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A Deep Learning based Clinical Decision Support System for Malaria Diagnosis and Detection

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Abstract

Malaria remains one of the major challenges faced in healthcare in Africa, especially in Nigeria with an estimated 300,000 children killed by malaria annually. Apart from low doctor to patient ratio in Nigeria, poor diagnosis is another major cause of increase in malaria death rate.

This research developed a Clinical Decision Support System (CDSS) to detect malaria infected patients using deep and machine learning technique. For this, we developed an in-depth learning method from camera captured Giemsa-stained thin blood smear slides from 150 *Plasmodium Falciparum* infected and 50 non-infected patients from a national center for biomedical communications. The dataset contains 27,558 cell images with equal number of malaria infected and non-infected cell images which are 13,779. The architecture of the proposed model predicted patient's malaria status and was evaluated using 5-fold cross-validation. The images were preprocessed and resized after which the learning stage began. Deep learning and classification were carried out using Convolutional Neural Network (CNN). The CNN model was trained by using Stochastic Gradient Descent (SGD) and Nesterov's momentum to optimizing the multinomial logistic regression objective. The proposed model achieved a training accuracy of 99%, validation accuracy of 97%, 40% train loss, 35% validation loss a 98% prediction.

Keywords: Malaria • Deep learning • Machine learning • CDSS • CNN

Introduction

In recent years, there has been a substantial resurgence in the optimistic disposition in the use of artificial intelligence tools and techniques in healthcare [1]. This revitalized optimism originates, at least in part, from the recent advancement and achievement in artificial intelligence techniques such as machine learning and deep learning research in the non-healthcare sector of the industry. The innovation and construct of various machine learning and deep learning algorithms to tackle health and other challenges have existed for some time, but the enhanced availability of the massive amount of data, matched with equally impressively powerful computers, enabled these achievements and breakthroughs seen in machine learning and deep learning this decade [2-4].

In medical domain diagnostic, classification and treatment are the main task for a physician. System development with such purposes is also a popular area in Artificial Intelligence (AI) research. Computer-Aided System or Decision Support System (DSS) that can simulate expert human reasoning or serve as an assistant of a physician in the medical domain is increasingly important. Today, clinical Decision Support System (DSS) are developed to act multi-purposed and are combined with more than one AI method and technique.

In Nigeria, there are several challenging health problems that need addressing utilizing public health rules in order to improve stability. Over the years, there have been some programs initiated to deal with these healthcare challenges in Nigeria but they have all brought about little or no betterment in our healthcare condition [5]. In addition, the persistent disregard of the necessity of dealing with public healthcare challenges would worsen matters for the majority of the Nigerian population who are directly impacted by these issues [6]. A report on non-communicable diseases by the World Health Organization stated that Nigeria and other developing countries are the worst impacted with a high mortality rate from non-communicable diseases [7]. Based on statistics released by the World Health Organization in 2017, the mortality rate of people infected by malaria in Nigeria is 146 per 100,000 population [8].

With malaria being the most prominent cause of death in Nigeria. It has the greatest effect of disease in the country. With an estimated 300,000 children killed by malaria annually. It causes more than 25%

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of infant deaths, 30% of childhood deaths, 11% of maternal deaths. Moreover, there are at least 50% of Nigerians with at least one encounter with malaria annually, at the same time, children below 5 years of age have around 2 to 4 encounters yearly. Malaria is predominantly severe amongst children below 5 years of age and pregnant women because of relatively weaker levels of immunity [9]. Classification of these parasites was carried out by with *P. Falciparum* the most predominant malaria parasite in Nigeria and subsequently the cause of most malaria associated deaths [10,11]. Other malaria parasites such as *P. vivax and P. Knowlesi* can also cause severe malaria and death but they put up significantly less effect than *P. Falciparum* [12]. Wrong diagnosis will lead to wrong treatment and eventually lead to more mortality coupled with the fact that the need for experts far outmatches the available supply in the developing nations and sometimes physician performance is mostly not straight-forward because of diagnostic mistakes due to Inefficient incorporation and collaboration of Health Information Technologies (Health IT), Gaps in communication among clinicians, patients, and their families as well as a healthcare work system which, by design, does not sufficiently support the diagnostic procedures [13,14]. There is therefore a need is to implement a deep learning based clinical decision support system that is capable of recognizing patterns in malaria patient symptoms to make a possible diagnosis so as to assist and hasten a suitable course of action.

Literature Review

Computer technology approach to diagnose different diseases is an ongoing research in information technology and health domain. Many clinical decision support systems are a two-layer knowledge base model of rule reasoning and they do not express knowledge very well since it simply infers disease from the presence of certain symptoms [15]. Proposed a three-layer knowledge base model (disease-symptom-property) to utilize more useful information in inference. The system iteratively calculates the probability of patients who may suffer from diseases based on a multi-symptom naive Bayes algorithm, in which the specificity of these disease symptoms is weighted by the estimation of the degree of contribution to diagnose of the disease and found that the three-layer model can improve the accuracy of predictions compared with the two-layer model and highlighted several areas that need continued improvement.

Machine learning vows to upset clinical decision making and diagnosis. In medical diagnosis a doctor expects to clarify a patient's manifestations by deciding the sicknesses causing them. However, existing machine learning approaches to diagnosis are purely associative, identifying diseases that are strongly correlated with a patient's symptoms, reformulates diagnosis as a counterfactual inference task and derive counterfactual diagnostic algorithms comparing their developed counterfactual algorithms to the standard associative algorithm showing that causal reasoning is a vital missing ingredient for applying machine learning to medical diagnosis [16].

A systematic review to investigate the association between the interactive use of ML-based diagnostic CDSSs and clinician performance to inspect the degree of the CDSSs' human variables assessment utilizing MEDLINE, Embase, PsycINFO, and dark writing between January 1, 2010, and May 31, 2019 was led by [17]. A sum of 8112 examinations were at first recovered and 5154 modified works were screened; of these, 37 investigations met the incorporation models. The middle number of taking part clinicians was 4 (interquartile range, 3-8). Of the 107 outcomes that detailed factual importance, 54 (half) were expanded by the utilization of CDSSs, 4 (4%) were diminished, and 49 (46%) showed no change or an indistinct change. Expressing that more exhaustive assessment ought to be directed prior to conveying ML based CDSSs in clinical based CDSSs in clinical settings with adding to the moral conversation by utilizing professionalization hypothesis as an insightful focal point for examining how clinical activity at the miniature level and the doctor patient relationship may be impacted by the work of ML-CDSS. Presuming that the more routinized the utilization of ML-CDSS becomes in clinical practice, the more that doctors need to zero in on the patient's anxiety and fortify patient independence, for example, by enough incorporating digital decision support in shared decision-making [18].

Machine Learning (ML) methods were used on blood tests data to predict COVID-19 mortality risk [19]. A powerful combination of five features: neutrophils, lymphocytes, Lactate Dehydrogenase (LDH), high-sensitivity C-Reactive Protein (hs-CRP), and age helps to predict mortality with 96% accuracy. Various ML models (neural networks, logistic regression, XGBoost, random forests, SVM, and decision trees) have been trained and performance compared to determine the model that achieves consistently high accuracy across the days that span the disease. The best performing technique utilizing XGBoost highlight significance and neural organization arrangement, predicts with a precision of 90% as right on time as 16 days before the result. Hearty testing with three cases dependent on days to result affirms the solid prescient exhibition and reasonableness of the proposed model. Performing nitty gritty examination and recognizable proof of patterns utilizing these critical biomarkers to give valuable bits of knowledge to natural application while developed a machine learning based Clinical Decision Support System (CDSS) for recommending initial treatment option in HCC and predicting Overall Survival (OS). The six multi-step classifier model was developed for treatment decision in a hierarchical manner, and showed good performance with 81.0% of accuracy for Radiofrequency Ablation (RFA) or resection versus not, 88.4% for RFA versus resection, and 76.8% for TACE or not.

Advancements in Deep Learning (DL) for healthcare cannot be left out and are tremendous in the recent years because of the way that there is accessible and immense measure of information for investigation. A wide assortment of DL algorithms are being utilized and being additionally evolved to tackle various issues in the medical healthcare environment. Clinical medical care is one of the premier regions in which learning algorithms have been attempted to help navigation. Such sort of wise decision making in medical services and clinical practice is likewise expected to bring about comprehensive therapy. Different existing DL procedures and their applications for choice help in clinical frameworks utilizing fundamentally three application floods of DL to be specific image analysis, natural language processing, and wearable, a segment on headings for future exploration like dealing with class lopsidedness in analytic information, DL for guess prompting preventive consideration, information protection and security were checked on and collected [19]. Improved patient safety and clinical outcomes by reducing the risk of prescribing errors, data from electronic health records were collated over a period of 18 months was proposed by

Corny, et al. Inferred scores at a patient level (probability of a patient's set of active orders to require a pharmacist review) were calculated using a hybrid approach (machine learning and a rule-based expert system), the areas under the receiving operating characteristic and precision-recall curves of our digital system were 0.81 and 0.75, respectively, thus demonstrating greater accuracy than the CDS system (0.65 and 0.56, respectively) and multicriteria query techniques (0.68 and 0.56, respectively). The innovative computerized instrument was notably more accurate than existing techniques (CDS system and multicriteria query) at catching expected remedy blunders. By essentially focusing high-risk patients, this novel hybrid decision support system improved the accuracy and reliability of prescription checks in a hospital setting [20-23].

Qjidaa, et al. proposed a clinical decision support system for the early detection of COVID-19 using deep learning based on chest radiographic images. An in-depth learning method which could extract the graphical characteristics of COVID-19 in order to provide a clinical diagnosis before the test of the pathogen was developed. 100 images of cases of COVID-19 confirmed by pathogens, 100 images diagnosed with typical viral pneumonia and 100 images of normal cases were collected. The design of the proposed model initially goes through a preprocessing of the input images followed by an expansion in information. Then, at that point, the model starts a stage to extricate the attributes followed by the learning step. At long last, the model starts a characterization and forecast process with a completely associated network framed of a few classifiers. Profound learning and characterization were done utilizing the VGG convolutional neural organization. The proposed model accomplished a precision of 92.5% in inward validation and 87.5% in outer validation. For the AUC basis, a worth of 97% in inside validation and 95% in outside validation were achieved. As to affectability model, we acquired a worth of 92% in inner approval and 87% in outer approval. The outcomes got by the model in the test stage show that the created model is extremely compelling in distinguishing COVID-19 and can be offered to health communities as a precise, rapid and effective clinical decision support system in COVID-19 detection.

Methodology

Publicly accessible dataset of blood smear images from both infected and non-infected malaria patients were obtained from Lister Hill National Center for Biomedical Communications (LHNCBC). Giemsa-stained thin blood smear slides from 150 *Plasmodium Falciparum* infected and 50 non-infected patients were captured at Chittagong medical college hospital, Bangladesh. The dataset contained 27,558 cell images with the same number of malaria-infected and non-infected cell images which are 13,779 each.

Convolutional Neural Networks (CNN) was used to train. The input to the CNN model formed sectioned cells of 100 x 100 x 3-pixel resolution having three convolution layers. Each convolution layer would use 3 x 3 filters with 2-pixel strides. The first and second convolutional layers would have 32 filters while the third convolutional layers would have 64 filters respectively. All convolutional layers would used ReLU activation (Figure 1).

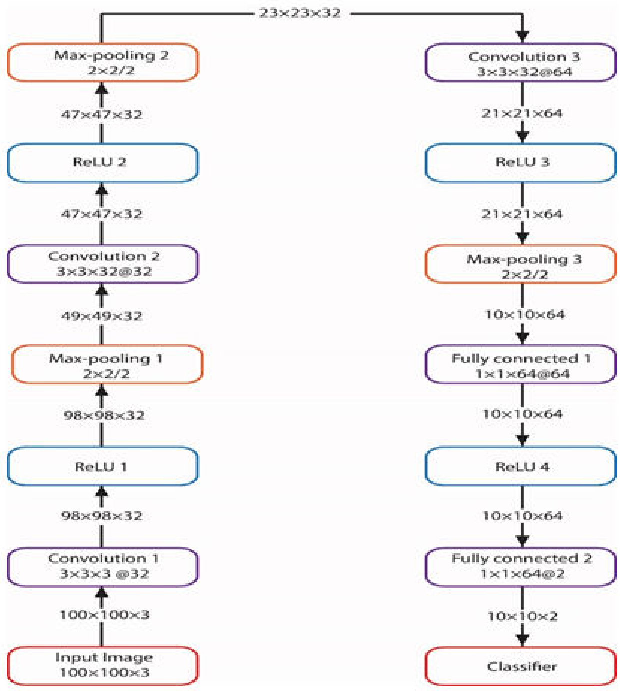


Figure 1. Architecture of the convolutional neural network model.

This shows various layers in the CNN, their input dimensions and output dimensions, the Rectified Linear Unit (ReLU) and the max-pooling layers used for the convolutional layers.

The Clinical Decision Support System (CDSS) consists of the main server that is comprised of a database for storing the classified images and a central PC for training the CNN model. The input and output of the system are connected to the main server through the internet. The patients digitalize blood smear images were used as input to the CDSS. The images were re-sampled to 100 x 100 pixels to match the dimensions of the dataset images that were used in training the CNN model. The output is a prediction as regard to the patient's malaria status. These classified images are stored in the database which can be subsequently used to train the CNN-model. The results can be retrieved on various output devices connected to the system (Figures 2 and 3).

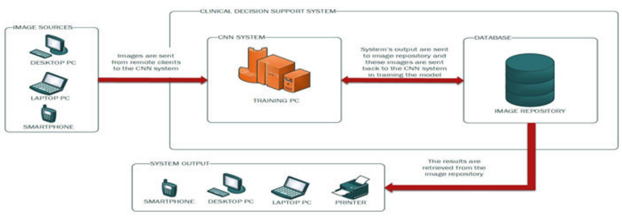


Figure 2. Conceptual frameworks of the clinical decision support system.

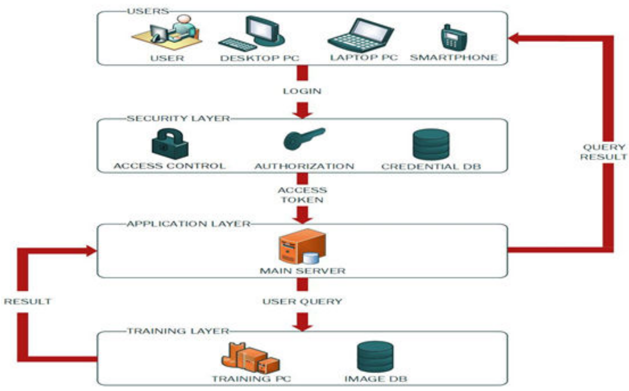
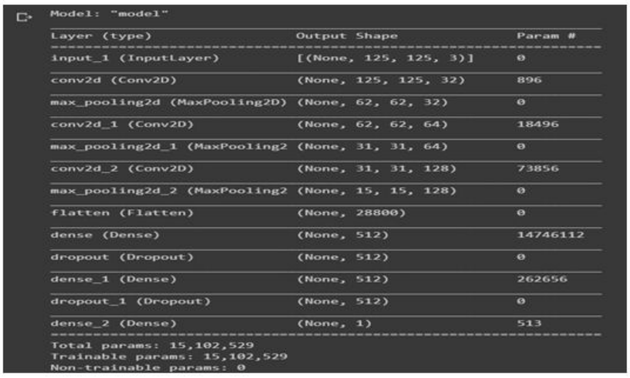


Figure 3. Data flow in the clinical decision support system.

This shows the information one layer to another in the clinical decision support system. The security layer controls access into the application system. The application layer sends user queries to the training layer and receives the results from the training layer. This result is subsequently sent to the privileged user by the application layer.

Results and Discussion

The layers of the CNN model were built using Keras which runs on Tensor flow. All layer specifications were done using Keras and the CNN model was compiled after (Figure 4).



Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 125, 125, 3)]	0
conv2d (Conv2D)	(None, 125, 125, 32)	896
max_pooling2d (MaxPooling2D)	(None, 62, 62, 32)	0
conv2d_1 (Conv2D)	(None, 62, 62, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 31, 31, 64)	0
conv2d_2 (Conv2D)	(None, 31, 31, 128)	73856
max_pooling2d_2 (MaxPooling2	(None, 15, 15, 128)	0
flatten (Flatten)	(None, 28800)	0
dense (Dense)	(None, 512)	14746112
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 512)	262656
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 1)	513

Total params: 15,102,529
Trainable params: 15,102,529
Non-trainable params: 0

Figure 4. The CNN model architecture.

The Figure shows the CNN model architecture after all the layers were build using their respective specifications and compiled. The model was trained on the dataset using keras. Using specified batch size, epoch, class numbers and input dimensions. The model is the validated using the validate dataset and evaluate its performance (Figure 5).

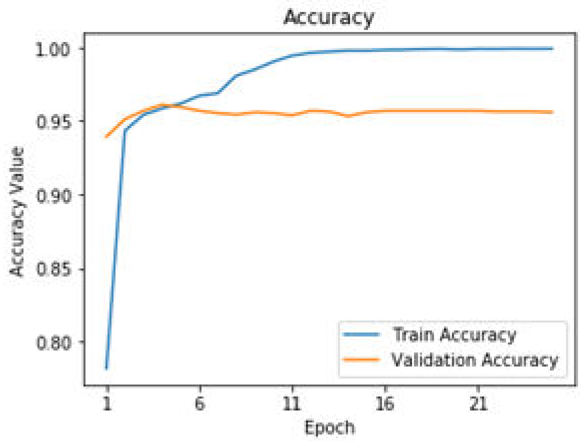


Figure 5. Graph of the accuracy for the at each epoch for both training and validation datasets.

Figure 5 shows the plot of the accuracy of the model against the number of epoch. This increases as the model learns the dataset. The blue line is the graph for the training dataset and the orange line is for the validation dataset (Figure 6).

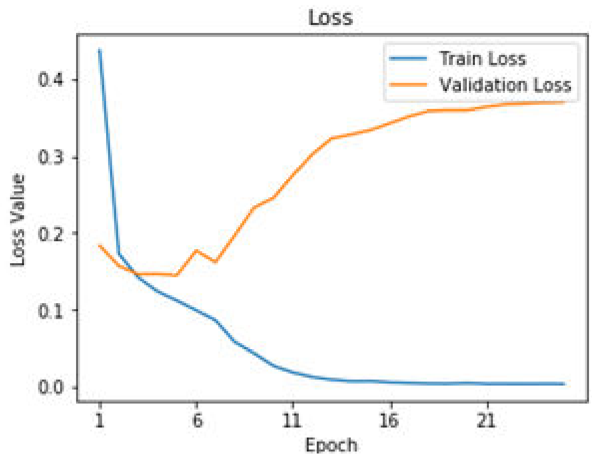


Figure 6. Graph of the accuracy for the at each epoch for both training and validation datasets.

Figure 6 shows the plot of the accuracy of the model against the number of epoch. This increases as the model learns the dataset. The blue line is the graph for the training dataset and the orange line is for the validation dataset (Figure 7).

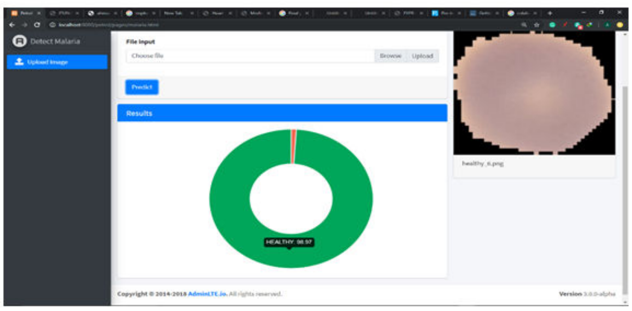


Figure 7. Prediction results.

Figure 7 shows the result of the prediction displayed as a pie-chart with two variables. One for the infected probability and the other of the healthy probability. The variables are in red and green respectively.

Conclusion

With a majority of people infected by malaria in Nigeria being children below 5 years of age. Most children in this age group are generally unable to properly describe their symptoms to the medical professionals during diagnosis this has led to the conclusion to use a machine learning technique that can automate Polymerase Chain Reaction (PCR) and Rapid Diagnostic Tests (RDT) used to analyze blood smears images for malaria detection. Moreover, with a rapid and reliable diagnosis being a requirement for this system, training the model using convolutional neural networks is a proficient choice. The proficiency of convolutional neural networks in image classification delivering very accurate results makes it an adept selection for training the model.

And with a very low doctor to patient ratio in Nigeria, this system would assist medical professionals receiving a potentially high amount of malaria infected patients rapidly diagnose and assign priority to his/her patients.

This work will be deployed in a hospital where other e-health facilities will be fully integrated. Additional modules will be added to extent the existing medical personnel and patient's information management system like the chatbot module that would help interact with patients

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