image is considered to have better quality than the red thick blood image because the thick blood image is considered to have a lot of noise. Hence the presence of this noise makes the diagnosis based on thick blood images less accurate in detecting malaria.

This study used 27,558 thin blood images obtained from the Lister Hill National Center for Biomedical Communications (NIH) dataset. The dataset containing malaria images is then prepared at the pre-processing stage with the aim of increasing the quality and enrichment of the data so that it is more qualified to be used in the development of deep learning models.

B. Development of Deep Learning Model

The next phase as well as the main and most crucial stage in this research is the development of a Deep Learning model for malaria diagnosis using the dataset that has been collected. The algorithm used in this study to build deep learning models is the Convolutional Neural Network (CNN) algorithm which is considered the best algorithm for image model recognition. To produce CAD with the best performance, this research uses various pre-trained CNN architectures that have been proven to have the best performance in extracting features and recognizing image patterns such as MobileNetV2, EfficientNetBO, RestNet50, InceptionV3 and Xception. However, as previously explained, a modification process was carried out on the top layer of all the pre-trained CNN architectures used. To be precise, modifications to the CNN architecture were carried out by adding additional layers, namely one dropout layer, Pooling2D and the ReLu activation function as illustrated in Figure 3 below.

Contrary to most research that applies the pre-trained CNN architecture directly, the top layer of the pre-trained architecture is removed to be replaced with an additional modified layer. This additional layer is expected to improve the performance of the CNN algorithm in extracting malaria image features while increasing its accuracy in detecting the presence of the plasmodium parasite in blood cells. In addition, the built deep learning architecture also uses the concept of transfer learning using weighting from ImageNet training to speed up the deep learning model training process. Thus, the time required by each architecture to achieve the best performance can be shorter. Finally, all of these architectures are then tested based on their performance to test whether each of these modified architectures can exceed the standard of success in the form of 97% accuracy and is feasible to be applied in CAD software development.

C. CAD Development

The final stage of this research is the development of a CAD software for malaria diagnosis based on a deep learning model that has been obtained previously. This CAD application developed is a web-based application that can be accessed by users from anywhere by utilizing an internet

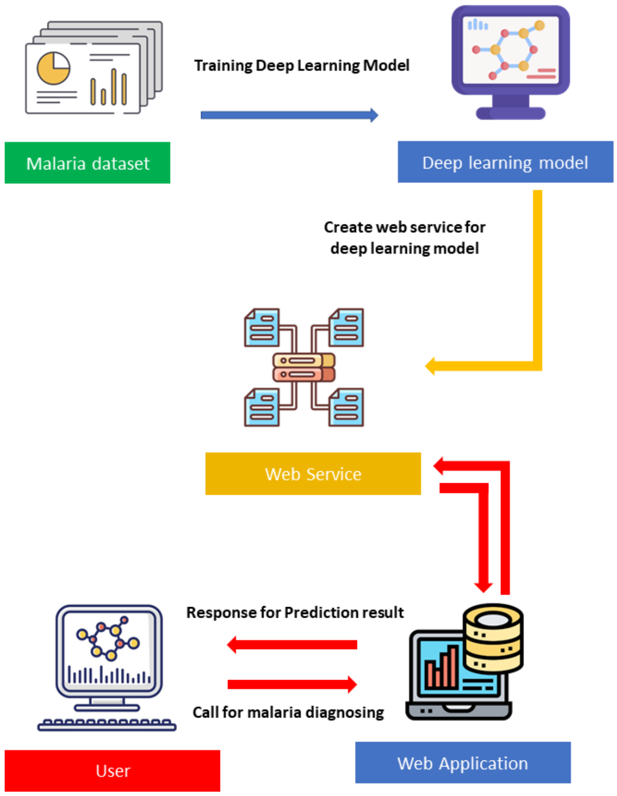

Figure 4. CAD development based on Deep learning Model

connection. Therefore, the problem of limited availability of medical experts who are able to diagnose malaria can be solved with the emergence of this CAD application. The overall architecture of CAD development is illustrated Figure 4.

As shown in Figure 4, this research utilizes a Rest API as web service to develop CAD for malaria. Rest API is a web service development method that is known to have many advantages such as being compatible with many programming languages and uncomplicated to be implemented. This research will build a web-based application that allows users to access deep learning models that have been developed previously through a web service.

4. Result and Discussion

This section describes the experimental results from the development of CAD software for early detection of malaria based on a modified pre-trained CNN architecture. At the beginning of this section, the results of the data collection and pre-processing will be explained. Then the discussion will be continued by describing the results of the development of the deep learning model and its performance in identifying malaria. In closing, the discussion will end by demonstrating CAD software which is expected to be an alternative for diagnosing malaria along with its features.

A. Dataset and Image Pre-processings

Prior to the development of deep learning models for malaria detection is carried out, the malaria dataset is splitted into training data, testing and validation. The separation process between training data and testing data is performed by using ratio of 80:20. Thus, total 22,062 and 5,516 data are generated for training and testing data respectively. Furthermore, further data separation was carried out on test data to obtain validation data with a data ratio of 50:50. Hence, the final data that will be used for early diagnosis of brain tumours were 22,062, 2,758 and 2,758 for each type of data training, testing and validation. In addition, to improve the quality of the data separation, randomization was conducted in the distribution of data so that each class of brain tumours images has representation for each data type.

As soon as the data separation process was completed, the research was continued by improving the quality and quantity of brain tumours images through the data pre-processing stage. The process of improving the quality of the brain tumours dataset is carried out by applying resolution rescaling and image augmentation methods. The rescaling method is intended to change the image resolution of brain tumours cells to a uniform size of 150x150 pixels. After that, an increase in the quantity of brain tumours cell images was conducted by applying the augmentation method by performing horizontal rotation. After data preparation is complete, the tumours cell dataset is ready to be processed for brain tumours diagnosis experiments using three variations of the CNN architecture. The final results of the data preparation stage are explained in Figure 5 below.

B. Development of Deep Learning Model and CAD Software

The experimental findings presented in this section discuss the comparison between pre-trained CNN architectures with and without architectural modifications to pre-processed data. This analysis was conducted to determine whether architectural modifications by adding several layers succeeded in improving the performance of the Deep Learning algorithm for diagnosing malaria. Based on a series of experiments conducted for each pre-trained CNN architecture, modification with the addition of layers has proven successful in improving the performance of the Deep Learning algorithm in classifying malarial images

The first experiment was carried out by utilizing the modified EfficientNetB0 pre-trained architecture. By utilizing this modified EfficientNetB0 architecture, the deep learning model achieves the best performance with an accuracy rate of 98.46%. The application of this modified architecture succeeded in increasing the accuracy rate to more than 1% when compared to the pre-trained EfficientNetB0 architecture without modification which has a value of 97.13%. The second experiment by applying the modified MobileNetV2 pre-trained architecture also showed satisfactory results. This architectural modification succeeded in

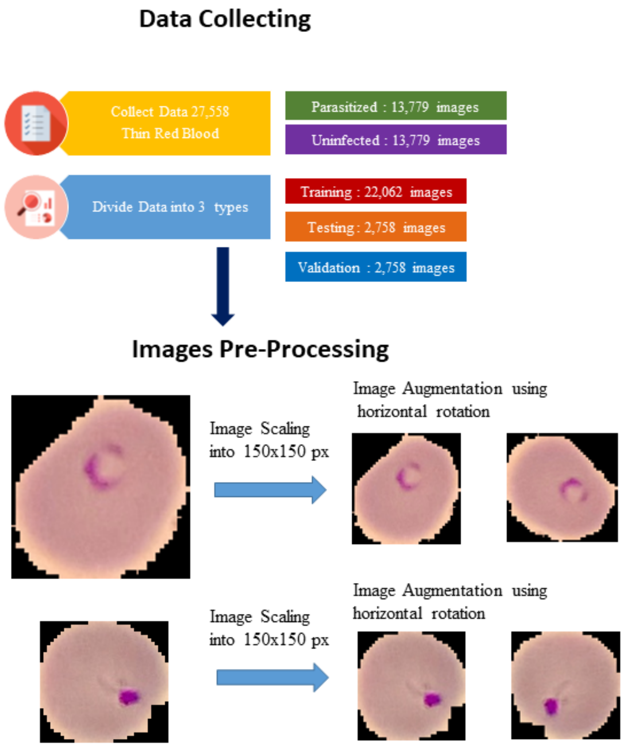

Figure 5. Result of Data Collection and Pre-processing

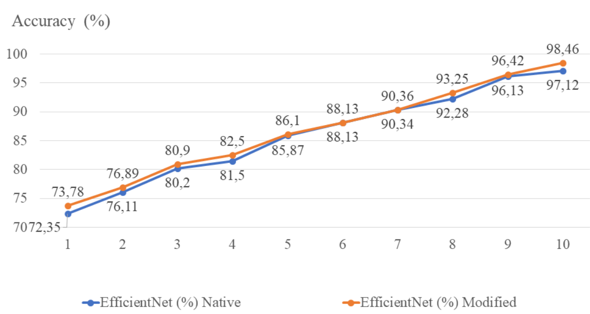

Figure 6. Comparison Accuracy of EfficientNetB0

increasing the accuracy from the initial value of 96.13% to 97.71%. Accuracy comparison graphs for pre-trained EfficientNetB0 and MobileNetV2 architectures are shown in Figures 6 and 7 below.

The success of architectural modifications in improving the performance of this deep learning model also occurs in other pre-trained architectures. By doing modifications, the other three pre-trained architectures also get an increase in accuracy of around 1.5%. The graph of increasing accuracy for the InceptionV3, ResNet50 and Xception architectures is illustrated in Figures 8 to 10 below.

To be concluded, based on all the experiments that have been carried out by modifying the 5 pre-trained architectures, it was found that the architectural modifi-

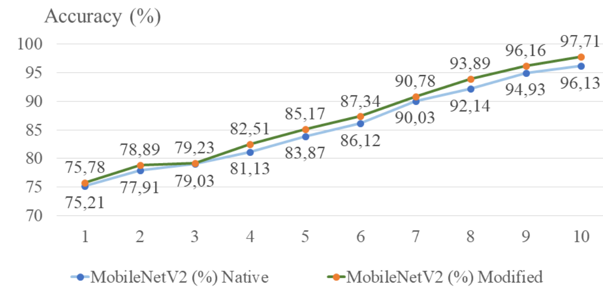

Figure 7. Comparison Accuracy of MobileNetV2

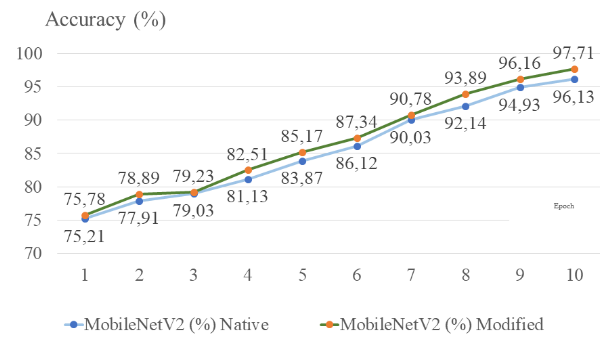

Figure 8. Comparison Accuracy of InceptionV2

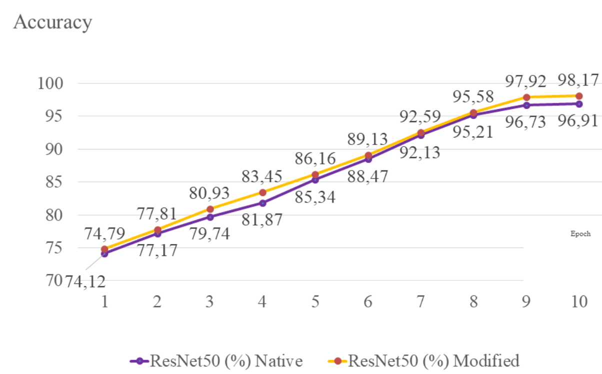

Figure 9. Comparison Accuracy of ResNet50

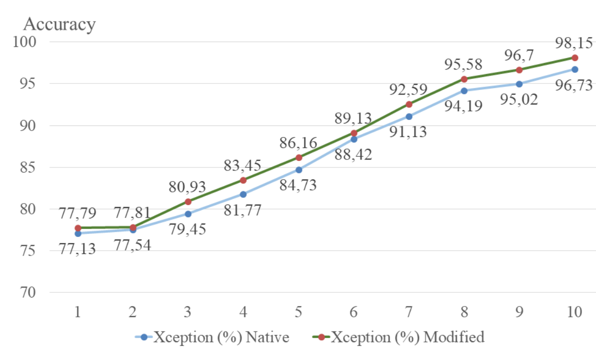

Figure 10. Comparison Accuracy of Xception

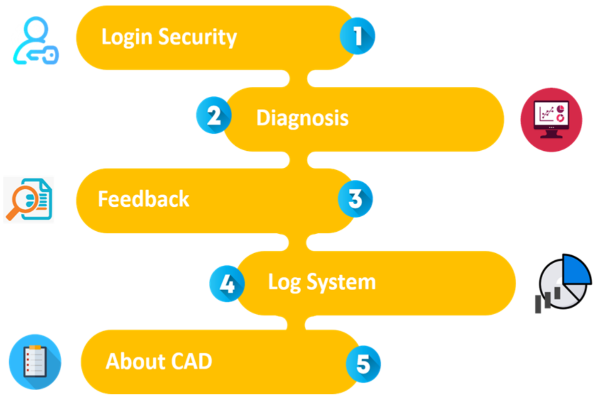

Figure 11. Feature of CAD Application for Malaria Diagnosis

cations succeeded in increasing the accuracy of the deep learning model. The five modified architectures succeeded in exceeding the accuracy benchmark from previous studies of 97%. This achievement is certainly very appropriate as an alternative for early diagnosis of malaria in order to detect malaria early. An overall comparison for all the performance of the modified CNN architectures is summarized in table III below.

Based on the research results described in table III, it can be seen that there was an increase in the complexity of the training phase caused by the addition of quite a lot of parameters as the pre-trained CNN architecture was modified. The addition of this parameter then causes an increase in the time needed to develop an optimal deep learning model. One solution that can be implemented to deal with this problem is to apply feature optimization or feature selection which is an important highlight to work on in further research.

After obtain the optimum model for diagnosing malaria that successfully surpassed the benchmarks of previous research, a CAD application was developed by utilizing web services. As mentioned previously, this CAD application use a lightweight RESTful-API as the back-end system which is developed by using python library namely flask. RESTfull API was chosen as the backend because it is very suitable to accommodate pre-trained deep learning models since it is a lightweight back-end type and also highly compatible with external web interfaces. This RESTful-API is designed separately from the web application to make it easy for users to make CAD-based malaria diagnosis. The developed CAD is useful Web application to classify thin blood microscopic malaria images consisting of parasitized and uninfected cell. The CAD application developed has the following main features as illustrated in Figure 11 below.

As in general for applications that deal with health problems, issues related to information security and confidentiality are important things to address. As for one of the most appropriate solutions to be implemented in order

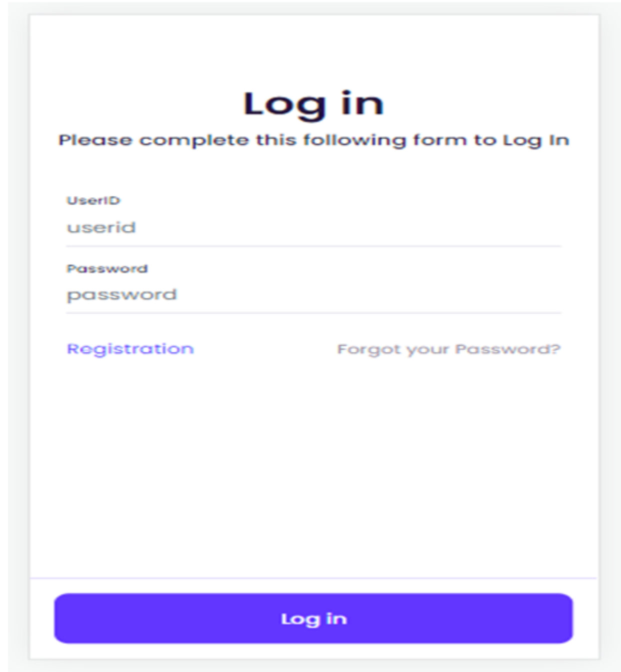

Figure 12. Screenshot of Interface for Login Page

to deal with these security and confidentiality issues is to implement the login feature. This feature is intended to maintain the security of CAD software by limiting this application from being used by unauthorized persons. Users who will use the CAD application are asked to enter a username and password before being able to use the CAD application for malaria diagnosis. In addition, this login mechanism will be utilized to record user activity which will be stored in the system log.

The second feature embedded in this CAD application is the malaria diagnosis feature. In accordance with the purpose of making a CAD application, this feature is the most important feature used by users to diagnose malaria. By using this feature, the user can simply upload an image of the blood that will be analyzed to determine whether the blood is infected with malaria or normal. Along with the diagnosis process, the performance of the deep learning architecture used, such as the level of accuracy, precision, and recall, will also be explained. Based on this information, the user can estimate the accuracy of the results of an early diagnosis of malaria. Meanwhile, if there are conditions where the results of the diagnosis are different from each deep learning architecture, the user can choose to refer to the prediction results from the architecture that has better performance. Furthermore, users can also note the differences of this diagnosis to be submitted as recommendations for improving CAD applications in the user feedback feature. The screenshot pages for the login and diagnosis features are depicted in Figures 12 and 13 below.

TABLE III. Comparison of Overall Modified CNN Architecture

CNN Architecture	Accuracy (%)		Parameter	
	N	M	N	M
EfficientNetB0	97.12	98.46	4,011,391	5,322,367
MobileNetV2	96.13	97.71	2,227,715	3,538,691
InceptionV3	96.28	97.73	21,772,450	23,868,578
ResNet50	96.91	98.17	23,538,690	25,634,818
Xception	96.73	98.15	20,811,050	22,907,178
Benchmark Accuracy (%)	97			
N = Native Architecture ; M = Modified Architecture				

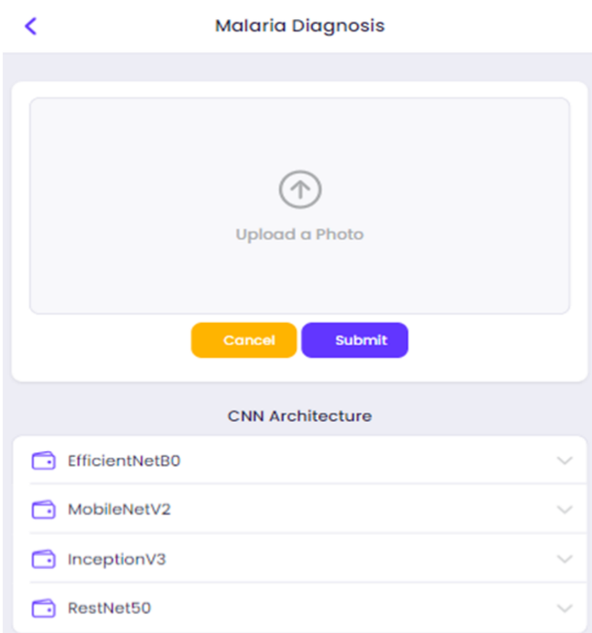

Figure 13. Screenshot of Interface for Diagnosis Page

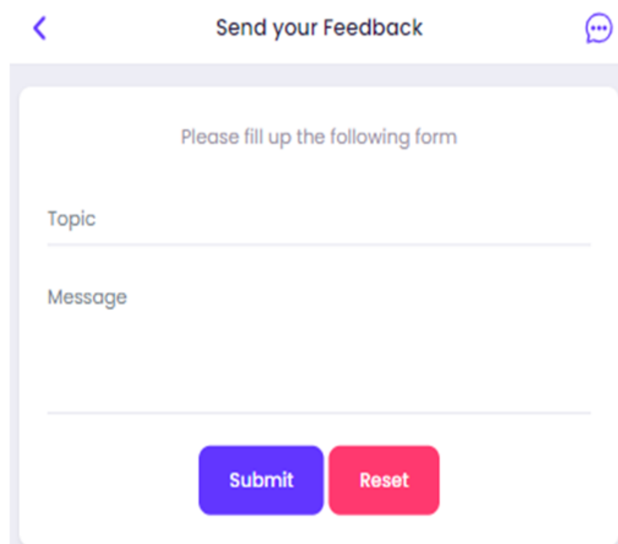

Figure 14. Screenshot of Interface for Feedback Page

This user feedback feature is intended as a tool for users to submit suggestions for improvements of CAD applications. As explained in the previous feature, by using this feature users can make a requests for improvements of CAD applications such as increasing the accuracy of diagnosis results, user interface as well as user experience and so on as illustrated in Figure 14 below

All of user activity will be recorded in the system log as a statistic of user usage patterns. These logs are very important for CAD applications in terms of checking and tracing various problems that will occur. In addition, usage patterns recorded in the log will also be very useful in developing CAD applications to make them more attractive and useful to users. The last feature provided in this CAD application is a brief explanation of the CAD application which is namely as about CAD feature. The information provided in this feature includes explanations regarding deep learning technology, the malaria image dataset used, contact persons and etc. The interface for about CAD and system log feature can be seen in Figure 15-16 below.

5. Conclusion and Future Direction

This research produces CAD software based on CNN by utilizing 5 pre-trained architectures such as EfficientNetB0, MobileNetV2, InceptionV3, ResNet50, and Xception as an alternative for early diagnosis of malaria. To improve the performance of the CAD software, a modification is made by adding several layers to each pre-trained CNN architecture. Based on all the experiments that have been done, all of these modified architectures are successful achieving excellent performance with accuracy above 97% which at the same time exceeds previous research benchmarks. The best performance is achieved by the EfficientNetB0 architecture with an accuracy rate of 98.46%. However, this increase in accuracy raises new problems because

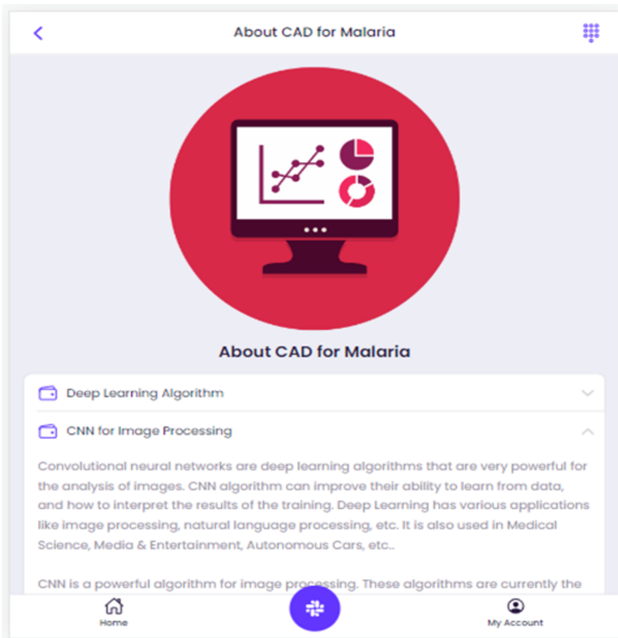

Figure 15. Screenshot of Interface for About CAD Page

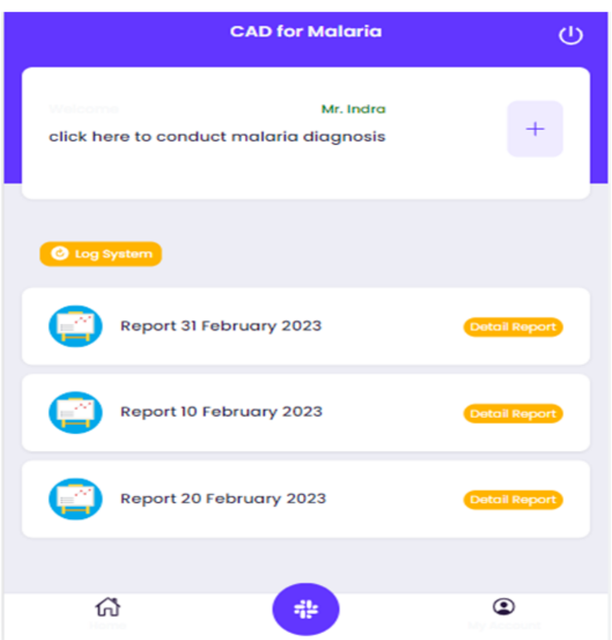

Figure 16. Screenshot of Interface for System Log

the training parameters used become more complex with increasing training parameters used to develop deep learning models. One solution that can be implemented to deal with this issue is by applying feature optimization or feature selection which is an important highlight to work on in further research. Various kinds of feature selection or optimization algorithms such as PCA, Genetic Algorithm are very promising to be applied before the image classification stage. This algorithm can reduce the level of complexity by selecting the best features from a feature data set.

To enrich and facilitate its use, the developed CAD application is equipped with several important features such as login, diagnosis, feedback, log system, and all about CAD. Although this research has succeeded in developing a CAD system to help early diagnosis of malaria, there is still room for further research development. However, future research can be directed to apply another algorithm in image classification such the CapsNet algorithm. This is because the use of CapsNet is considered to be able to improve image classification performance by being able to utilize vectors for more detailed image representation. As previously mentioned, the discussion regarding the application of feature selection to optimize training parameters is another interesting thing to be carried out.

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References

[1] M. Dagen, "History of malaria and its treatment," *Antimalarial agents*, pp. 1–48, 2020.

[2] W. H. Organization, "World malaria report 2022," 2022.

[3] ——, "Fact Sheet about Malaria 2019," accessed 2023-02-27. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/malaria

[4] ——, "Fact Sheet about Malaria 2020," accessed 2023-02-27. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/malaria

[5] M. Poostchi, K. Silamut, R. J. Maude, S. Jaeger, and G. Thoma, "Image analysis and machine learning for detecting malaria," *Translational Research*, vol. 194, pp. 36–55, 2018.

[6] K. Sriporn, C.-F. Tsai, C.-E. Tsai, and P. Wang, "Analyzing malaria disease using effective deep learning approach," *Diagnostics*, vol. 10, no. 10, p. 744, 2020.

[7] G. R. L. Del Prado, C. H. García, L. M. Cea, V. F. Espinilla, M. F. M. Moreno, A. D. Márquez, M. J. P. Polo, and I. A. García, "Malaria in developing countries," *The Journal of Infection in Developing Countries*, vol. 8, no. 01, pp. 001–004, 2014.

[8] P. Pattanaik, M. Mittal, M. Z. Khan, and S. Panda, "Malaria detection using deep residual networks with mobile microscopy,"

Journal of King Saud University-Computer and Information Sciences, vol. 34, no. 5, pp. 1700–1705, 2022.

[9] Y. M. Kassim, K. Palaniappan, F. Yang, M. Poostchi, N. Palaniappan, R. J. Maude, S. Antani, and S. Jaeger, "Clustering-based dual deep learning architecture for detecting red blood cells in malaria diagnostic smears," *ieee journal of biomedical and health informatics*, vol. 25, no. 5, pp. 1735–1746, 2020.

[10] Z. Liang, A. Powell, I. Ersoy, M. Poostchi, K. Silamut, K. Palaniappan, P. Guo, M. A. Hossain, A. Sameer, R. J. Maude *et al.*, "Cnn-based image analysis for malaria diagnosis," in *2016 IEEE international conference on bioinformatics and biomedicine (BIBM)*. IEEE, 2016, pp. 493–496.

[11] F. Yang, M. Poostchi, H. Yu, Z. Zhou, K. Silamut, J. Yu, R. J. Maude, S. Jaeger, and S. Antani, "Deep learning for smartphone-based malaria parasite detection in thick blood smears," *IEEE journal of biomedical and health informatics*, vol. 24, no. 5, pp. 1427–1438, 2019.

[12] D. Bibin, M. S. Nair, and P. Punitha, "Malaria parasite detection from peripheral blood smear images using deep belief networks," *IEEE Access*, vol. 5, pp. 9099–9108, 2017.

[13] P. Manescu, C. Bendkowski, R. Claveau, M. Elmi, B. J. Brown, V. Pawar, M. J. Shaw, and D. Fernandez-Reyes, "A weakly supervised deep learning approach for detecting malaria and sickle cells in blood films," in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference, Lima, Peru, October 4–8, 2020, Proceedings, Part V 23*. Springer, 2020, pp. 226–235.

[14] M. Delgado-Ortet, A. Molina, S. Alférez, J. Rodellar, and A. Merino, "A deep learning approach for segmentation of red blood cell images and malaria detection," *Entropy*, vol. 22, no. 6, p. 657, 2020.

[15] C. S. Islam and M. S. H. Mollah, "A novel idea of malaria identification using convolutional neural networks (cnn)," in *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*. IEEE, 2018, pp. 7–12.

[16] M. Umer, S. Sadiq, M. Ahmad, S. Ullah, G. S. Choi, and A. Mehmood, "A novel stacked cnn for malarial parasite detection in thin blood smear images," *IEEE Access*, vol. 8, pp. 93 782–93 792, 2020.

[17] C. Mehanian, M. Jaiswal, C. Delahunt, C. Thompson, M. Horning, L. Hu, T. Ostbye, S. McGuire, M. Mehanian, C. Champlin *et al.*, "Computer-automated malaria diagnosis and quantitation using convolutional neural networks," in *Proceedings of the IEEE international conference on computer vision workshops*, 2017, pp. 116–125.

[18] S. S. Prakash, B. C. Kovoor, and K. Visakha, "Convolutional neural network based malaria parasite infection detection using thin microscopic blood smear samples," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*. IEEE, 2020, pp. 308–313.

[19] H. K. Ragb, I. T. Dover, and R. Ali, "Deep convolutional neural network ensemble for improved malaria parasite detection," in *2020 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*. IEEE, 2020, pp. 1–10.

[20] A. Vijayalakshmi, "Deep learning approach to detect malaria from microscopic images," *Multimedia Tools and Applications*, vol. 79, pp. 15 297–15 317, 2020.

[21] A. M. Joshi, A. K. Das, and S. Dhal, "Deep learning based approach for malaria detection in blood cell images," in *2020 IEEE region 10 conference (TENCON)*. IEEE, 2020, pp. 241–246.

[22] K. F. Fuhad, J. F. Tuba, M. R. A. Sarker, S. Momen, N. Mohammed, and T. Rahman, "Deep learning based automatic malaria parasite detection from blood smear and its smartphone based application," *Diagnostics*, vol. 10, no. 5, p. 329, 2020.

[23] S. C. Kalkan and O. K. Sahingoz, "Deep learning based classification of malaria from slide images," in *2019 scientific meeting on electrical-electronics & biomedical engineering and computer science (EBBT)*. IEEE, 2019, pp. 1–4.

[24] N. Singla and V. Srivastava, "Deep learning enabled multi-wavelength spatial coherence microscope for the classification of malaria-infected stages with limited labelled data size," *Optics & Laser Technology*, vol. 130, p. 106335, 2020.

[25] P. Manescu, L. N. Zajiczek, M. J. Shaw, M. Elmi, R. Claveau, V. Pawar, J. Shawe-Taylor, I. Kokkinos, M. A. Srinivasan, I. Lagunju *et al.*, "Deep learning enhanced extended depth-of-field for thick blood-film malaria high-throughput microscopy," *arXiv preprint arXiv:1906.07496*, 2019.

[26] N. Alok, K. Krishan, and P. Chauhan, "Deep learning-based image classifier for malaria cell detection," *Machine learning for healthcare applications*, pp. 187–197, 2021.

[27] A. Maqsood, M. S. Farid, M. H. Khan, and M. Grzegorzek, "Deep malaria parasite detection in thin blood smear microscopic images," *Applied Sciences*, vol. 11, no. 5, p. 2284, 2021.

[28] A. Abubakar, M. Ajuji, and I. U. Yahya, "Deepfmd: computational analysis for malaria detection in blood-smear images using deep-learning features," *Applied System Innovation*, vol. 4, no. 4, p. 82, 2021.

[29] A. S. Sayyed, D. Saha, A. R. Hossain, and C. Shahnaz, "Effectiveness of convolutional and capsule network in malaria parasite detection," in *2019 IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON)*. IEEE, 2019, pp. 68–73.

[30] F. J. P. Montalbo and A. S. Alon, "Empirical analysis of a fine-tuned deep convolutional model in classifying and detecting malaria parasites from blood smears," *KSII Transactions on Internet and Information Systems*, vol. 15, no. 1, p. 2021, 2021.

[31] Y. Dong, Z. Jiang, H. Shen, W. D. Pan, L. A. Williams, V. V. Reddy, W. H. Benjamin, and A. W. Bryan, "Evaluations of deep convolutional neural networks for automatic identification of malaria infected cells," in *2017 IEEE EMBS international conference on biomedical & health informatics (BHI)*. IEEE, 2017, pp. 101–104.

[32] S. Sağlam, F. Tat, and S. Bayar, "Fpga implementation of cnn algorithm for detecting malaria diseased blood cells," in *2019 International Symposium on Advanced Electrical and Communication Technologies (ISAECT)*. IEEE, 2019, pp. 1–5.

[33] A. Rahman, H. Zunair, M. S. Rahman, J. Q. Yuki, S. Biswas, M. A. Alam, N. B. Alam, and M. Mahdy, "Improving malaria parasite detection from red blood cell using deep convolutional neural networks," *arXiv preprint arXiv:1907.10418*, 2019.

[34] M. Masud, H. Alhumyani, S. S. Alshamrani, O. Cheikhrouhou, S. Ibrahim, G. Muhammad, M. S. Hossain, and M. Shorfuzzaman, "Leveraging deep learning techniques for malaria parasite detection using mobile application," *Wireless Communications and Mobile Computing*, vol. 2020, pp. 1–15, 2020.

[35] A. Alqudah, A. M. Alqudah, and S. Qazan, "Lightweight deep learning for malaria parasite detection using cell-image of blood smear images." *Rev. d'Intelligence Artif.*, vol. 34, no. 5, pp. 571–576, 2020.

[36] U. Adamjee and S. Ghani, "Malaria cell identification from microscopic blood smear images," in *2019 8th International Conference on Information and Communication Technologies (ICICT)*. IEEE, 2019, pp. 82–86.

[37] G. Shekar, S. Revathy, and E. K. Goud, "Malaria detection using deep learning," in *2020 4th international conference on trends in electronics and informatics (ICOEI)(48184)*. IEEE, 2020, pp. 746–750.

[38] A. B. A. Qayyum, T. Islam, and M. A. Haque, "Malaria diagnosis with dilated convolutional neural network based image analysis," in *2019 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON)*. IEEE, 2019, pp. 68–72.

[39] S. V. Militante, "Malaria disease recognition through adaptive deep learning models of convolutional neural network," in *2019 IEEE 6th International Conference on Engineering Technologies and Applied Sciences (ICETAS)*. IEEE, 2019, pp. 1–6.

[40] S. P. Singh, P. Bansal, S. Kumar, and P. Shrivastava, "Malaria parasite recognition in thin blood smear images using squeeze and excitation networks," in *2019 IEEE Conference on Information and Communication Technology*. IEEE, 2019, pp. 1–5.

[41] A. Kumar, S. B. Singh, S. C. Satapathy, and M. Rout, "Mosquito-net: a deep learning based cadx system for malaria diagnosis along with model interpretation using gradcam and class activation maps," *Expert Systems*, vol. 39, no. 7, p. e12695, 2022.

[42] S. Rajaraman, S. Jaeger, and S. K. Antani, "Performance evaluation of deep neural ensembles toward malaria parasite detection in thin-blood smear images," *PeerJ*, vol. 7, p. e6977, 2019.

[43] S. Rajaraman, S. K. Antani, M. Poostchi, K. Silamut, M. A. Hossain, R. J. Maude, S. Jaeger, and G. R. Thoma, "Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images," *PeerJ*, vol. 6, p. e4568, 2018.

[44] A. Huq and M. T. Pervin, "Robust deep neural network model for identification of malaria parasites in cell images," in *2020 IEEE Region 10 Symposium (TENSYMP)*. IEEE, 2020, pp. 1456–1459.

[45] A. S. B. Reddy and D. S. Juliet, "Transfer learning with resnet-50 for malaria cell-image classification," in *2019 International Conference on Communication and Signal Processing (ICCSP)*. IEEE, 2019, pp. 0945–0949.

[46] P. A. Pattanaik, M. Mittal, and M. Z. Khan, "Unsupervised deep learning cad scheme for the detection of malaria in blood smear microscopic images," *IEEE Access*, vol. 8, pp. 94 936–94 946, 2020.

[47] F. Yang, H. Yu, K. Silamut, R. J. Maude, S. Jaeger, and S. Antani, "Smartphone-supported malaria diagnosis based on deep learning," in *Machine Learning in Medical Imaging: 10th International Workshop, MLMI 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 13, 2019, Proceedings 10*. Springer, 2019, pp. 73–80.

[48] A. Rahman, H. Zunair, T. R. Reme, M. S. Rahman, and M. R. C. Mahdy, "A comparative analysis of deep learning architectures on high variation malaria parasite classification dataset," *Tissue and Cell*, vol. 69, p. 101473, 2021.

[49] K. Torres, C. M. Bachman, C. B. Delahunt, J. Alarcon Baldeon, F. Alava, D. Gamboa Vilela, S. Proux, C. Mehanian, S. K. McGuire, C. M. Thompson *et al.*, "Automated microscopy for routine malaria diagnosis: a field comparison on giemsa-stained blood films in peru," *Malaria journal*, vol. 17, pp. 1–11, 2018.

[50] P. Manescu, M. J. Shaw, M. Elmi, L. Neary-Zajiczek, R. Claveau, V. Pawar, I. Kokkinos, G. Oyinloye, C. Bendkowski, O. A. Oladejo *et al.*, "Expert-level automated malaria diagnosis on routine blood films with deep neural networks," *American Journal of Hematology*, vol. 95, no. 8, pp. 883–891, 2020.

[51] D. Shah, K. Kawale, M. Shah, S. Randive, and R. Mapari, "Malaria parasite detection using deep learning:(beneficial to humankind)," in *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*. IEEE, 2020, pp. 984–988.

[52] R. Sivaramakrishnan, S. Antani, and S. Jaeger, "Visualizing deep learning activations for improved malaria cell classification," in *Medical informatics and healthcare*. PMLR, 2017, pp. 40–47.

[53] P. Rahul Das, G. Karuna, V. Srilakshmi, and B. Rupa, "An efficient smartphone based parasite malaria detection with deep neural networks," in *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)*. IEEE, 2021, pp. 539—-544.

[54] K. Mitrović and D. Milošević, "Classification of malaria-infected cells using convolutional neural networks," in *2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI)*. IEEE, 2021, pp. 000 323–000 328.

[55] C. K. Tan, C. M. Goh, S. A. Z. B. S. Aluwee, S. W. Khor, and M. T. Chai, "Malaria parasite detection using residual attention u-net," in *2021 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*. IEEE, 2021, pp. 122–127.

[56] A. E. B. Alawi, M. A. Mosleh, Z. Almohagry, and A. Y. Saeed, "Parasitized cell recognition using alexnet pre-trained model," in *2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA)*. IEEE, 2021, pp. 1–4.

[57] C. B. Delahunt, M. S. Jaiswal, M. P. Horning, S. Janko, C. M. Thompson, S. Kulhare, L. Hu, T. Ostbye, G. Yun, R. Gebrehiwot *et al.*, "Fully-automated patient-level malaria assessment on field-prepared thin blood film microscopy images," in *2019 IEEE Global Humanitarian Technology Conference (GHTC)*. IEEE, 2019, pp. 1–8.

[58] P. Elangovan and M. K. Nath, "A novel shallow convnet-18 for malaria parasite detection in thin blood smear images: Cnn based malaria parasite detection," *SN computer science*, vol. 2, no. 5, p. 380, 2021.

[59] G. P. Gopakumar, M. Swetha, G. Sai Siva, and G. R. K. Sai Subrahmanyam, "Convolutional neural network-based malaria diagnosis from focus stack of blood smear images acquired using custom-

built slide scanner," *Journal of biophotonics*, vol. 11, no. 3, p. e201700003, 2018.

[60] K. E. D. Peñas, P. T. Rivera, and P. C. Naval, "Malaria parasite detection and species identification on thin blood smears using a convolutional neural network," in *2017 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*. IEEE, 2017, pp. 1–6.

[61] M. P. Horning, C. B. Delahunt, C. M. Bachman, J. Luchavez, C. Luna, L. Hu, M. S. Jaiswal, C. M. Thompson, S. Kulhare, S. Janko *et al.*, "Performance of a fully-automated system on a who malaria microscopy evaluation slide set," *Malaria journal*, vol. 20, no. 1, pp. 1–11, 2021.

[62] B. Qin, Y. Wu, Z. Wang, and H. Zheng, "Malaria cell detection using evolutionary convolutional deep networks," in *2019 Computing, Communications and IoT Applications (ComComAp)*. IEEE, 2019, pp. 333–336.

[63] T. Jameela, K. Athota, N. Singh, V. K. Gunjan, S. Kahali *et al.*, "Deep learning and transfer learning for malaria detection," *Computational intelligence and neuroscience*, vol. 2022, 2022.

[64] D. Uzun Ozsahin, M. T. Mustapha, B. Bartholomew Duwa, and I. Ozsahin, "Evaluating the performance of deep learning frameworks for malaria parasite detection using microscopic images of peripheral blood smears," *Diagnostics*, vol. 12, no. 11, p. 2702, 2022.

[65] K. Hemachandran, A. Alasiry, M. Marzougui, S. M. Ganie, A. A. Pise, M. T.-H. Alouane, and C. Chola, "Performance analysis of deep learning algorithms in diagnosis of malaria disease," *Diagnostics*, vol. 13, no. 3, p. 534, 2023.

[66] D. R. Loh, W. X. Yong, J. Yapeter, K. Subburaj, and R. Chandramohanadas, "A deep learning approach to the screening of malaria infection: Automated and rapid cell counting, object detection and instance segmentation using mask r-cnn," *Computerized Medical Imaging and Graphics*, vol. 88, p. 101845, 2021.

[67] Y. M. Kassim, F. Yang, H. Yu, R. J. Maude, and S. Jaeger, "Diagnosing malaria patients with plasmodium falciparum and vivax using deep learning for thick smear images," *Diagnostics*, vol. 11, no. 11, p. 1994, 2021.

[68] R. Nakasi, E. Mwebaze, A. Zawedde, J. Tusubira, B. Akera, and G. Maiga, "A new approach for microscopic diagnosis of malaria parasites in thick blood smears using pre-trained deep learning models," *SN Applied Sciences*, vol. 2, pp. 1–7, 2020.

[69] J. Hung and A. Carpenter, "Applying faster r-cnn for object detection on malaria images," in *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2017, pp. 56–61.

[70] R. Nakasi, E. Mwebaze, and A. Zawedde, "Mobile-aware deep learning algorithms for malaria parasites and white blood cells localization in thick blood smears," *Algorithms*, vol. 14, no. 1, p. 17, 2021.

[71] R. Nakasi, J. F. Tusubira, A. Zawedde, A. Mansourian, and E. Mwebaze, "A web-based intelligence platform for diagnosis of malaria in thick blood smear images: A case for a developing country," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 2020, pp. 984–985.

[72] F. Yang, H. Yu, K. Silamut, R. J. Maude, S. Jaeger, and S. Antani, "Parasite detection in thick blood smears based on customized faster-rcnn on smartphones," in *2019 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*. IEEE, 2019, pp. 1–4.

[73] G. Madhu, A. Govardhan, B. S. Srinivas, S. A. Patel, B. Rohit, and B. L. Bharadwaj, "Capsule networks for malaria parasite classification: An application oriented model," in *2020 IEEE International Conference for Innovation in Technology (INOCON)*. IEEE, 2020, pp. 1–5.

[74] M. Maity, A. Jaiswal, K. Gantait, J. Chatterjee, and A. Mukherjee, "Quantification of malaria parasitaemia using trainable semantic segmentation and capsnet," *Pattern Recognition Letters*, vol. 138, pp. 88–94, 2020.

[75] W. Kudisthalert, K. Pasupa, and S. Tongsima, "Counting and classification of malarial parasite from giemsa-stained thin film images," *IEEE Access*, vol. 8, pp. 78 663–78 682, 2020.

[76] F. Abdurahman, K. A. Fante, and M. Aliy, "Malaria parasite detection in thick blood smear microscopic images using modified yolov3 and yolov4 models," *BMC bioinformatics*, vol. 22, no. 1, pp. 1–17, 2021.

[77] F. A. Shewajo and K. A. Fante, "Tile-based microscopic image processing for malaria screening using a deep learning approach," *BMC Medical Imaging*, vol. 23, no. 1, pp. 1–14, 2023.

[78] M. Bhuiyan and M. S. Islam, "A new ensemble learning approach to detect malaria from microscopic red blood cell images," *Sensors International*, vol. 4, p. 100209, 2023.

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