

## Utilizing deep transfer learning models and data augmentation to improve image classification

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### Abstract

VBDs (vector-borne diseases) have a significant influence on people's health and economies all around the globe. Malaria is a disease spread by female Anopheles mosquitoes, which give the host a motile infectious version of the disease. Malaria is characterised by fever, headache, fatigue, and vomiting. In extreme circumstances, it might cause coma and death. The most of these deaths are caused by a delayed or incorrect diagnosis. Malaria is best diagnosed using a manual microscope. However, it is labour-intensive and prone to errors caused by humans. This is a severe worldwide health risk; hence it is essential that the review process be automated. Therefore, a highly accurate automated computational approach is needed to aid in the timely identification of malaria in order to lower fatality rates. In order to improve diagnosis accuracy, researchers are using deep-learning technologies like convolutional neural network (CNNs) and image processing to assess Parasitemia in tiny blood slides. ResNet50, VGG-16, and VGG-19 are three CNN architectures that were trained using the same dataset and are fed images of both infected and uninfected erythrocytes. Fine-tuning is contrasted with transfer learning in terms of its consequences. Based on the evaluated parameters and data set, the VGG-19 model had the highest accuracy.

**Keywords:** Deep learning, CNN, transfer learning, VGG 19, data augmentation, malaria

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## 1. Introduction

According to the annual estimations of the WHO (World Health Organization), 3.2 billion individuals throughout the global are at significant risk of contracting malaria. With the appropriate treatment, malaria may be treated and prevented. A significant percentage of the population in many newly industrialised and developing countries suffers from malaria every year, putting a heavy burden on healthcare resources worldwide [1]. For this reason, it is crucial to diagnose and treat malaria as soon as possible. This gives motivation to improve malaria diagnostics' efficacy and timeliness in the future. The most crucial step in detecting malaria is determining if parasites are present. Using a blood sample is the most prevalent way for diagnosing malaria. However, there are drawbacks to using such techniques, for instance the actuality that the proficiency of the pathologist has a significant role in the accuracy of the diagnosis, which might lead to the formation of new illnesses [2]. Recent studies of biomedicine have shown that deep learning algorithms are among the most promising of the

current generation of machine learning methods. For analysing and diagnosing biological and healthcare issues, deep learning (DL) has gained immense popularity over the last decade because to the simplicity with which vital information can be extracted and tasks that were before impossible to perform using traditional methodologies. In biomedical applications, machine learning is used for many purposes: to enhance medical treatment for patients by developing more personalised drugs; as a computer-aided analysis and diagnosis to help doctors make more accurate and fast diagnoses with better harmonised and less contradicting diagnoses; and to promotes social well-being through the investigation of transmission of infection and social behaviour in relation to the environment [3]. Deep learning is a machine learning technology that might be used to analyse this kind of medical data. Malaria is a devastating disease that afflicts a large number of individuals annually around the globe and is avoidable. Multiple investigations, especially in rural regions where malaria is widespread, have revealed that manual microscopy is an inaccurate screening technique when undertaken by nonexperts owing to an inadequate training [2]. We present a model based on VGG for the detection of infected cells and show its efficacy by comparing it to models developed earlier. On a broad variety of performance criteria, our model beats the most of previously created models.

## 2. Related Work

Images of extremely minute blood smears are examined by skilled microscopists using specialised equipment. This investigation may be carried out on a computer using current deep-learning methods. The ability to detect malaria, in keeping with past discoveries, is among the most significant outcomes of employing DL in the medical sector, as shown by this research. If an accurate and efficient automated model can be created, the need for highly skilled workers may be drastically reduced. This study presents the malaria detection approach, a CNN-based approach for malaria diagnosis in microscopic blood smears. In recent years, blood smear pictures have become more complicated, making it feasible to detect malaria using a variety of artificial intelligence systems. Machine learning algorithms only need a little quantity of data, but deep learning models need a large volume of high-quality, the ability to learn from labelled data and predict the future with high precision. Unexpectedly, a method termed TL (transfer learning), which is discussed here, may be used to trained deep-learning models to tackle issues in a number of diverse but related applications. Pretrained deep-learning models are trained to handle a related problem to the one being addressed. TL is one of the three techniques to implement DL algorithms it into training environment [4]. In order to visualize salient network activation, to investigate the chest X-ray screening job, Sivaramakrishnan et al. [5] developed a DL model using a custom-built CNN. Jane Hung et al. [6] have created a unique approach for item detection utilising a CNN that has been pre-trained on ImageNet and then fine-tuned utilizing their data. There have also been other works on using DL techniques to the problem of finding malaria parasites reported in the literature.

Dong et al. [7] examined the effectiveness of support vector machine with pre-trained DL models in distinguishing between parasitized & uninfected cells on a customised data - set of parasitized & uninfected cells. Investigators randomly divided the images of thin blood smears

containing red blood cells into two training and testing groups. GoogleNet allowed an image size of 256X256, but in case of LeNet and AlexNet, the supplied image size was set to 60.

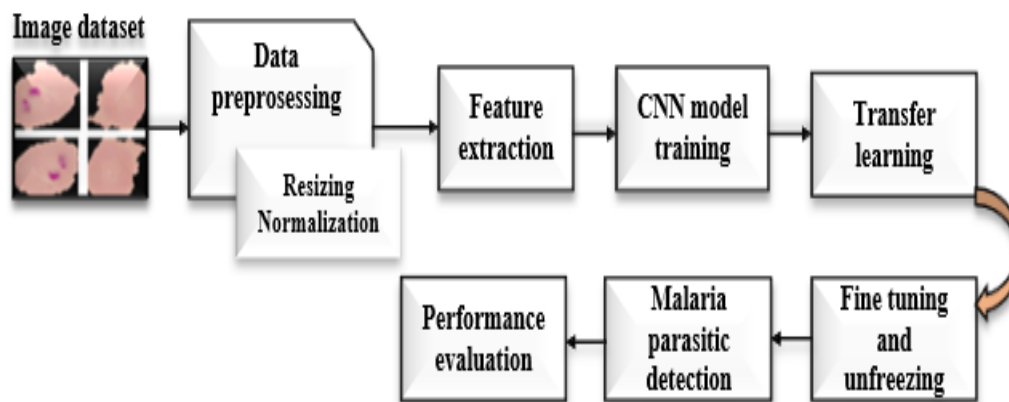
All of the pre-trained models performed better than SVM on their dataset, and GoogleNet outperformed with the highest accuracy of 98.13%. In order to evaluate the efficacy of their proposed model, Liang et al. [8] contrasted it to a CNN that had been pretrained to distinguish between infected and uninfected cells by utilising the AlexNet as a feature extraction base. According to their findings, Shaik et al. [9] found that a CNN with 3 convolutional and two fully connected layers produced the best results. The performance of many pretrained convolutional neural networks (CNNs) was evaluated. Features were extracted from the AlexNet & VGG-16 models on the second fully - connected layers, and from the Xception, DenseNet-121, and ResNet-50 models on the layer well before final classification layer. Overall, ResNet-50's 95.7% accuracy was the highest of all of the pretrained CNNs and bespoke CNN models tested. Suryanarayana et al. [10] created AOCT-NET, an eighteen- layer transfer learning architecture. The performance measures of AOCT-NET were compared by the authors of this research to those of recently published contemporary designs. The former received the highest possible score in the assessment. While investigating the efficacy of TL, Alqudah [11] compared the effectiveness of a customized CNN model to that of VGG-16 and VGG-19, two pretrained models (95.33 percent). This accuracy has the potential to increase with the addition of additional optimization techniques [12]. For the diagnosis of malaria, brain tumours, and TB across several imaging modalities, Narayanan et al. [17] studied the outcomes produced by deep neural networks. Despite the availability of various machine learning models for medical image analysis, few have been applied in practise owing to the unpredictability of the network's conclusions. Bibin et al [18] suggested a new approach that makes use of a deep belief network to detect the existence of plasmodium falciparum in images of human peripheral blood smears (DBN). The use of a DBN in this study is the first such application to the identification of malaria parasites with an accuracy of 96.35.

Dong et al. [19] compared the LeNet, AlexNet, and GoogLeNet, three prominent convolutional neural networks. Simulation findings shown that each of these DCNNs had classification accuracy over 95%. By combining the current (VGG) Visual Geometry Group network with the SVM (support vector machine), as suggested by Vijayalakshmi et al. [20], a transfer learning technique may be accomplished. By collecting blood smear images from patients with and without malaria, a digital corpus of malaria cases and controls was produced, which was then used to investigate the proposed technique VGG-SVM against other leading CNN methods. Vijayalakshmi et al. [21] presented a unique approach for detecting malaria based on deep learning. It is hypothesised that a CNN design with 20 weighted layers can distinguish between parasitized and uninfected microscopic pictures. The process of doing this analysis may be automated by modern deep-learning algorithms. It is advised that the malaria diagnostic method be automated due to the challenges involved with human diagnosis. Automation of the diagnostic process will lead to more precise illness diagnosis, and as a consequence, it may be possible to provide dependable healthcare in regions with limited resources. In order to implement automated malaria diagnosis, conventional microscopy methods, knowledge, and practises must be adapted to a computerised system

architecture. With 97.2 percent accuracy, we were able to identify malarial parasites in microscopic images to show the effectiveness of our deep-learning-based approach.

### 3. Proposed methodology

The methodology flow diagram in Figure 1 illustrates the use of deep learning to the detection of malaria. When a model is trained via supervised learning, its actions and results are determined only by the information it is given. CNN is now one of the most often used DL architecture. Convolutional, nonlinearity, pooling, and fully linked layers make up the four layers that make up CNN's architecture. CNNs are superior to traditional neural networks in that they can extract feature data while maintaining the spatial relationship of the input. In this study, the same dataset was used to evaluate the transfer learning techniques, and the outcomes were compared.



**Figure 1. Schematic parasite detection flow diagram**

#### 3.1 Data pre-processing

Supervised learning involves basing a model's actions and results only on the information provided to it. Running experiments is difficult without data pre-processing. The data augmentation method is used to maintain the label while increasing the shape and size of an image. It alleviates two problems: (1) it maximises data generation from a finite dataset, and (2) it reduces the likelihood of the dataset being overfit. Data Augmentation is utilized to scale or normalise images prior to feeding them to the "Learner" class, which gathers all the necessary information to train the model using data. Before feeding the input images into the "Learner" class, Fastai used to perform data augmentation to re-size or normalise them.

#### 3.2 Transfer learning (TL) and Fine tuning

Transfer learning is an area of ML research which demands the ability to remember and transfer information acquired while solving one problem to a task that is closely related. Instead of utilising the ImageNet dataset to predict hundreds of categories, and to make predictions about the two sets of blood-smear images, we start with a pre - trained model and make some adjustments to it. To match our number of classes, the last component of the model must be modified. Most convolutional models often terminate with a few linear layers. As an image

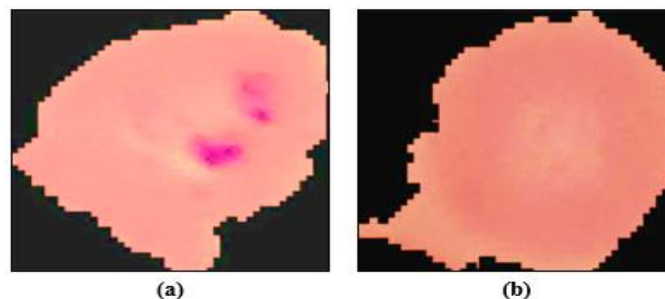
passes through convolutional layers, convolutional neural networks may recognise and evaluate characteristics in the image.

To implement transfer learning, we first pretrained a model on ImageNet and then, using a random initialization strategy, we build a new set of convolutional layers for the head while retaining all of the backbone layers and their weights. The model's frozen core layers will be unfrozen and fine-tuned later. But first, we will quit bulking up and start training only the brain to transform the evaluated characteristics into predictions using our data. At the end of the fine-tuning process [13], the final set of ultimately linked CNN layers is discarded, and a new set is added.

Any accumulated weight from the layers immediately under the head will now be unalterably fixed there. Although the model's first few layers will be pre-trained to recognize general features like lines and gradients, the layers ultimately responsible for achieving our goal will require further instruction. Furthermore, this approach could be more precise and accurate compared to feature extraction-based transfer learning.

### 3.3 Dataset description

A dataset including 27,558 segmented RBCs, split evenly between infected and uninfected cells utilized to perform the investigation. Researchers from the National Library of LHCNCB have meticulously collected and analysed images (infected and uninfected) blood smears. Figure 2 displays the data set's differentiation between RBCs that have been altered by malaria and those that have not. The Visual Geometry Group (VGG) CNN architecture was developed by Simonyan et al. [14] of Oxford University.



**Figure 2: Images of parasitized (a) and uninfected (b) red blood cells**

For the ImageNet Challenge, the VGG produced outstanding results. Modern object recognition models are based on this approach and are constructed using the VGG architecture.

The two most often used models contain sixteen and nineteen convolution layers, respectively, and are known as VGG16 and VGG19. Rashid et al. [15] introduced the deep residual learning theory for image identification for the first time in 2015. This model performed quite well (3.57 percent error rate) in the 2015 ILSVRC classification competition.

### 3.4 Performance Indicators

The method is predicted using performance analysis based on several measures, including precision, accuracy, specificity, sensitivity, and F1-score, among others. Performance analysis compares the performance and accuracy of various models. As shown in equations (1-5), four measurements are utilised to evaluate the metrics: TP (true positive), TN (true negative), FP (false positive), and FN (false negative).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (4)$$

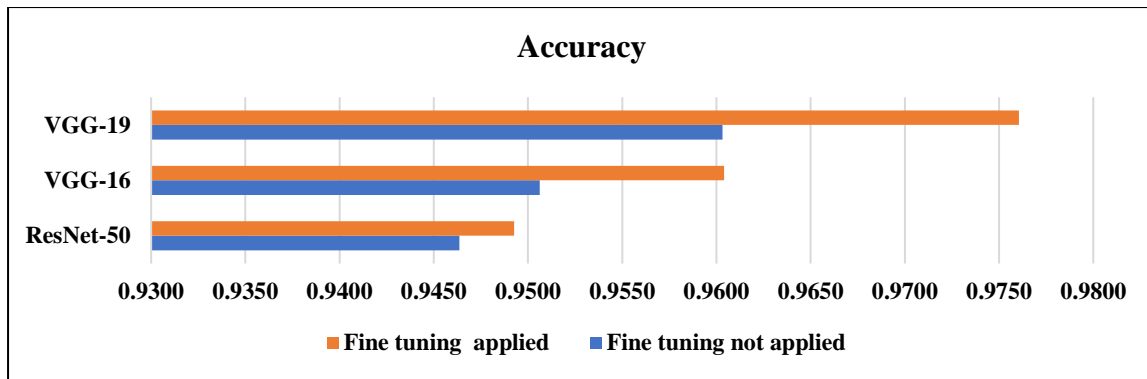
$$\text{F1 score} = \frac{2 * (\text{sensitivity} * \text{precision})}{(\text{sensitivity} + \text{precision})} \quad (5)$$

### 4. Results and Analysis

The dataset was submitted to transfer learning using previously trained CNN algorithms followed data augmentation. Fine-tuning was done once the layers were frozen. Before and after fine-tuning, accuracies of models have been obtained. After some fine-tuning, it became clear that the models were doing better than they had with only transfer learning. The accuracy results for the TL models both prior and after (fine-tuning) are listed in Table 1. Transfer learning models' accuracy is shown graphically in Figure 3 both before and after fine-tuning. VGG-19 outperformed in both cases. By fine-tuning, we may use pre-trained TL models to identify classes. On the other hand, transfer learning through feature extraction yields a lesser degree of accuracy.

**Table 1. Evaluations of accuracy before and after (fine-tuning)**

Model	Fine tuning (not applied)	Fine tuning (applied)
ResNet-50	0.9464	0.9493
VGG-16	0.9506	0.9604
VGG-19	0.9603	<b>0.9761</b>



**Figure 3. Accuracies obtained prior to and after fine-tuning**

**Table 2. comparative analysis of the categorization of performance measure**

Model	Accuracy	Specificity	Sensitivity	F1 score
ResNet-50	0.949323	0.936559	0.958976	1.908328
VGG-16	0.960467	0.941968	0.963342	1.918177
VGG-19	<b>0.976159</b>	0.976166	0.978569	1.937759

When compared to other pre-trained models, VGG-19 performs the best as shown in Table 2. An accuracy of 0.976159, a sensitivity of 0.978569, a specificity of 0.976166, and F1 score of 1.937759 have been attained. A measure of our model's efficacy is the proportion of times its predictions turn out to be correct. Sensitivity may also be referred to as true positive Rate (TPR). Specificity affects how well a model can predict the future when an observation does not fit into a specified category. Table 3 completely contrasts the results achieved with the method that outperformed (VGG-19) and those obtained using state-of-the-art methodologies.

**Table 3. Evaluating the proposed method's performance in comparison to existing DL models on an image dataset**

Reference no.	Dataset	Number of images	Technique	Findings
[17]	Obtained from NIH	27,558	GoogleNet, ResNet	Accuracy obtained from ResNet-96.6%, and GoogleNet-96.5% respectively
[18]	Collected from published article	4100	DBN (deep belief network)	Accuracy achieved from DBN is 96.35%

[19]	Collected from University (Alabama)	2565	LeNet, GoogleNet AlexNet	Overall accuracy achieved by models are 95%
[20]	Collected from repository	27,558	VGG, SVM	Proposed model VGG-SVM obtained accuracy of 93.13%
[21]	Taken dataset from NIH	27,558	Convolutional neural network	CNN achieved accuracy of 95.28%
Proposed VGG-19	Obtained dataset from LHNCBC	27,558	ResNet50, VGG-16, VGG-19	VGG-19 outperformed by having accuracy of 97.61%

## 5. Conclusion

In this research, we used fully-automated deep-learning neural networks to improve the accuracy with which malaria diagnoses were classified. Experiments indicated that transfer learning strategies may achieve excellent image classification performance. After working with Fastai, we've come to the conclusion that a layered API for DL has the potential to greatly advance the field of study. However, it is far more compatible with preset architectures than custom-built CNN models. Based on the results of our experiments, we draw the conclusion that for the categorization of blood smears, the pre - trained model VGG-19 outperforms ResNet-50, and VGG-16. The effectiveness of these pretrained models was improved by transfer learning and fine-tuning, and the results were encouraging. Transfer learning & fine-tuning enhanced these pretrained models, yielding promising results. We developed a web-based tool to help users classify blood smear images using this approach. Future work will focus on refining the design of the CNN architectures to increase their performance, leading to a significant improvement in malaria diagnosis accuracy. Other alternatives for increasing the capability of the end-user application include cloud-based implementation and mobile devices. Adding more images to the malaria corpus may also enhance transfer learning performance. The proposed approach may be expanded in the future to include classification of more plasmodium species types.

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