RESEARCH ARTICLE OPEN ACCESS

A Review of a Malaria Diagnostic System using Deep Learning

Rosemary Chika Nweze, Confidence Ifeoma Odoh, Ukamaka Victoria Maduahonwu, Nneka MaryAnn Okafor, Ogbonnaya Sunday Ogah, Inyang Unoh Nkanu

1,2,3 (Computer Science Department, State University of Medical and Applied Sciences Igbo Eno, Enugu State, Nigeria). 4 (Federal Radio Corporation of Nigeria, Enugu State Nigeria). 5(Computer Science Department, Evangel University, Abakaliki Ebonyi State, Nigeria). 6(ICT Unit, Ministry of Agriculture, Calabar, Cross River State, Nigeria).

Email: rosemary.nweze@sumas.edu.ng, confidence.odoh@sumas.edu.ng, ukamaka.maduahonwu@sumas.edu.ng, nekafrcn@gmail.com, tedi242010@gmail.com, unoh2007@yahoo.com)

--************************----------------------------------

Abstract:

Malaria remains one of the major public health problems in Africa, contributing significantly to high morbidity and mortality rate in the region. Nigeria suffers the world's greatest malaria burden. Out of the various methods of diagnosing malaria, microscopy remains the gold standard for laboratory confirmation of malaria parasite in endemic countries. However, the process requires a trained personnel, it is time consuming, labour intensive, and depends on the quality of the microscope thus the need for a computer aided approach. In this article, we explore a deep learning model (convolutional neural network) for detecting malaria in blood samples with high validation accuracy and sensitivity.

Keywords — Deep Learning, Artificial Intelligence. Convolutional Neural Network, Transfer Learning, Graphic Processing Unit

--************************----------------------------------

I. INTRODUCTION

Malaria is a life-threatening disease caused by the plasmodium parasites. It is transmitted through the bites of the female anopheles mosquitoes. The early diagnosis and treatment of malaria are essential for reducing morbidity and mortality rates especially in developing countries like Africa. According to World Health Organization world malaria report 2021, there were 241 million cases of malaria worldwide in 2020, resulting in an estimated 627, 000 deaths. In 2022, the African region was home to approximately 95% of all malaria cases and 96% of deaths, with children under the age of five accounting for 80% of all malaria deaths (WHO, 2022). Plasmodium falciparum is mainly found in sub-Saharan Africa, constituting 99.7% of all cases there in 2020 (WHO, 2022). Different studies have shown that the occurrence of malaria parasite has increased since 2015 (Kassam *et al.*, 2021). Malaria diagnostic tools have advanced significantly, evolving from traditional microscope examination of Giemsa-stained blood films to a variety of modern techniques. These include rapid diagnostic tests (RDTs), serology tests, and molecular methods such as polymerase chain reaction (PCR), flow cytometry assay (FCM), loop-mediated isothermal amplification (LAMP), and quantitative buffy coat (QBC) (Onile-ere et al., 2016). Artificial intelligence (AI) as an umbrella word in the intelligent computing is the design and implementation of machines behaving at the level of a human expert (Dong *et al.,* 2017). When addressing the medical diagnosis field, AI-based systems can be beneficial in their ability to mimic human brain in more simple tasks. Rapid development in the field of artificial intelligence especially machine learning and deep neural networks have emerged as a highly beneficial solution in the diagnosis of various diseases. In medical diagnosis, deep learning is particularly useful as they can quickly capture unforeseen patterns within complex and large datasets.

II. RELATED LITERATURE

The introduction of deep convolutional neural networks has brought about breakthroughs in computer vision and image processing problems. Convolutional neural network (CNN) provides an efficient way to capture features of an image. Recent studies have reported that CNN show higher performances in image recognition and classification tasks (Rawat *et al*., 2017).

Mohanty *et al*., (2019) in their paper titled" Automatic detection of malaria parasites using unsupervised techniques" developed a system for automatic malaria parasite identification from blood smear images using two unsupervised techniques- Auto Encoder and Self Organizing Map. The models were trained using 1182 thick blood smear malaria images dataset consisting of 750 ×750 pixels obtained from android smart phone attached to a Brunel SP150 microscope from Makerere University. Self-Organizing Map technique achieved an accuracy of 79.07%, sensitivity of 80%, specificity 78% while Auto Encoder achieved an accuracy of 87.5%, sensitivity of 84% and specificity of 80%. More dataset should be used in future works. Data augmentation should be performed on the datasets to prevent the system from over fitting. Also, other supervised data reduction techniques should be applied in future work to increase the accuracy of the model.

Reddy *et al*., (2019) developed a model for malaria detection using resnet-50. The dataset consists of a total number of 27, 558 divided equally into infected and uninfected images. A training accuracy of 95.91% and validation accuracy of 95.4% was achieved. The model was trained on a local computer which took more time when compared with training on google colaboratory environment using GPU or TPU. The use of modern hardware might increase the accuracy and can bring down run time to a great extent.

Nakasi *et al.,* (2019) presented a remote system that provides fast, accurate and timely malaria diagnosis using faster R CNN model. A dataset of 643 thick malaria blood images were used to train the model. The images are of dimension 750 x 750 pixels. Image labeling and data augmentation were performed on the dataset. The pre trained faster R-CNN performed well with a mean average above 0.9306 and a sensitivity of 90%.

Shah *et al*., (2020) developed a model for faster and cheaper plasmodium parasite detection in blood smears using 17400 images of which 8,760 images were parasitized while the other 8,700 images were uninfected. The model yielded an accuracy of 95%. Data augmentation should be performed on the dataset to help improve the models robustness and prevent over fitting.

Prakash *et al*., (2020) in their paper titled" Convolutional neural network based malaria parasite infection detection using thin microscopic blood smear samples" developed a deep convolutional neural network that can predict malaria parasite infection from thin blood smear samples using 24, 960 malaria samples obtained from national library of science hosted by Lster Hill National Center for Biomedical Communications USA. Data augmentation was performed on the dataset to increase data points. The model delivered an F1 score of over 94%. Future work will be to predict malaria parasite infection utilizing transfer learning technique such as ResNet and VGG-16. Other preprocessing techniques such as image resizing and normalization should be performed on the dataset to increase the accuracy.

Manescu *et al.,* (2020) leveraged routine clinical-microscopy malaria blood samples to train a deep malaria convolutional neural network classifier (Deep MCNN). The model also provides total malaria parasite (MP) and white blood cell (WBC) counts allowing parasite estimation as recommended by World Health Organization. A total of 300 blood samples were used for training and validation. The system achieved sensitivity and specificity of 0.92/0.90 respectively. More datasets should be used in future research to achieve a robust model. Because only 300 samples were used to train the model, data augmentation should be performed in future work to introduce variance and prevent over fitting

Chibunta *et al.,* (2020) proposed a low-cost alternative and complementary solution for rapid malaria screening for low resource settings. Their aim was to develop a model that will potentially reduce the dependence on manual microscopy. Two datasets were used to train the model. Datasets A contains 2703 images (1024 × 768 pixels) and dataset B contains 1182 images (750 × 750 pixels). Image labeling and image augmentation were performed on the dataset. The model achieved 97.46% accuracy. The datasets were not resized to fit the models input dimensions before feeding them into the neural network. Also more dataset should be used in future.

Silka et al., 2023 presents malaria detection using advanced deep learning architecture. The blood samples were smeared and the images are projected using a mirror. The sample is used with the CNN model to determine if the sample is infected or not. Experiments are performed using infected and uninfected samples for malaria. The model generated an accuracy of 97.1% after 1000 epochs.

The paper by Kumar et al., 2024 investigates the capability of deep learning models for determining the type of parasitic organisms. Deep learning models used are VGG19, ResNet50V2 and EfficientNetB3 on a large dataset with six classes. A classification accuracy of 99% was reported by fine-tuning different parameters**.**

Shekar *et al*., (2021) developed a pre trained model that automatically classifies malaria blood samples as infected or uninfected. The model was trained using 27, 558 malaria blood images. Data Augmentation -Images resizing, image labeling, image encoding were performed on the dataset. The fine- tuned CNN model attained an accuracy of 96% with sensitivity score of 93%, basic model achieved accuracy of 94% with sensitivity of 92% and frozen models achieved total accuracy of 92% with sensitivity of 90%. Future work should be to improve the models accuracy and sensitivity scores using other pre trained models such as VGG 19, VGG 16, denseNet and efficientNet.

Diyasa *et al*., (2021) proposed a deep convolutional neural network that predicts malaria parasite infection from thin blood samples. Their model was trained on 27, 558 malaria blood images obtained from the national library of science. Data augmentation (rotating, random image cutting), image normalization (mean and standard deviation) were performed on the dataset to increase data points and prevent over fitting. They used two different CNN architectures: Google Net model achieved a total accuracy of 93.89% while Shuffle Net achieved 92.50%. Precision, recall and f1 score ranges from 0.92-0.95. Other CNN models such as ResNet, VGG-16 and 19 should be used in order to improve the accuracy. The image should be resized as the input patch size of the CNN model can influence the experimental results.

III. CONCEPT OF DEEP LEARNING

Deep Learning (DL) also referred to as deep neural networks are improved version of artificial neural networks with multiple layers. The deep learning approach is a subset of machine learning stimulated by the human brain's data processing pattern (Xi *et al*., 2019; Rizk *et al*., 2019). The multiple layers in a deep neural network allow models to become more efficient at learning complex features (Bengio *et al*., 2009). Deep neural networks (DNNs) are currently the foundation for many modern artificial intelligence (AI) applications (LeCun *et al*., 2015). Since the breakthrough application of DNNs to speech recognition (Deng *et al*., 2013; Hinton *et al*., 2012), natural language processing (Bordes *et al*., 2014; Sutskever *et al*., 2014), medical image analysis (Ker *et al*., 2017) and image recognition (Szegedy *et al*., 2015; Shin *et al*., 2016), the number of applications that uses DNNs has exploded. They are employed in numerous applications from self-driving cars to detecting different diseases (Chen *et al*., 2015), audio and speech processing (Adeel *et al*., 2020), visual data processing (Tian *et al*., 2020), and natural language processing (Young *et al*., 2018). The superior performance of DNNs comes from its ability to extract high-level features from images (Lillicrap *et al*., 2015; Bengio, 2013) which helps in the analysis and prediction ability of complex problems. This is different from earlier approaches that use rule designed by experts or hand-crafted features. Deep learning has proven more effective than conventional machine learning algorithms in solving classification problem with high dimensionality and complex features, especially when trained with big data. The accuracy of DNNs, however, comes at the cost of high computational complexity. Today we have more powerful computer that runs in very high central processing unit (CPU), graphic processing unit (GPU) and tensor processing unit (TPU) giving deep learning the ability to accommodate many hidden layers of neurons. The DNN models are very popular due to their excellent performance to learn not only complex features but also the underlying structure of the input data. Features are automatically deduced and optimally tuned for desired outcome without human intervention. In DNN, an algorithm scans the data to identify features which correlate and then combine them to promote faster learning. As the name deep learning suggests, it consists of higher or deeper number of processing layers, which contrasts with shallow learning model with fewer layers of units. The advancement of deep learning can be attributed to the explosion of big data in the last ten years (Goodfellow *et al.,* 2016; Shorten *et al*., 2021). Deep learning will continue to impact in all areas of our lives from education, finance, governance, healthcare, manufacturing, marketing and others (Jordan *et al*., 2015). Various deep learning architectures have emerged over time such as multilayer perceptron, deep belief network, radial basis, convolutional neural network, modular neural network, recurrent neural network (Leijnen *et al.,* 2020; Pouyanfar *et al*., 2019; Young *et al*., 2018).

A. Types of Deep Learning Models

1. Multilayer Perceptron (MLP)

The multilayer perceptron (MLP) is the fundamental example of a deep neural network. The architecture of a MLP consists of hidden layers to capture complex relationships in the training dataset. It is the most popular, effective, and easy to learn model for complex, multilayered networks (Zhao *et al*., 2010). A typical multilayer perceptron network consists of a set of source nodes forming the input layer, one or more hidden layers of computation nodes, and an output layer of nodes. The input signal propagates through the network layer-by-layer. Multi-layer feed forward back propagation algorithm is used to train the network and tests the performance of the network. MLP networks are typically used in supervised learning problems. This means that there is a training set of input-output pairs and the network must learn to model the dependency between them. Multilayer perceptron network is a popular learning algorithm in a sense that neural network knows the desired output and adjusting of weight coefficients is done in such way, that the calculated and desired outputs are as close as possible. MLP are usually applied in speech recognition and classification tasks. Suppose we have a 28 x 28 pixel set of image data, a feed forward neural network or multilayer perceptron will need 784 input weights plus a bias. This is a lot of learning parameters which is very expensive in terms of memory and computations. By flattening an image in MLP, the spatial relationships of the pixels in the images are lost.

2. Recurrent Neural Network (RNN)

A recurrent neural network (RNN) is any network whose neurons send feedback signals to each other. They are developed to solve learning problems where information about the past (i.e., past instants/events) is directly linked to making future predictions. RNNs have traditionally been used in analyzing sequential data, such as the words in a sentence. Due to their ability to generate text (Sutskever *et al*., 2011), RNNs have been employed in text analysis tasks, like machine translation, speech recognition, language modeling, time-series data, event sequence, text prediction and image caption generation (Karpathy *et al*., 2015). In a plain RNN, the output of a layer is added to the next input, and this is fed back into the layer, resulting in a capacity for contextual `memory'. Such sequential examples play up frequently in many real-world tasks such as language modeling where the previous words in the sentence are used to determine what the next word will be. Also in stock market prediction, the last hour/day/week stock prices define the future stock movement. RNNs are particularly tuned for time series or sequential tasks. This feedback framework enables the network to incorporate information from past sequences or from time-dependent datasets when making a prediction.

3. *Modular Neural Network (MNN)*

A modular neural network is characterized by a series of independent neural networks. Each independent neural network serves as a module and operates on separate inputs to accomplish some subtasks of the main task (Azam, 2000). The intermediary takes the outputs of each of the module and processes them to produce the output of the network as a whole. As a result, large and complex computational processes are done significantly faster by breaking it down into independent components. The computation speed increases because the networks are not interacting with one another. Applications of modular neural networks are in stock market prediction systems and compression of high level input data.

In image related binary or multi-class classification tasks, convolution neural networks are used because of their automatic feature extraction and ability to reduce the size of the image. It performs better with large datasets when compared with machine and other deep learning methods.

4. *Convolutional Neural Network*

Convolutional Neural Network (CNN) is an artificial neural network and a class of deep neural networks that are extremely successful in image classification problems (Zhang *et al.*, 2018). In convolutional neural network is the most famous and commonly employed algorithm in the field of deep learning (Zhou, 2020; Jhang *et al.*, 2020; Al-Azzani *et al.*, 2020; Wang *et al.*, 2020; Li *et al.*, 2021). Tremendous progress has been made in image recognition, primarily due to the availability of large scale annotated datasets such as ImageNet and deep convolutional neural networks (Krizhevsky *et al.*, 2012). They are multi-layered networks that attempts to mimic the neural connectivity found in the visual cortex of the brain and are designed to recognize visual patterns. CNN works with multi-dimensional image data. CNNs are the most researched deep learning algorithm in medical image analysis (Litjens *et al.*, 2017). The reason for this is that CNNs preserve spatial relationships when filtering input images. The role of the convolutional network is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction. CNN neurons have sparse connections, meaning that only some inputs are connected to the next layer. By having a small, local receptive field (i.e., the area covered by the filter per stride), meaningful features can be gradually learnt, and the number of weights to be calculated can be drastically reduced, increasing the algorithm's efficiency. Most active solutions that improve the performance of CNN are by expanding the dataset with data augmentation or using transfer learning, regularization techniques and hyper parameter tuning. Convolutional neural network consists of five layers: an input layer, a convolutional layer, a pooling layer, a fully-connected layer, and an output layer (Simonyan *et al.*, 2015). These layers are divided into two stages: feature extraction and classification. Feature extraction consists of an input layer, a convolutional layer, and a pooling layer, while classification consists of a fully-connected layer and an output layer.

A CNN takes an input image of raw pixels, and transforms it through the convolutional layers and the pooling layers. This is fed into a fully connected layer which assigns class scores or probabilities, thus classifying the input into the class with the highest probability.

Each layer consists of neurons that have learnable weights and biases. CNN uses filter or kernel as its weights. The ideal model is achieved after feeding data into the network and minimizing the loss function at the top layer. During training, CNN automatically learn features based on these filters. If a photograph of a face was fed into a CNN, initially low-level features such as lines and edges will be discovered by the filters. These build up to progressively higher features in subsequent layers, such as a nose, eye or ear, as the feature maps become inputs for the next layer in the CNN architecture..

I. The first layer extract basic features from raw pixel data such as horizontal or vertical edges, dots, lines, corners etc.
II. The output is passed to the second layer which uses these edges to detect shapes in the second layer.
III. As you move deeper into the network, it uses the shapes to detect more complex features like faces, body, objects.
IV. Finally, it uses the highest-level features to make prediction in the last layer.

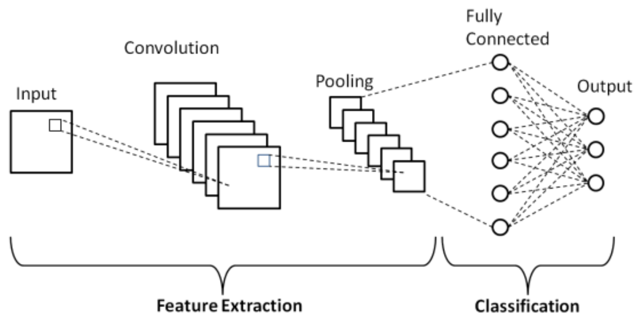

Figure 1: Convolutional Neural Network (Szegedy *et al.*, 2015)

Figure 1 shows how a convolutional neural network works. CNN is in two stages. The first is the feature extraction stage and the second is the classification stage. The feature extraction stage is made up of the input layer, convolutional layers and pooling layers. The input is the image we want to extract features from and use these features for classification. The convolutional layers are the heart of a convolutional neural network. The pooling layer is also called the sub sampling layer. Pooling extracts dominant features from the feature maps. It helps to further reduce the image dimensions which also reduces the computation required. It also helps to avoid over fitting. The reduced image can then be flatten and fed into the classification stage of the convolutional neural network. The classification part is made up of the fully connected layers. It is also called the dense layer because every neuron in the next layer is connected to every other neuron in the previous layer. The fully connected transforms these features to produce an output by assigning class score or probability scores to the images using sigmoid activation function.

B. Transfer Learning

Generally, transfer learning refers to a process where a model that was trained on one problem is used in some way on a second related problem (Kermany, 2018). Deep neural network requires large number of images to perform well. Deep learning models are data hungry, and the quality of dataset has always been the key parameter for models to achieve optimum results. This is very important when handling medical dataset because their quality is crucial for proper analysis. Unlike general image recognition tasks, the field of medical imaging suffers from lack of sufficient data for training deep neural networks. According to the Conference on Machine Intelligence in Medical Imaging (C-MIMI) that was held in 2016 (Kohli *et al.*, 2017), machine learning and deep learning are starving for large scale annotated datasets. Another challenge is obtaining well annotated medical dataset in a systematic fashion. It is also difficult to obtain high quality and balanced datasets with labels in the medical domain. Medical images are mostly imbalanced in most cases as negative samples are much more numerous than positive ones and vice versa (Johnson *et al.*, 2019). Researchers often rely on field experts to label these images; however, this process is costly and time consuming (Tan *et al.*, 2018). In addition, medical images are hard to obtain due to privacy issues (Price *et al*, 2019).

Building and training deep learning model requires large datasets to avoid a cold start. Fortunately, models do not always have to be trained from scratch. Primarily, lack of data and time needed to train a CNN from scratch are the reasons for using transfer learning (Szegedy *et al.*, 2015). The concept of transfer learning allows models that are trained on general datasets such as ImageNet, CIFAR 100, or MNIST to be specialized for specific tasks by using a considerably smaller dataset that is problem-specific (Pouyanfar *et al.*, 2019). As these pre-trained models were trained on huge dataset, they have learned a good representation of low level features like edges, corners, lighting, shapes and these features can be shared across to enable the knowledge transfer. Transfer learning approach enables one to adopt a pre-trained network that has already learned a rich set of low-level features. These new images might be of completely different categories from the source dataset, but the pre trained model should still be able to extract relevant features from these images based on the principles of transfer learning. In other words, pre trained models generalizes well to images outside imagenet.

There are a lot of pre trained convolutional neural network models that can be used for image classification and computer vision tasks. They include AlexNet (Krizhevsky *et al*., 2017), Resnet (He *et al*., 2016), Googlenet (Szegedy *et al*., 2015), Lenet, Visual Geometry Group (Simonyan *et al.,* 2015). These models were trained on ImageNet dataset.

IV. METHODOLOGY

Software system development life cycle (SDLC) provide the foundation for the processes used to develop an information system. There are many different systems development methodologies, and they vary in terms of the progression that is followed through the phases of the SDLC. Cross Industry Standard Process Data Mining (CRISP-DM) can be closely aligned and integrated with agile development methodology. Cross Industry Standard Process Data Mining (CRISP-DM) is an open standard process model that describes common approaches used by data mining experts. It is a process model with six phases that naturally describes the data science life cycle. It helps to plan, organize and implement data science projects. CRISP DM is the most widely used form of data mining model (Chapman *et al*., 2000). It is a robust, flexible and well proven methodology that provides structured approach to any data science problems. We chose this methodology because it clearly defines the different approach needed to realize the aim of our research work.

Agile methodology is an iterative approach to software development projects. It embraces changing requirements and the sequence of the phase is not rigid. Moving back and forth between different phases is always required. CRISP DM and agile complement each other for efficient and effective data science delivery. CRISP DM guides data science projects on what to deliver and in what sequence while agile helps on how to deliver working product successfully. There are several approaches to agile development such as extreme, scrum and dynamic system development method. Extreme programming emphasizes communication between stakeholders and programmers, customer satisfaction, teamwork, simplicity and feedback.

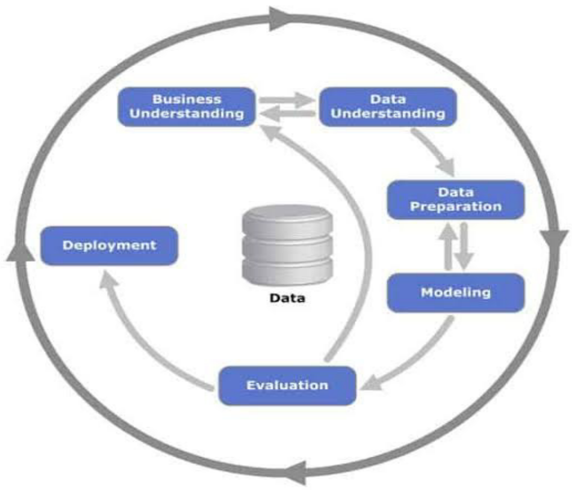

Figure 2: Flow Diagram of a Cross Industry Standard Process Data Mining (Workneh, 2020)

C. Data Preprocessing, Augmentation and Splitting

Before training a deep learning model, datasets must undergo essential preprocessing transformations, which significantly impact the model's performance and learning. Neural networks rely on high-quality datasets for accuracy. Preprocessing steps for malaria image classification include tasks like data augmentation (image resizing and normalization), data cleaning, labeling, and noise removal. Skipping these steps can lead to misclassification errors (Murtaza et al., 2019). For example, the Visual Geometry Group 16 (VGG16) model requires input images with dimensions 224 x 224 x 3. Effective preprocessing is critical, as the quality of formatted data determines the model's ability to learn effectively.

Data augmentation is a preprocessing technique used to enhance datasets by generating additional data points through manipulations of the base data. This is particularly valuable for deep learning models, which require large datasets for effective training. In fields like medical diagnosis (e.g., malaria and cancer), where data availability is limited due to privacy concerns, augmentation creates diverse versions of similar content, exposing models to a broader range of examples. Commonly used in image-based deep neural networks, augmentation increases dataset size and introduces variance by applying transformations while preserving core features (Shorten et al., 2019; Saleh et al., 2021; Hirahara et al., 2020). This process helps models learn more robust features, improving classification accuracy and generalization.

Splitting datasets into three parts—training, validation, and test sets—is essential in machine and deep learning to promote model generalization. Generalization refers to a model's ability to adapt to new, unseen data.

Training datasets uses about 70-80% of the total dataset. This is used to train the model. Validation data makes up of 10-20% of the data. It evaluates the model's accuracy and performance during hyper parameter tuning (e.g., adjusting weights and learning rates). Test data uses 10-20% of the dataset. This portion evaluates the model's performance on unseen data, ensuring it generalizes well beyond the training phase.

D. Model Training and Testing

Deep learning frameworks and libraries have significantly streamlined model training, yielding improved results. Due to hardware limitations, training the model on Google Colaboratory environment using Python libraries like Keras 2.2, TensorFlow 2.0, NumPy, Matplotlib, Scikit-learn, and Seaborn is better than using a local computer. The system operated on Windows 10, with 4 GB RAM and a 64 GB CPU. This approach facilitated efficient and effective model development.

E. Performance Evaluation

Evaluating a model is a core part of building an effective deep learning model. Evaluation metrics explain the performance of a model. Different evaluation metrics are used such as confusion matrix - sensitivity, f1 score, accuracy, specificity, f- beta score, receiver-operating characteristics curve (ROC), and area under the curve according to some specific regularities and criteria. Classification evaluation metrics are confusion matrix- accuracy, f1 score and sensitivity scores.

V. Summary and Conclusion

Malaria has had a profound effect on human lives for thousands of years and remains one of the most serious, life threatening disease. Early and accurate malaria diagnosis is essential for effective treatment. Delay and misdiagnosis of malaria can jeopardize a patient health which may lead to serious complications. This paper presents a novel solution for malaria diagnosis using deep learning. It is a neural network model that is used to train and analyze images of blood smears and identify the presence of malaria parasites. It accurately identifies malaria parasites with a high sensitivity score and validation accuracy. This is a valuable tool in the fight against malaria. The model also helps in timely malaria diagnosis and treatment in line with meeting WHO global target of reducing malaria mortality rates by 90% by 2030 along with completely eradicating malaria worldwide by 2040. This will help reduce the workload on healthcare professionals and improve the efficiency of the diagnostic process.

REFERENCES

Adeel, A, Gogate, M, and Hussain, A. (2020). Contextual Deep Learning-based Audio-Visual Switching for Speech Enhancement in Real-world Environments. *Journal of Information Fusion*; **59**:163–170.

Al-Azzawi, A, Ouadou, A, Max, H, Duan, Y, Tanner, J. J, and Cheng, J. (2020). Deepcryopicker: Fully Automated Deep Neural Network for Single Protein Particle Picking in Cryo-EM. BMC *Journal of Bioinformatics* **21**(1):1–38.

Azam, F. (2000). Biologically Inspired Modular Neural Networks. Ph. D Dissertation. Virginia Technology.

Bengio, D, *and* Yoshua, M. (2009). Learning Deep Architectures for Artificial Intelligence: Foundations and Trends in Machine Learning. pp 1-127.

Bengio, Y. (2013). Deep Learning of Representations: Looking Forward. In: Lecture Notes in Computer Science (Including its Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), pp 1–37.

Bordes, A., Chopra, S., *and* Weston, J. (2014). Question Answering with Sub-graph Embeddings arXiv preprint arXiv:1406.3676.

Chapman, P, Clinton, J, Kerber, R, Khabaza, T, Reinartz, T, Shearer, C, *and* Wirth, R. (2000). CRISP-DM 1.0 Step by Step Data Mining Guide, CRISP-DM Consortium.

Chen, C, Seff, A, Kornhauser, A, *and* Xiao, A. (2015).“Deep Driving: Learning Affordance for Direct Perception in Autonomous Driving,” 2015 IEEE International Conference on Computer Vision (ICCV).

Chibunta, S., *and* Acar, A. C. (2020). Real-time Malaria Parasite Screening in Thick Blood Smears for Low-resource Setting. Journal of digital imaging, 33 (3), 763-775.

Deng, L, Li, J, Huang, T, Yao, K, Yu, D F, Seide, Seltzer, M, Zweig, G, He, X, *and* Williams, J. (2013).“Recent Advances in Deep Learning for Speech Research at Microsoft,” In International Conference on Acoustics, Speech, and Signal Processing (ICASSP).

Diyasa, I. G. S. M., Fauzi, A., Setiawan, A., Idhom, M., Wahid, R. R., *and* Alhajir, A. D. (2021). Pre-trained Deep Convolutional Neural Network for Detecting Malaria on the Human Blood Smear Images. In 2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC) (pp. 235-240).IEEE.

Dong, Y., Jiang, Z., Shen, H., *and* Pan, W. D. (2017). Classification Accuracies of Malaria Infected Cells using Deep Convolutional Neural Networks Based on Decompressed Images. In Southeast Conference 2017 (pp. 1-6).IEEE.

Goodfellow, I, Bengio, Y, *and* Courville, A. (2016). Deep Learning.the MIT Press, Cambridge, MA, USA.

He K, Zhang X, Ren S, *and* Sun J. (2016).Deep Residual Learning for Image Recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

Hinton, G. , Deng, L. , Yu, D. , Dahl, G. E. , Mohamed, A.-R. *and* Jaitly, N. (2012). Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups. IEEE Signal Processing Magazine, 29: 82–97.

Hirahara, D, Takaya, E, Takahara, T, *and* Ueda, T. (2020).Effects of Data Count and Image Scaling on Deep Learning Training.Peer Journal of Computer Science 6:312.

Jhang, S. Y, Tseng, P. Y, Siriphockpirom, N, Hsia, C. H, Huang, M. S, Hua, K. L, *and* Chen, Y. Y. (2020). An Automated Biometric Identification System using CNN-Based Palm Vein Recognition. In: 2020 International Conference on Advanced Robotics and Intelligent Systems (ARIS). IEEE. pp. 1-6.

Johnson, J. M, *and* Khoshgoftaar, T. M. (2019). Survey on Deep Learning with Class Imbalance. Journal of Big Data. 6 (1):27.

Jordan, M. I, *and* Mitchell, T. M. (2015). ``Machine Learning: Trends, Perspectives, and Prospects," Journal of Science, 6245 (349), 255-260.

Karpathy, A., *and* Fei-Fei, L., (2015).“ Deep Visual Semantic Alignments for Generating Image Descriptions," In Proceeding IEEE Conference Computer Visual Pattern Recognition (ICMVPR) pp. 3128-3137.

assam, N. A., Robert, D., Kaaya, I., Damian, J. D., Christentze, S., Reginald, A., Kavishe,1., Michael, A., *and* Christian W. W. (2021). Ten years of Monitoring Malaria Trend and Factors Associated with Malaria Test Positivity rates in Lower Moshi. Malaria Journal 20: 193.

Kassani, S.H.; Kassani, P.H.; Wesolowski, M.J.; Schneider, K.A.; *and* Deters, R. (2019). Classification of Histopathological Biopsy Images Using Ensemble of Deep Learning Networks. arXiv, :1909.11870.

Ker, J, Wang, L, Rao, J, *and* Lim, T. (2017). Deep Learning Applications in Medical Image Analysis. IEEE Access. 6: 9375–9389.

Kermany, D. (2018). Identifying Medical Diagnoses and Treatable Diseases by Image-based Deep Learning, Journal of medical science 172 (5):1122–1131.

Khan, S, Islam, N, Jan, Z, Din, I, *and* Rodriguez, J. (2019). "A Novel Deep Learning based Framework for the Detection and Classification of Breast Cancer Using Transfer Learning," Pattern Recognition Letters. pp. 1-6.

Kohli, M.D., Summers, R.M., *and* Geis, J.R. (2017). Medical Image Data and Datasets in the Era of Machine Learning—Whitepaper from the 2016 C-MIMI Meeting Dataset Session. Journal of Digital Imaging 30 (4), 392–399.

Krizhevsky, A, Sutskever, I, *and* Hinton, G. E. (2012).“Image Net Classification with Deep Convolutional Neural Networks” In Advances in Neural Information Processing Systems. Pp 1097-1105.

Krizhevsky, A., Sutskever, I., *and* Hinton, G. E. (2017). Imagenet Classification with Deep Convolutional Neural Networks. Journal of Communication of ACM; 60 (6):84–90.

Kumar, Y. et al. (2024). Enhancing parasitic organism detection in microscopy images through deep learning and fine-tuned optimizer. Sci. Rep. 14 (1): p. 5753.

LeCun, Y, Bengio, Y, *and* Hinton, G. (2015) “Deep learning,” Nature Journal, 521 (7553) 436–444.

Leijnen, S., Van, *and* V. F. (2020).The Neural Network Zoo Proceedings. 47(1): 9.

Li, G, Zhang M, Li J, Lv F, *and* Tong G. (2021). Efficient Densely Connected Convolutional Neural Networks. Pattern Recognition.109:107610

Lillicrap, T. P, Hunt, J. J, Pritze, l.A, Heess, N, Erez, T, Tassa, Y, Silver, D, *and* Wierstra, D. (2015). Continuous Control with Deep Reinforcement Learning. Journal of Clinical Linguistics and Phonetics 1: 10

Litjens, G., Thijs, K., Babak, E. B, Arnaud, A. A., Francesco, C., Mohsen, G., Jeroen, A.W.M., Bram, G., *and* Clara I. S. (2017). A Survey on Deep Learning in Medical Image Analysis. Journal of Medical Image Analysis, 42: 60-88.

Manescu, P., Shaw, M. J., Elmi, M., Neary-Zajiczek, L., Claveau, R., Pawar, V. *and* Fernandez-Reyes, D. (2020). Expert-level Automated Malaria Diagnosis on Routine Blood Films with Deep Neural Networks. American Journal of Hematology, 95(8), 883-891.

Mohanty, I., Pattanaik, P. A., *and* Swarnkar, T. (2019). Automatic Detection of Malaria Parasites using Unsupervised Techniques. In International conference on ISMAC in computational vision and bio-engineering (pp. 41-49).Springer, Cham.

Murtaza, G, Shuib, I, Wahab, A. W.A, Mujtaba, G, Nweke, H. F., Al-garadi, M.A, Zulfiqar, F., Raza, G, *and* Azmi, N. A. (2019). Deep Learning-based Breast Cancer Classification through Medical Imaging Modalities: State of the art and Research Challenges. Journal of Artificial Intelligence 53: 1655-1720.

Nakasi, R., Tusubira, J. F., Zawedde, A., Mansourian, A., and Mwebaze, E. (2019). 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 (pp. 984-985).

Onile-ere, O, Openibo, J, *and* Olasehinde, G.I, (2016). Malaria Diagnosis: Current Approaches and Future Prospects. In: 3rd International Conference on African Development Issues (CU-ICADI), May 9–May 11. Covenant University. Nigeria: Ota.

Pouyanfar, S., Sadiq, S., Yan, Y., Tian, H., Tao, Y., Reyes, M. P.,Shyu, M.-L., Chen, S.-C., *and* Iyengar, S. S. (2019). A Survey on Deep Learning: Algorithms, Techniques, and Applications. Journal of ACM Computing Surveys, 51 (5), 1–36.

Prakash, S. S., Kovoor, B. C., *and* Visakha, K. (2020). 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) (pp. 308-313). IEEE.

Price, W. N., *and* Cohen, I. G. (2019). Privacy in the Age of Medical Big Data. National Medical Journal. 25:37-43.

Rawat, W, *and* Wang, Z. (2017). Deep convolutional neural networks for image classification: a
comprehensive review, Journal of Neural Computing. 29:2352–2449.

Reddy, A. S. B., *and* Juliet, D. S. (2019). Transfer Learning with ResNet-50 for Malaria Cell-image Classification. In 2019 International Conference on Communication and Signal Processing (ICCSP) (pp. 0945-0949).IEEE.

Rizk, Y., Hajj, N., Mitri, N., *and* Awad, M. (2019). Deep belief networks and cortical algorithms: A comparative study for supervised classification. Applied Computing and Informatics 15 (2), 81–93.

Saleh, A. M, *and* Hamoud, T. (2021). Analysis and Best Parameters Selection for Person Recognition Based on Gait Model Using CNN Algorithm and Image Augmentation. Journal of Big Data. 8 (1):1–20.

Shah, D., Kawale, K., Shah, M., Randive, S., *and* Mapari, R. (2020). Malaria Parasite Detection using Deep Learning: (Beneficial to humankind). In 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS) (pp.984-988).IEEE.

Shekar, G., Revathy, S, *and* Goud, E. K. (2021). Malaria Detection using Deep Learning. In 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184) (pp. 746-750). IEEE.

Shin, H.C.; Roth, H.R.; Gao, M.; Lu, L.; Xu, Z.; Nogues, I. *and* Summers, R.M. (2016). Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Transactional Medical Imaging 35: 1285–1298.

Shorten, C, Khoshgoftaar, T. M, *and* Furht, B. (2021). Deep Learning Applications for COVID-19. Journal of Big Data. 8 (1):1–54.

Shorten, C, *and* Khoshgoftaar, T. M. (2019). A Survey on Image Data Augmentation for Deep Learning. Journal of Big Data. 6 (1):60.

Siłka, W., Wieczorek, M., Siłka, J. and Woźniak, M. (2023). Malaria detection using advanced deep learning architecture. Sensors 23 (3): p. 1501.

Simonyan, K, *and* Zisserman, A. (2015). Very Deep Convolutional Networks for Large-scale Image Recognition, Computer Vision and Pattern Recognition. pp. 1409-1556.

Slyuan, L, Zhihai L, Soriya, A, *and* Logan, G. (2018) "Fruit Classification Based on Six Layer Convolutional Neural Network "International Conference on Digital Signal Processing. pp 231-233.

Sutskever, I. , Vinyals, O. and Le, Q. V. (2014). Sequence to Sequence Learning with Neural

Networks.In Advances in Neural Information Processing Systems pp. 3104–3112.

Sutskever, I., Martens, J., *and* Hinton, G. E. (2011).“Generating Text with Recurrent Neural Networks” In Proceeding 28th International Conference Machine Learning.(ICML) pp. 1017-1024.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., *and* Rabinovich, A. (2015). Going Deeper with Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 1–9.

Tan, C., Sun, F, Kong, T, Zhang, W, Yang, C, *and* Liu, C. (2018). A Survey on Deep Transfer Learning. In: International Conference on Artificial Neural Networks. Springer; pp. 270–279.

Tian, H, Chen, S. C, *and* Shyu, M. L. (2020). Evolutionary Programming Based Deep Learning Feature Selection and Network Construction for Visual Data Classification. Journal of Infusion System Front; 22 (5):1053–66.

Wang, T, Lu C, Yang M, Hong F, *and* Liu C. (2020).A Hybrid Method for Heartbeat Classification via Convolutional Neural Networks, Multilayer Perceptron and Focal Loss. Peer Journal of Computer Science. 6 :324.

Workneh, Y. (2020). Adapting CRISP-DM for Idea Mining: A Data Mining Process for Generating ideas using a Textual Dataset. International Journal of Advanced Computer Sciences and Applications.11 (6): 20-32.

World Health Organization (2022).World Malaria Health Observatory Report. Geneva.

Xi, X., Meng, X., Yang, L., Nie, X., Yang, G., Chen, H., Fan, X., Yin, Y., *and* Chen, X. (2019). Automated Segmentation of Choroidal Neo Vascularization in Optical Coherence Tomography Images using Multi-scale Convolutional Neural Networks with Structure prior.Journal of Multimedia System. 25 (2), 95–102.

Young, T., Hazarika, D., Poria, S., *and* Cambria, E. (2018). Recent Trends in Deep Learning Based Natural Language Processing. Journal of IEEE Computational Intelligence Magazine, 13 (3): 55–75.

Zhang, Y, Pan, C, Chen, X, and Wang, F. (2018). Abnormal Breast Identification by nine-layer Convolutional Neural Network with Parametric Rectified Linear Unit and Rank-based Stochastic Pooling. Journal of Computer Science 27:57–68.

Zhao, Z., Haiping, X., and Xuesong, G. (2010). "Application and Comparison of BP Neural Network Algorithm in MATLAB International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Vol. 1. IEEE.

Zhou, D. X. (2020). Theory of Deep Convolutional Neural Networks: Down Sampling. Journal of Neural Network.124:319–27.

