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Leveraging Deep Learning Techniques for Definitude Malaria Detection Using Microscopic Images

Dr.R.G.Suresh Kumar[1], Mr.Gokula kannan C[2], Mr.Anbuselvan J[3], Mr.Narasimman P[4], Mr. Suryaprasath S[5]
[1]Professor, [2, 3, 4, 5]B.Tech(CSE),RGCET, Puducherry

Abstarct: Artificial intelligence (AI) is transforming malaria detection by enabling faster, more accurate diagnosis through the analysis of blood samples with high precision, identifying malaria parasites within minutes. Malaria, a potentially fatal disease caused by the Plasmodium bacterium and transmitted via mosquito bites,requiresearlyandaccuratediagnosisforeffective treatment and prevention. Current systems use the ResNetalgorithmtoanalyzeimages,identifyingpatterns inmalariaparasitesto differentiate betweeninfectedand healthy cells. However, these systems suffer from low prediction accuracy, limiting their real-world effectiveness. To address this, we propose the use of EfficientNet and Vision Transformers (ViT), which applyNLPtechniquesdirectlytoimagepatches,treating each patch as a token to capture long-range dependencies and global context, thereby enhancing efficiency, accuracy, and precision.

Keywords: AI, malaria detection, ResNet, EfficientNet, Vision Transformers, NLP, image classification, prediction accuracy.

I. INTRODUCTION

Malaria,alife-threateningdiseasecausedbyPlasmodium parasites, remains a significant public health challenge, especiallyintropicalregions.Earlyandaccuratediagnosis is essential to prevent severe outcomes. Traditional diagnostic methods, such as microscopy, rely heavily on the expertise of parasitologists, making them labor- intensive and prone to variability. To address these challenges, computer-aided detection (CAD) systems usingdeeplearninghaveemergedasaneffectivesolution. This research aims to investigate various deep learning models and hybrid approaches for improving malaria detection accuracy and efficiency. The key research questionsinclude:Howeffectivearedeeplearningmodels compared to traditional methods? What role do hybrid techniques play in enhancing detection accuracy?

Malaria is a life-threatening disease caused by the Plasmodium parasite, which is transmitted to humans throughthebitesofinfectedfemaleAnopheles mosquitoes. Despite global efforts, malaria remains a significant health issue, particularly in tropical and subtropical regions. According to the World Health Organization (WHO), in 2021, there were approximately 247millionmalariacasesand619,000deathsworldwide. The majority of these cases and deaths occurred in the WHO African region, with children under five years old being the most affected group[4][5].

Thetopiccentersondetectingmalariaviaautomateddeep learning models, especially in regions lacking diagnostic resources. The studies highlight malaria's impact, emphasizing its prevalence in areas with limited healthcare infrastructure. The goal is to use machine learning to improve diagnosis accuracy and efficiency, overcoming the limitations of traditional methods like microscopic examination[7][9].

Theriseofdeeplearningandmobiletechnologiespresents new opportunities to automate malaria diagnosis, particularly by leveraging pre-trained models and mobile devices to detect malaria parasites and white blood cells (WBCs)inthickbloodsmears. Thestudyfocusesonusing deep learning to improve diagnostic accuracy and facilitate deployment through mobile applications[10].

II. LITERATURE SURVEY

A combination of optimized threshold and deeplearning-based approach to improve malaria detectionand segmentation on PlasmoID dataset [1] P.A.Pattanaika,MohitMittalb,MohammadZubairKhanc, S.N. Panda [1] This study presents a hybrid approach combining image processing and deep learning to detect and segment malaria parasites in blood smear images. Using the PlasmoID dataset, the method achieved a high F1-score of 0.91, outperforming traditional detection techniques.This approach enhances diagnostic accuracy and efficiency, particularly beneficial in resource-limited settings, enabling quicker and more reliable malaria diagnosis.

Such advancements could improve timely treatmentandoveralldiseasemanagement, contributingtoreduced malaria prevalence and better public health outcomes in affected areas.

Malaria Detection Using Deep Residual Networks With MobileMicroscopy[2] AmitSundas1,SumitBadotra2, Gurpreet Singh Shah [2] The MM-ResNet model is an advanced solution designed to classify blood smear images for malaria detection, addressing issues like poor image quality and the scarcity of skilled professionals. Traditionalmethodsrelyonexpertanalysisofmicroscope images, which can be a significant challenge in high- burden regions with limited resources. MM-ResNet leverages deep learning to automate this process, providingfastandaccurateparasiteclassificationinblood samples.

This reduces the reliance on healthcare workers and enhances diagnostic accessibility in resource-constrained areas. The model has shown impressive accuracy, even with imagescaptured viamobile phones, which are often affected by variable quality and lighting. This capability highlights MM-ResNet's robustness in handling such challenges,demonstratingitspotentialforwidespreaduse inmobilehealthapplications.Byenablingreliablemalaria detection through commonly available technology, MM- ResNet can improve diagnosis and treatment in underservedregions,supportingmoretimelyandeffective healthcare delivery.

Anewensemblelearningapproachtodetectmalariafrom microscopicredbloodcellimages[3]MosabbirBhuiyan, Md Saiful Islam[3]This paper presents an ensemble deep learning model combining VGG16, VGG19, and DenseNet201 architectures to improve the detection of malaria parasites in red blood cell images. The model addresses the common issue of limited accuracy in individualdeeplearningmodelsbyleveragingthediverse feature extraction strengths of these architectures. By integrating these networks, the ensemble enhances the overall reliability and robustness of malaria parasite identification.

Themodelalsoincorporatesimageprocessingtechniques to improve input data quality, facilitating more accurate detection by the deep learning models. Additionally, a max voting mechanism is used to aggregate predictions from each model in the ensemble, ensuring that the final decision reflects a consensus among the different architectures. This approach not only boosts detection accuracy but also underscores the potential for precise, automated malaria diagnosis, which is particularly valuable in regions with limited healthcare resources.

A deep architecture based on attention mechanisms for effectiveend-to-enddetectionofearlyandmaturemalaria parasites[4]LucaZedda,AndreaLoddo,CeciliaDi Ruberto[4]ThepaperintroducesYOLO-SPAManditsimprovedversion,YOLO-SPAM++,deeplearning-based systems designed for early malaria parasite detection in blood samples. YOLO-SPAM++ offers significant enhancements in detection accuracy, particularly for tiny parasites, outperforming its predecessor and even YOLOv5 by up to 20%. These systems automate the detection process, increasing diagnostic speed and reducinghumanerror, makingthemespeciallyvaluablein resource-limited regions.

Theadvancementsin YOLO-SPAM++markacrucialstep toward more efficient and accurate malaria diagnostics, enablingtimelyinterventionsandbetterhealthoutcomes.

A deep architecture based on attention mechanisms for effectiveend-to-enddetectionofearlyandmaturemalaria parasites [5] Kenia Hoyos , and William Hoyos [5] The studyintroducesadeeplearningapproachusingYOLOv8 to detect malaria parasites and leukocytes in blood smear images,addressingtheneedformoreefficientdiagnostics. YOLOv8 enhances the speed and accuracyofidentifying these components, streamlining the traditionally labor- intensive diagnostic process.

Themodel'sperformanceisfurtherimprovedthroughdata augmentation,whichincreasesthediversityofthetraining set, allowing it to handle variations in image quality and preparation. Additionally, aspecialized countingformula accurately quantifies parasites and leukocytes, offering valuable numerical data for clinical assessments. This integrated approachprovidesamorepreciseandefficient diagnostictool,improvingpatientcareinmalaria-endemic regions.

Revolutionizing malaria diagnosis: deep learning- powered detectionofparasite-infected red bloodcells [6] Md.JiabulHoque,Md.SaifulIslam,Md. Khaliluzzaman,AbdullahAlMuntasir,MohammadAbdullahMohsin[6] The paper presents an advanced convolutional neural network (CNN)-based method to automate malaria detection in red blood cell images, addressing the critical need for efficient diagnostics. It compares several well- established models, including ResNet-50, MobileNet-v2, and Inception-v3, to assess their performance in key metrics like accuracy, specificity, sensitivity, and F1 score.

This comparative analysis provides insights into the strengths and weaknesses of each model in detecting malaria parasites, helping identify the most effective approachforautomateddiagnostics.Inmalariadetection, accuracy is crucial as incorrect classification of infected and non-infected cells can result in improper treatment decisions. The proposed method aims to improve the model's precision in distinguishing between these categories,minimizingfalsepositivesandfalsenegatives.

The research findings contribute to the development of more reliable automated diagnostic tools, which could enhance decision-making for treatment and control, especially in malaria-endemic regions. The adoption of theseadvanced CNNtechniquesholds promiseforearlier diagnosis, reduced transmission, and better health outcomes, thus improving malaria management globally.

III. PROPOSED WORK

TheproposedsystemleveragestheEfficientNetalgorithm for malaria parasite prediction in blood smear images, utilizing its high performance and efficiency in image classification. EfficientNet's compound scaling method adjusts the model’s depth, width, and resolution in a balancedmanner,achievingoptimalperformancewithout excessive computational demands. This scalingapproach is especially beneficial in medical diagnostics, where resource limitations often exist. By employing EfficientNet, the system can effectively identify malaria parasites with high accuracy, precision, and recall. The modeliscapable oflearning complexpatternsandfeatures from the data, leading to reliablepredictions. The system is designed to handle varying image qualities and complexities, ensuring robust performance in diverse healthcaresettings. Itsefficiencyhelps reduce processing time, enabling faster diagnoses. This approach not only enhances diagnostic accuracy but also streamlines the workflow for healthcare professionals, allowing for quicker decision-making. By automating the detection process, the system reduces the reliance on human expertise, making it particularly useful in resource- constrained environments. Ultimately, this innovative system improves treatment outcomes by facilitating timely and precise malaria detection.

Architecture of Proposed System:

The given diagram illustrates the process of malaria cell image classification using a machine learning-based approach, with EfficientNet-B0 as the proposed model. The process begins with a malaria cell image dataset, which undergoes preprocessingto enhanceimagequality and remove noise. The dataset is then split into training andtestingsetsformodeldevelopment.Featureextraction is performed to obtain relevant features from the images before feeding them into the EfficientNet-B0 model. EfficientNet-B0,alightweightyetpowerfulconvolutional neuralnetwork(CNN),isutilized fortraining,leveraging its depth-wise convolutions and efficient architecture to improve accuracy while maintaining computational efficiency. After training, the model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, AUC, and loss. Finally, the trained model classifies the cell images into two categories: parasitized anduninfected.Thisapproachensuresanoptimalbalance between accuracy and efficiency, making it a suitable choice for malaria detection in medical applications.

IV. IMPLEMENTATION DETAILS

A. *Data Collection*

The first step in the malaria prediction system involves gathering a large dataset of blood smear images. Kaggle, an open-source platform for data science and machine learning, offers a variety of datasets that are publicly available. These datasets, such as the "Malaria Cell Images Dataset," include annotated images of red blood cells,someinfectedwithmalariaparasitesandothersnot. By utilizing this rich resource, researchers can access diverse and high-quality data that is essential for training andevaluatingdeeplearningmodels.Thedatasettypically containslabeledimages, which arecritical for supervised learning tasks like malaria detection.

B. *Pre-Processing*

Oncethedatasetiscollected,pre-processingisperformed to prepare the images for model training. This step involvesseveraltaskssuchasresizingimagestoauniform size,normalizingpixelvaluestoensurethemodelreceives consistent input, and augmenting the data to increase variability in the training set. Techniques like rotating, flipping,andadjusting brightnessor contrastcansimulate real-worldvariationsandhelpthemodelgeneralizebetter to unseen data. Pre-processing also includes splitting the dataintotraining,validation,andtestingsetstoensurethe model is properly evaluated during and after training.

C. *Feature Extraction*

In this phase, relevant features that distinguish malaria parasites from healthy cells are extracted from the blood smear images. Feature extraction can involve detecting keypatternsliketheshape,color,texture,andsizeofcells or parasites. In the context of deep learning models like EfficientNet, feature extraction is primarily handled automaticallybythe model’s convolutional layers.

These layers learn hierarchical representations of the images, identifying complex patterns that are crucial for distinguishing between infected and non-infected cells. The model leverages these learned features during the training process to make accurate predictions.

D. Model Creation Using Efficient Net:

After pre-processing and feature extraction, the next step isthecreationofamodelusingEfficientNet.EfficientNet is a powerful convolutional neural network (CNN) architecture that employs compound scaling to optimize the depth, width, and resolution of the model. By scaling all three dimensions, EfficientNet achieves higher accuracy with fewer parameters, making it efficient in both computationalcostandpredictionperformance.The model is trained on the pre-processed dataset, allowing it to learn fromthe features and patterns in the blood smear images.EfficientNet'sarchitectureensuresthemodel performs well on complex image classification tasks like malaria detection.

E. Test Data:

Oncethemodelistrained,itisevaluatedusingaseparate set oftestdata. Thetest dataconsists ofimages that were not part of the training or validation sets, allowing for an unbiasedassessmentofthemodel'sperformance.Thetest data provides real-world scenarios to see how well the model generalizes to new, unseen data. Keyperformance metrics such as accuracy, precision, recall, and F1-score arecalculatedtodeterminetheeffectivenessofthemodel in detecting malaria parasites in blood smear images.

F. Prediction

Inthefinalstep,thetrainedEfficientNetmodelisusedto make predictions on new blood smear images. When presented with an image, the model analyzes the features and patterns it learned during training and outputs a classificationlabel,indicatingwhetherthebloodsampleisinfectedwithmalariaornot.Thepredictionprocessisfastandautomated,offeringhealthcareprofessionalsatoolto assist in the timelyand accurate diagnosis of malaria. By leveragingthe powerofdeeplearning,thesystemcanhelp in early detection, leading to better treatment outcomes andmoreefficientresourceallocationinmalaria-endemic areas

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V. RESULT AND DISCUSSION

The results of the malaria detection system using EfficientNetdemonstratedsignificantpromise,achieving high performance metrics such as accuracy, precision, recall, and F1-score. This indicates the model's abilityto reliablyidentifymalariaparasites inblood smearimages. TheEfficientNetarchitecture'scompoundscalingmethod optimized the model's efficiency, ensuring accurate predictions without excessive computational cost, which is crucial for medical diagnostics in resource-limited settings. Data pre-processing, including augmentation, helpedimprovethemodel'srobustnessbyenablingbetter generalization to real-world conditions. Compared to traditional methods and other deep learning models, EfficientNet outperformed in both accuracy and efficiency, even handling challenging images such as those with low quality or partial obstructions. The system's fast processing time is especially beneficial in clinical settings, ensuring timely diagnoses and quicker treatment decisions. However, future work should focus on further enhancing the model's adaptability to varying datasets and improving its performance across different conditions.

A. Data Pre-Processing and Visualize Class Distribution

Thiscodesnippetdemonstrateshowtocreatetrainingand validationdatasetsfromadirectoryofimagesusing TensorFlow's image_dataset_from_directory function. Thedata_dirvariablepointstothedirectorycontainingthe images, organized into subdirectories by class. The datasets are split into training and validation sets, with 20% of the data reserved for validation (validation_split=0.2). The subset parameter specifies whether the data is for training or validation. A random seed (seed=123) ensures reproducibility of the split. The images are resized to the specified dimensions (image_size=(img_height, img_width)) and batched accordingtothegivenbatchsize(batch_size=batch_size). This setup facilitates efficient loading and preprocessing of images for model training and evaluation.

B. Displaying the Sample Image

A few sample images from each class in the dataset. It iterates over a list of class names (class_names), and for each class, it retrieves the first four images from the corresponding directory within data_dir. A figure with a size of10x10 inches iscreated for displaying the images. Withineachiteration,asubplotiscreatedforeach,andthe imageisloadedanddisplayedusingplt.imshow.

Thetitle of each subplot is set to the class name, and the axes are turned off for a cleaner presentation. This process allows foraquickvisualinspectionofafewsampleimagesfrom each class, helping to understand the dataset's content better.

C. Accuracy

InthecontextofmalariapredictionusingEfficientNetB0, accuracy would measure how well the model correctly classifies images of malaria-infected cells and non- infected cells. EfficientNetB0, being a convolutional neural network (CNN), extracts features from input images(suchasbloodsmears)andclassifiesthemintotwo classes: "Infected" and "Non-Infected." Accuracy evaluates the proportion of correct classifications (both infected and non-infected) to the total number of predictions made by the model.

D. Loss

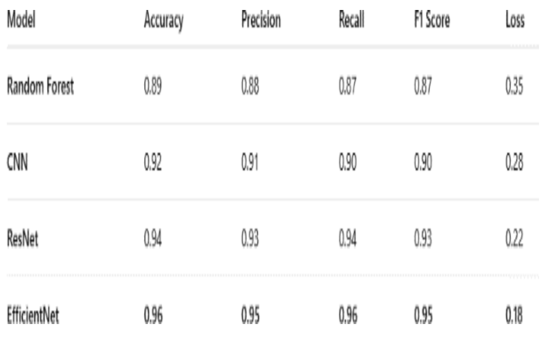
Loss is a critical metric in training machine learning models, as it quantifies how well the model's predictions align with the actual labels. It provides a measure of the discrepancy between the predicted outputs and the true values. In classification tasks, cross-entropy loss is commonly used, especially for multi-class or binary classification problems. This loss function calculates the difference between the true label and the predicted probability distribution over the classes. It penalizes the model more heavily for confident but incorrect predictions, encouraging it to assign higher probabilities to the correct class. The objective during training is to minimize this loss, which indicates that the model is improvinginitsabilitytocorrectlyclassifyinputs.Lower cross-entropylosscorrespondstobetterperformance, guiding the optimization process to refine the model's parameters and improve prediction accuracy.

E. Binary Classification

Thenegativesignensuresthatthelossisminimizedwhen thepredictionsareaccurate,pushingthemodeltoimprove its predictions by adjusting its parameters. This loss function is particularly effective for models that output probabilities, such as logistic regression or neural networks.

F. Confusion Matrix

The confusion matrix displayed in the image represents the performance of a classification model, likely in the context of malaria cell detection. The matrix consists of four values, indicating the proportions of correctly and incorrectly classified instances. The diagonal elements (0.9and0.98)representthetruepositiveandtruenegative rates,where90%ofuninfected(class0)samplesand98% of parasitized (class 1) samples were correctly classified. The off-diagonal elements (0.099 and 0.019) indicate the misclassification rates, meaning that 9.9% of uninfected samples were incorrectly classified as parasitized, and 1.9%ofparasitizedsampleswereincorrectlyclassifiedas uninfected.Thesevaluessuggestthatthemodelperforms well,achievinghighaccuracywithminimalfalsepositives and false negatives. However, there is a slightly higher misclassificationrateforuninfectedsamples,whichmight require further optimization to improve specificity.



Model	Accuracy	Precision	Recall	F1 Score	Loss
Random Forest	0.89	0.88	0.87	0.87	0.35
CNN	0.92	0.91	0.90	0.90	0.28
ResNet	0.94	0.93	0.94	0.93	0.22
EfficientNet	0.96	0.95	0.96	0.95	0.18

VI. CONCLUSION

In conclusion, integrating the EfficientNet architecture intomalariapredictionoffersatransformativesolutionby addressing the limitations of traditional models. EfficientNet's compound scaling approach enhances accuracy while maintaining low computational costs, making it an efficient choice for analyzing malaria cell images.Itsabilitytolearnintricatepatternsinbloodsmear images allows for precise classification, improving malariadetectionandprediction.Additionally, EfficientNet's adaptability to diverse datasets and geographicalvariationsstrengthensitsreliabilityinglobal malaria surveillance. By providing accurate risk assessments, the model empowers health authorities to implement timely interventions, allocate resources efficiently, and enhance preventive measures. This advanced approach not only aids in reducing malaria's global burden but also contributes to improving health outcomes, particularly in vulnerable regions. Ultimately, adopting EfficientNet for malaria prediction represents a significantstepforwardindiseasepreventionandcontrol, supporting global public health efforts with a more accurate and efficient diagnostic tool. Further fine-tuning of the EfficientNet model could be explored by experimenting with different hyperparameters, such as learning rates, dropout rates, and batch sizes, to optimize performance. Additionally, combining EfficientNet with other advanced architectures or hybrid models (e.g., EfficientNet+Transformer-basedmodels)couldenhance feature extraction and prediction accuracy.

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