Malarial Cell Classification using Deep Learning

Completed by:

Fahim Faisal Ratul 1712697642

Hasibul Hossain 1821534042

Reajus Salahin Shyon – 1822187042

Supervisor name:

Dr. Mohammad Monirujjaman Khan

Associate Professor

Department of Electrical and Computer Engineering,

North South University, Bashundhara, Dhaka-1229, Bangladesh

Submission Date:

1. Background study: Malaria is a serious and sometimes fatal disease caused by a parasite that commonly infects a certain type of mosquito which feeds on humans. People who get malaria are typically very sick with high fevers, shaking chills, and flu-like illness. Although malaria can be a deadly disease, illness and death from malaria can usually be prevented. [1]

Five species of Plasmodium (single-celled parasites) can infect humans and cause illness:

Plasmodium falciparum (or P. falciparum)

Plasmodium malariae (or P. malariae)

Plasmodium vivax (or P. vivax)

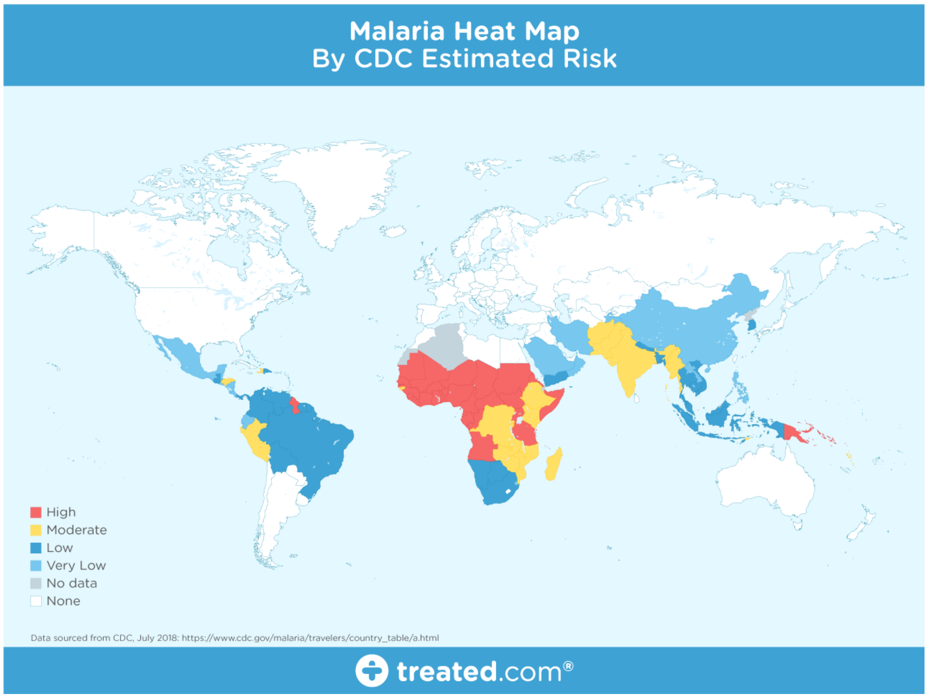
Plasmodium ovale (or P. ovale)

Plasmodium knowlesi (or P. knowlesi)

Falciparum malaria is potentially life-threatening. Patients with severe falciparum malaria may develop liver and kidney failure, convulsions, and coma. Although occasionally severe, infections with P. vivax and P. ovale generally cause less serious illness, but the parasites can remain dormant in the liver for many months, causing a reappearance of symptoms months or even years later. [2]

Malaria is an ancient disease and references to what was almost certainly malaria occur in a Chinese document from about 2700 BC, clay tablets from Mesopotamia from 2000 BC, Egyptian papyri from 1570 BC and Hindu texts as far back as the sixth century BC. Such historical records must be regarded with caution but moving into later centuries we are beginning to step onto firmer ground. The early Greeks, including Homer in about 850 BC, Empedocles of Agrigentum in about 550 BC and Hippocrates in about 400 BC, were well aware of the characteristic poor health, malarial fevers and enlarged spleens seen in people living in marshy places. For over 2500 years the idea that malaria fevers were caused by miasmas rising from swamps persisted and it is widely held that the word malaria comes from the Italian mal'aria meaning spoiled air although this has been disputed. [3]

Globally, the World Health Organization estimates that in 2019, 229 million clinical cases of malaria occurred, and 409,000 people died of malaria, most of them children in Africa. Because malaria causes so much illness and death, the disease is a great drain on many national economies. Since many countries with malaria are already among the poorer nations, the disease maintains a vicious cycle of disease and poverty.



Usually, people get malaria by being bitten by an infective female Anopheles mosquito. Only Anopheles mosquitoes can transmit malaria and they must have been infected through a previous blood meal taken from an infected person. When a mosquito bites an infected person, a small amount of blood is taken in which contains microscopic malaria parasites. About 1 week later, when the mosquito takes its next blood meal, these parasites mix with the mosquito's saliva and are injected into the person being bitten.

Because the malaria parasite is found in red blood cells of an infected person, malaria can also be transmitted through blood transfusion, organ transplant, or the shared use of needles or syringes contaminated with blood. Malaria may also be transmitted from a mother to her unborn infant before or during delivery ("congenital" malaria).

Plasmodium falciparum is the type of malaria that most often causes severe and life-threatening malaria; this parasite is very common in many countries in Africa south of the Sahara Desert. People who are heavily exposed to the bites of mosquitoes infected with P. falciparum are most at risk of dying from malaria. People who have little or no immunity to malaria, such as young children and pregnant women or travelers coming from areas with no malaria, are more likely to become very sick and die. Poor people living in rural areas who lack access to health care are at greater risk for this disease. As a result of all these factors, an estimated 90% of deaths due to malaria occur in Africa south of the Sahara; most of these deaths occur in children under 5 years of age.

You can take medicine to treat malaria. You can also take medicine to make it less likely you'll get the disease.

Using drugs to prevent sickness is known as prophylactic medicine. You don’t have the disease, and you’re taking medicine to keep it that way.

But malaria pills aren’t 100% effective in preventing the disease. The pills should be used with other preventive steps, such as wearing insect repellant, wearing long sleeves, and protecting your sleeping area with a net or other kind of bed treatment. [4]

2. Problem Statement: If someone has malaria virus within him then he has to do a blood test in the hospital. To detect malaria the doctor has to see a smear image of the blood whether his blood is affected by malaria or not. If it is affected then he is malaria positive and if not, he is negative. But the maximum time the image of a healthy blood smear image and affected blood smear image is very much the same. It’s hard to identify the malaria virus from the image in the naked eye. For that, the patient has to test his blood multiple time to see malaria or go home knowing that he is not affected but the reality is the opposite. Sometimes the malaria virus can be found in a very minor position. So, it’s not possible to detect many times. If it remains undetected then it can spread and people can die.

With the help of deep learning, our model can detect the malaria virus from the blood smear image very fine. Our model can analyze and identify which blood report is affected and which is not. So, it will be very easy to detect and many people’s lives can be saved by this deep learning model.

3. Related Work:

Using computing algorithms for cost-effective solutions to support interoperable healthcare [5] in lowering diseases has been a major focus of research in recent decades. Neto et al. [6], for example, suggested a simulator for replicating epidemiological events in real time. For malaria identification and classification, Kaewkamnerd et al. [7] presented a five-phase image analysis approach. Anggraini et al. [8] created a program that uses image segmentation techniques to separate blood cells from their surroundings. In addition, Rajaraman et al. [9] created feature extractors for uninfected and parasitized blood cell categorization using pretrained CNN-based deep learning models to aid illness detection. Using the underlying data, the researchers employed an experimental technique to find the best model layers. Two fully connected dense layers and three convolutional layers make up the CNN model. The performance is tested by extracting features from uninfected and parasitized blood cells using VGG-16, AlexNet, Xception, DenseNet-121, and ResNet-50. Gopakumar et al. [10] and Liang et al. [11] both offer exclusively CNN-based malaria classifiers, in contrast to [12].

MOMALA [13] is a smartphone and microscope-based application designed to swiftly and inexpensively detect malaria. On a standard blood-smeared slide, the MOMALA app can detect the presence of malaria parasites. The blood smear is photographed using a phone camera mounted to the microscope's ocular, which is subsequently analyzed. Currently, the application is heavily reliant on microscopes that are large, bulky, and difficult to carry.

[14] developed a mobile app that captures photographs of blood samples and detects malaria almost instantly. We can evaluate blood samples without consulting microscope technicians by using a smartphone app. The program works by clamping a smartphone to the eyepiece of a microscope, then

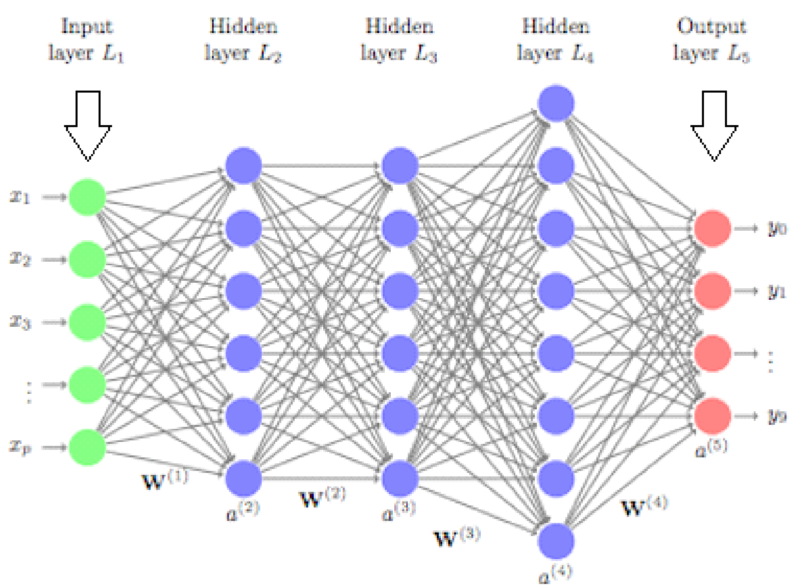
analyzing the photos of the blood sample and drawing a red circle on malaria parasites. The case is later reviewed by a lab worker. Any machine learning method's effectiveness hinges on the extraction of useful features. The majority of computer-assisted diagnosis solutions that employ machine learning models for image analysis rely on manually created features to make decisions [15–16]. In order to examine the diversity in image size, color, background, angle, and position of interests, the method also requires computer vision knowledge. Deep learning algorithms can be used successfully to overcome the obstacles that a hand-engineered feature extraction approach presents [17]. Deep learning models use a series of consecutive layers with hidden nonlinear processing units to discover hierarchical feature relations in raw image data. The low-level features that are abstracted from higher-level characteristics help with operations including nonlinear decision-making, learning complexity, feature extraction, and classification [18]. Furthermore, deep learning models outperform kernel-based methods like Support Vector Machines (SVMs) when dealing with enormous amounts of data and computational resources, making them highly scalable [19].

A related body of work in the cognitive computing field has made a similar contribution. Zhang et al. [20] recommended utilizing an interactive robot as a security method for authentication and access control while controlling access to private data stored in the cloud. In a second effort [21], they proposed a revolutionary cognitive IoT paradigm based on cognitive computing technologies. A group of researchers [22] also proposed Mech-RL, an agent-based literary consultant and a novel channel of the meta-path learning approach. Furthermore, similar to our battery-operated mobile-based malaria detection application that can be easily deployed to edge and IoT devices, there is a slew of research aimed at developing frameworks on mobile edge to deliver a variety of related services such as secure in-home IoT therapy, content recommendations, and position-based services for network amenities.

To conclude, relevant work in the literature generally used several pretrained CNN variants for malaria diagnosis in blood smear pictures, such as AlexNet, VGG-16, ResNet-50, Xception, DenseNet-121, and customized CNN models, and produced relatively better results than utilizing a bespoke CNN architecture. However, these results were produced by feature extraction and subsequent training, which took a considerable time in some situations a little over 24 hours in certain cases. Furthermore, the size and intricacy of these models make them unsuitable for usage with battery-powered mobile devices. In contrast, we created a simpler and more computationally efficient CNN model with fewer trainable parameters (discussed in the Model Configuration section), yet it produced comparable or better results, keeping in mind that our model would be deployed on battery-powered edge and IoT devices like a smart phone. Furthermore, most techniques in the literature use a de facto SGD optimizer with a variety of learning rate schedules, including adaptive learning rates, which suffer from saddle point or local minima problems. Using an SGD optimizer with cyclical learning rate schedule and an automatic optimal learning rate finder, we were able to achieve faster model convergence with fewer experiments and hyperparameter changes. Finally, most cutting-edge models include picture augmentation to improve model generalizability at the cost of increased training time. By properly optimizing hyperparameters such as learning rate, regularization by batch normalization, and moderate dropouts in convolutional and dense layers, our model without data augmentation displays faster convergence and generalizability to unseen data.

Among the studied malaria detection models in the literature, the models proposed in based on custom CNN and its pretrained variants seem to be closest to our model. Hence, we performed a state-of-the-art comparison with these models to demonstrate the feasibility of using our model in a mobile-based system especially in remote disaster survival areas.

4. Project proposal: To solve that problem we want to implement deep learning. Our model based on deep learning can solve this problem accurately. As anyone who has witnessed firsthand knows, healthcare delivery in low-resource settings is fundamentally different from more affluent settings. Artificial Intelligence, including Machine Learning and more specifically Deep Learning, has made amazing advances over the past decade. Significant resources are now dedicated to problems in the field of medicine, but with the potential to further the digital divide by neglecting underserved areas and their specific context. In the general case, Deep Learning remains a complex technology requiring deep technical expertise. Deep learning, also known as hierarchical learning or deep structured learning, is a type of machine learning that uses a layered algorithmic architecture to analyze data. In deep learning models, data is filtered through a cascade of multiple layers, with each successive layer using the output from the previous one to inform its results. Deep learning models can become more and more accurate as they process more data, essentially learning from previous results to refine their ability to make correlations and connections. Deep learning is loosely based on the way biological neurons connect with one another to process information in the brains of animals. Similar to the way electrical signals travel across the cells of living creates, each subsequent layer of nodes is activated when it receives stimuli from its neighboring neurons. In artificial neural networks (ANNs), the basis for deep learning models, each layer may be assigned a specific portion of a transformation task, and data might traverse the layers multiple times to refine and optimize the ultimate output. These "hidden" layers serve to perform the mathematical translation tasks that turn raw input into meaningful output.



One type of deep learning, known as convolutional neural networks (CNNs), is particularly well-suited to analyzing images, such as MRI results or x-rays. CNNs are designed with the assumption that they will be processing images, according to computer science experts at Stanford University, allowing the networks to operate more efficiently and handle larger images. As a result, some CNNs are approaching – or even surpassing – the accuracy of human diagnosticians when identifying important features in diagnostic imaging studies.

5. Objective of the project:

We want to use deep learning to solve this problem. We want to increment Convolutional Neural Networks (CNNs),Long Short Term Memory Networks (LSTMs),Recurrent Neural Networks (RNNs) algorithms in our project.

6. Output of the project/expected result of the project:

With our output of the project, we want to write a journal and publish it. And our expected result will be to get the highest accuracy than any other existing similar system.

7.Feasibility study indicating at least two possible solutions:

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks.

We are going to explain 2 of our algorithms.

Convolutional Neural Networks (CNN): A Convolutional Neural Network (CNN) is a type of neural network that specializes in processing data with a grid-like architecture, such as an image. A binary representation of visual data is a digital image. It consists of a grid-like arrangement of pixels with pixel values indicating how bright and what color each pixel should be. The second we perceive an image, our brain analyzes a massive amount of data. Each neuron has its own receptive field and is coupled to other neurons in such a way that the full visual field is covered. In the biological vision system, each neuron responds to stimuli only in a limited part of the visual field called the receptive field, and each neuron in a CNN analyzes data only in its receptive field. A CNN typically has three layers: a convolutional layer, a pooling layer, and a fully connected layer.

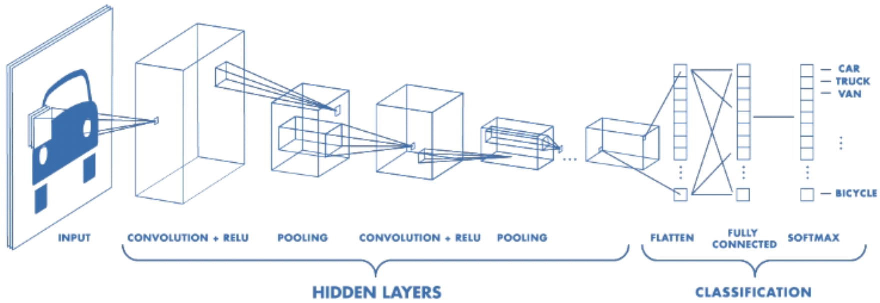


Figure 1: Architecture of a CNN

The CNN's main building block is the convolution layer. It is responsible for the majority of the network's computational load. This layer does a dot product between two matrices, one of which is a set of learnable parameters known as a kernel, and the other is the restricted section of the receptive field. The kernel is less in size than a picture, but it has more depth. This means that if the image has three (RGB) channels, the kernel height and width will be modest spatially, but the depth will span all three.

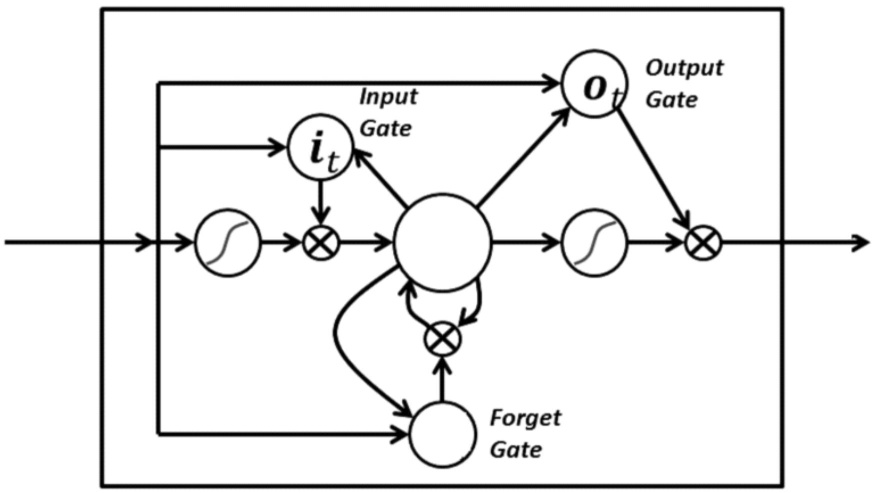
The kernel slides over the image's height and breadth during the forward pass, providing an image representation of that receptive region. This creates an activation map, a two-dimensional representation of the image that shows the kernel's response at each spatial place in the image. The sliding size of the kernel is called a stride.

If we have an input of size W x W x D and Dout number of kernels with a spatial size of F with stride S and amount of padding P, then the size of output volume can be determined by the following formula:

$$W_{out} = \frac{W - F + 2P}{S} + 1$$

Formula for Convolution Layer

Long Short Term Memory Networks (LSTMs): Long Short-Term Memory (LSTM) networks are an extension of RNN that extend the memory. LSTM are used as the building blocks for the layers of a RNN. LSTMs assign data “weights” which helps RNNs to either let new information in, forget information or give it importance enough to impact the output. The units of an LSTM are used as building units for the layers of a RNN, often called an LSTM network. LSTMs enable RNNs to remember inputs over a long period of time. This is because LSTMs contain information in a memory, much like the memory of a computer. The LSTM can read, write and delete information from its memory. This memory can be seen as a gated cell, with gated meaning the cell decides whether or not to store or delete information (i.e., if it opens the gates or not), based on the importance it assigns to the information. The assigning of importance happens through weights, which are also learned by the algorithm. This simply means that it learns over time what information is important and what is not. In an LSTM you have three gates: input, forget and output gate. These gates determine whether or not to let new input in (input gate), delete the information because it isn't important (forget gate), or let it impact the output at the current timestep (output gate). Below is an illustration of a RNN with its three gates:



The gates in an LSTM are analog in the form of sigmoids, meaning they range from zero to one. The fact that they are analog enables them to do backpropagation.

The problematic issues of vanishing gradients is solved through LSTM because it keeps the gradients steep enough, which keeps the training relatively short and the accuracy high.

8. Solutions adopted and the reasons for that:

Deep learning involves the use of computer systems known as neural networks. In neural networks, the input filters through hidden layers of nodes. These nodes each process the input and communicate their results to the next layer of nodes. This repeats until it reaches an output layer, and the machine provides its answer.

There are different types of neural networks based on how the hidden layers work. Image classification with deep learning most often involves convolutional neural networks, or CNNs. In CNNs, the nodes in the hidden layers don't always share their output with every node in the next layer (known as convolutional layers).

LSTM models need to be trained with a training dataset prior to its employment in real-world applications. Some of the most demanding applications are discussed below:

1.Language modelling or text generation, that involves the computation of words when a sequence of words is fed as input. Language models can be operated at the character level, n-gram level, sentence level or even paragraph level.

2.Speech and Handwriting Recognition

3.Music generation which is quite similar to that of text generation where LSTMs predict musical notes instead of text by analyzing a combination of given notes fed as input.

For these kinds of advantages, we adopted this solution.

9. Working steps (Work plan):

First week: Collecting dataset.

Second week: Reading a lot of papers about deep learning

Third week: Pre-processing the data.

Fourth week: Feature selection of data.

Fifth week: Implement one algorithm.

Sixth week: implement the 2nd algorithm

Seventh week: Implement the 3rd algorithm.

8th week: Start writing report.

10. Major Milestones:

1. Analyze existing system.

2. Dataset collection.

3. Data pre-processing.

4. Feature selection.

5. Training.

6.Testing.

11. Research methodology:

In this paper, data are obtained from Kaggle dataset. There are 2 types of data classes. These data are used to diagnose malaria. The data in the first class are non-parasitic and in the second class there are parasitic data. The data set contains 3730 parasitic data and 3000 healthy data. malaria images were classified using CNN methods, which are very popular in recent years. The application was implemented in Matlab environment and using AlexNet, ResNet50, DenseNet201, Vgg19, GoogleNet and Inceptionv3 models. First, the original data was classified into 6 different architectures and then the Gauss filter and Median filter were applied to the data set.

https://www.kaggle.com/itsdaniyal/malerial-cell-classification-dataset

12. Detailed diagrams for the complete system and all subsystems:

Deep learning allows computers to process and learn data. The biggest feature that distinguishes deep learning models from traditional neural networks is that deep learning models consist of multiple layers. Deep learning goes back to pause in 2012. After the Deep Learning model won the ImageNet competition in 2012, the popularity of deep learning began to increase rapidly. One of the reasons that deep learning has become popular recently is the development of cards with increased processing speed. Increasing amounts of data also increased the tendency to deep learning.

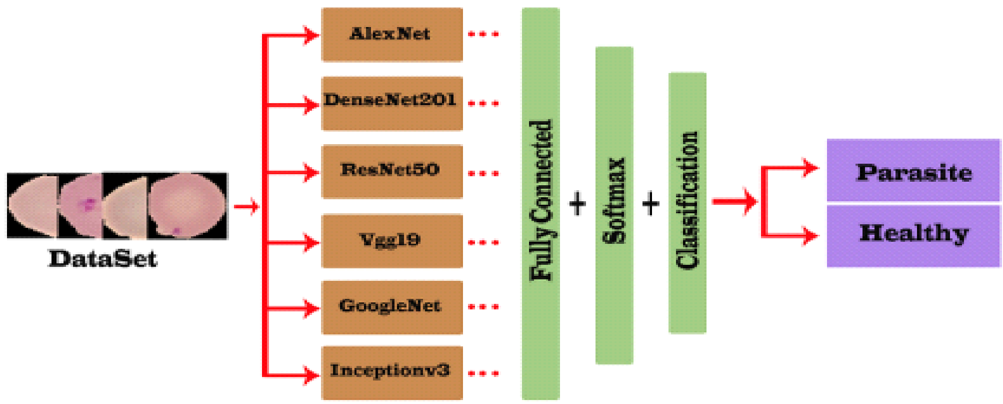


Figure 1. Classification of original data with CNN architectures

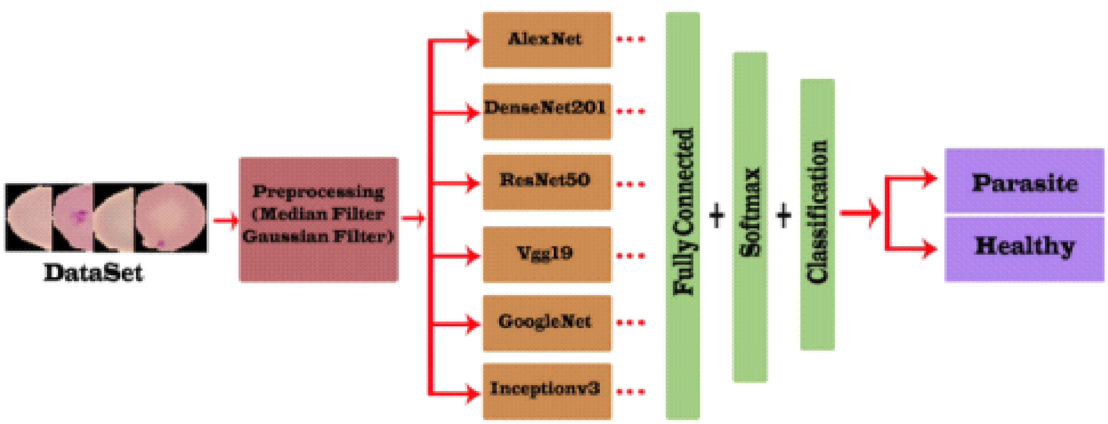
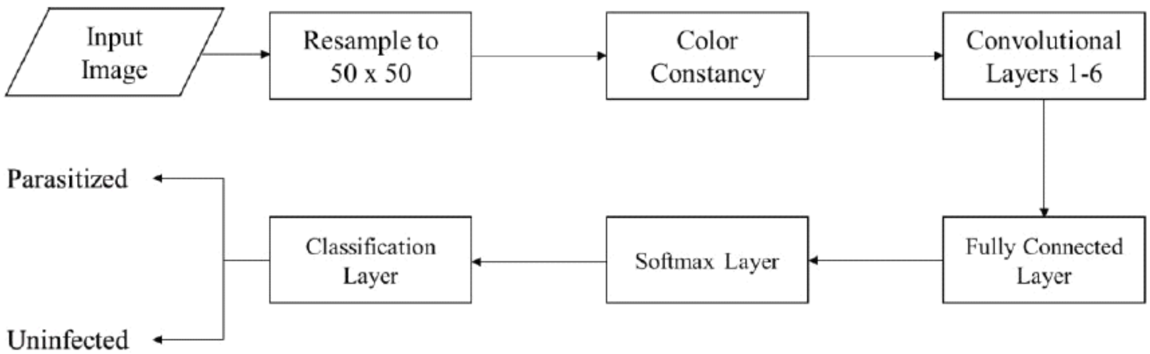


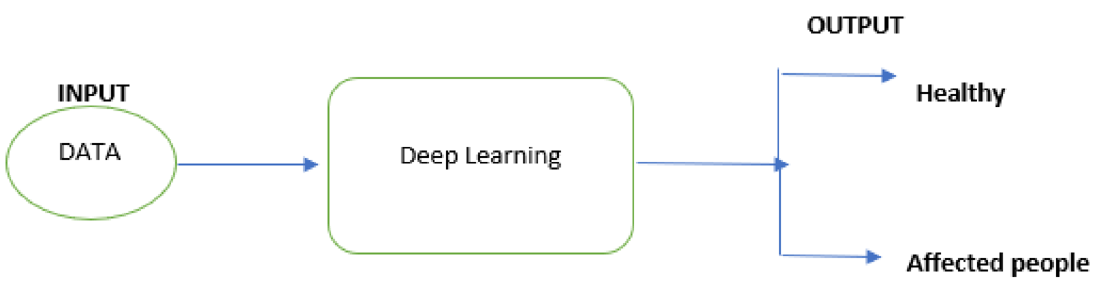
Figure 2. Classification of data after filters with CNN architectures



13. Explanation of the functioning of the complete system, and all subsystems:

In this paper, convolutional neural networks are used. CNNs are one of the most preferred deep learning networks for computer vision applications such as image classification. CNN networks consist of multiple layers. These layers can be classified as Convolution Layer, Fully Connected Layer, Pooling Layer, Rectified Linear Unit (Relu) Layer, Dropout Layer, Normalization Layer and Softmax Layer.
CNN is primarily trained with network data. When the network is fed with input images, it passes through multiple layers to complete the learning process. Figure 1 shows how the original data is classified. Original images are individually processed with DenseNet201, ResNet50, Alexnet, Vgg19, G oogleNet and Inceptionv3 architectures and then classified as parasite and healthy. Then, Median Filter and Gaussian Filter were operative separately to all data in dataset. The structure of Figure 2 is used for the classification of the data obtained.

17. Figures and graphs showing inputs and outputs, as applicable:



Required Software and tools:

In this project we are going to use anaconda, jupyter notebook. For programming language, we are going to use python.

Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda® distribution that allows you to launch applications and easily manage conda packages, environments, and channels without using command-line commands. Navigator can search for packages on Anaconda.org or in a local Anaconda Repository. It is available for Windows, macOS, and Linux

The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more.

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together. Python's simple, easy to learn syntax emphasizes readability and therefore reduces the cost of program maintenance. Python supports modules and packages, which encourages program modularity and code reuse. The Python interpreter and the extensive standard library are available in source or binary form without charge for all major platforms, and can be freely distributed.

Target Population:

Our project is for the welfare of common people of the world. In this project the patient can see if he is malaria affected or not. Normally malaria is detected by doctors. So sometimes it is hard to detect malaria in cell. So doctors can’t decide the patient is affected or not. Our system will detect is accurately and very quickly. It can reduce the death rate of the malaria in the world.

Is it innovative?

Yes, it is innovative. In other related paper work we can see that the accuracy of the result is below 90%. Our attempt will be to get accuracy more than 90%. We are taking our dataset from Kaggle website which is very efficient.

Is this project sustainable?

Yes, this project is sustainable. We don’t need to change it. It is a software project. So, in near future it needs an update it will update automatically.

Is there any possibility to scale up the project?

Yes, it is possible to scale up the project. We are just implementing the model. In future we can expand our work by application development. We can also implement bigger dataset to expand our work.

Is there any opportunity of income generation from the project?

No. But in future of we turn work into application in mobile or make a website we might get paid.

Do you need financial support for future extension?

No. We don't need any financial support for future extension.

How people will be benefit from the project?

Our project is for the common people. This system can detect malaria in cell very accurately and quickly. So, for this many people's life can be save. They can get proper treatment.

What are the risks? How the risks will be managed?

There is no risk. Sometimes if we implement our algorithm, it can show lower accuracy. If the accuracy is low then we can add more algorithm and manipulate our data.

Disabled will benefit?

Yes. People who can't reach hospital they can see their test result from their mobile and computer. So it will greatly help the disabled people.

36. Is there any research publication on the problem statement?

Title: Visualizing Deep Learning Activations for Improved Malaria Cell Classification

Author: Rajaraman Sivaramakrishnan, Sameer Antani, Stefan Jaeger

In this study, we propose the advantages offered through visualizing the features and activations in a simple, customized deep learning model. We apply it to the challenge of malaria cell classification, and as a result the model achieves 98.61% classification accuracy with lower model complexity and computation time. It is found to considerably outperform the state of the art including other pre-trained deep learning models.

Title: Performance analysis of machine learning and deep learning architectures for malaria detection on cell images.

Author: Barath Narayanan Narayanan, Redha Ali, Russell C. Hardie.

In this research, we have presented several deep learning-based classification approaches for CAD of Plasmodium. All the classification algorithms presented in this paper performed relatively well with minimum performance being 86% and 0.932 in terms of overall accuracy and AUC respectively. All the deep learning and transfer learning-based approaches performed better than bag-of-features and SVM based classification model.

Title: Classification of Malaria-Infected Cells Using Deep Convolutional Neural Networks.

Author: W. David Pan, Yuhang Dong and Dongsheng Wu

This comparative study indicated that data augmentation in the feature domain seemed to be more robust in terms of preserving the high classification accuracies. We plan to expand the existing dataset by including more pathologist-curated cell images and further evaluate the effectiveness of the proposed data augmentation methods.

38.Conclusion: In this paper, malaria images were classified using CNN methods, which are very popular in recent years. The application was implemented in Matlab environment and using AlexNet, ResNet50, DenseNet201, Vgg19, GoogleNet and Inceptionv3 models. First, the original data was classified into 6 different architectures and then the Gauss filter and Median filter were applied to the data set. After both filters, the dataset was again classified into the AlexNet, ResNet50, DenseNet201, Vgg19, GoogleNet and Inceptionv3 architectures. As a result, 6 different accuracy values were obtained in 6 different architectures for the original data, 6 different accuracy values with Gauss filter applied data and 6 different accuracy values with median filter applied data. The highest accuracy value was obtained from the Gauss filter images with 97.83% classification of DenseNet201 architecture. The accuracy of Gaussian filtered data increased significantly. Working with Gaussian filtered data increased our accuracy when classifying. More successful results were obtained with Gaussian filter applied data. Once malaria data is classified, it will be easier to draw conclusions and diagnose the disease by specialists. Given the wide acceptance of deep learning, the importance of large annotated data image repositories for training is now widely understood, leading to a great support of data acquisition efforts. This will likely lead to larger test suites on patient level, allowing for more standardized evaluations and extensive field testing. Given these developments, automated microscopy is very much in the race toward a cheap, simple, and reliable method for diagnosing malaria.

18. Bibliography:

[1] Centers for Disease Control and Prevention https://www.cdc.gov/malaria/about/faqs.html

[2] Standford Health Care. What Are the Different Types of Malaria Parasites? https://stanfordhealthcare.org/medical-conditions/primary-care/malaria/types.html

[3] History of the discovery of the malaria parasites and their vectors https://parasitesandvectors.biomedcentral.com/articles/10.1186/1756-3305-3-5

[4] https://www.webmd.com/a-to-z-guides/malaria-pills

[5] M. Masud, M. S. Hossain, and A. Alamri, "Data interoperability and multimedia content management in e-health systems," IEEE Transactions on Information Technology in Biomedicine, vol. 16, no. 6, pp. 1015–1023, 2012.

[6] O. B. Leal Neto, C. M. Albuquerque, J. O. Albuquerque, and C. S. Barbosa, "The schisto track: a system for gathering and monitoring epidemiological surveys by connecting geographical information systems in real time," JMIR Mhealth Uhealth, vol. 2, no. 1, article e10, 2014.

[7] S. Kaewkamnerd, C. Uthaipibull, A. Intarapanich, M. Pannarut, S. Chaotheing, and S. Tongsima, "An automatic device for detection and classification of malaria parasite species in thick blood film," BMC Bioinformatics, vol. 13, Supplement 17, p. S18, 2012.

[8] D. Anggraini, A. S. Nugroho, C. Pratama, I. E. Rozi, A. A. Iskandar, and R. N. Hartono, "Automated status identification of microscopic images obtained from malaria thin blood smears," in Proceedings of the 2011 International Conference on Electrical Engineering and Informatics, Bandung, Indonesia, July 2011.

[9] S. Rajaraman, S. K. Antani, M. Poostchi et al., "Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images," PeerJ, vol. 6, article e4568, 2018.

[10] G. P. Gopakumar, M. Swetha, G. S. Siva, and G. R. K. Sai Subrahmanyam, "Convolutional neural network-based malaria diagnosis from focus stack of blood smear images acquired using custom-built slide scanner," Journal of Biophotonics, vol. 11, no. 3, 2018.

[11] Z. Liang, A. Powell, I. Ersoy et al., "CNN-based image analysis for malaria diagnosis," in 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 493–496, Shenzhen, China, December 2016.

[12] S. Rajaraman, S. K. Antani, M. Poostchi et al., "Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images," PeerJ, vol. 6, article e4568, 2018.

[13] "MOMALA," https://momala.org/malaria-diagnosis/.

[14] "This New App Helps Doctors Diagnose Malaria in Just 2 Minutes," https://www.globalcitizen.org/en/content/app-diagnose-malaria-uganda.

[15] N. E. Ross, C. J. Pritchard, D. M. Rubin, and A. G. Dusé, "Automated image processing method for the diagnosis and classification of malaria on thin blood smears," Medical & Biological Engineering & Computing, vol. 44, no. 5, pp. 427–436, 2006.

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

[17] M. S. Hossain, M. Al-Hammadi, and G. Muhammad, "Automatic fruit classification using deep learning for industrial applications," IEEE Transactions on Industrial Informatics, vol. 15, no. 2, pp. 1027–1034, 2019.

[18] M. Usama, B. Ahmad, J. Wan, M. S. Hossain, M. F. Alhamid, and M. A. Hossain, "Deep feature learning for disease risk assessment based on convolutional neural network with intra-layer recurrent connection by using hospital big data," IEEE Access, vol. 6, pp. 67927–67939, 2018.

[19] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," Journal of Machine Learning Research, vol. 15, pp. 1929–1958, 2014.

[20] Y. Zhang, Y. Qian, D. Wu, M. Shamim Hossain, A. Ghoneim, and M. Chen, "Emotion-aware multimedia Systems security," IEEE Transactions on Multimedia, vol. 21, no. 3, pp. 617–624, 2019.

[21] Y. Zhang, X. Ma, J. Zhang, M. S. Hossain, G. Muhammad, and S. U. Amin, "Edge intelligence in the cognitive internet of things: improving sensitivity and interactivity," IEEE Network, vol. 33, no. 3, pp. 58–64, 2019.

[22] X. Ma, R. Wang, Y. Zhang, C. Jiang, and H. Abbas, "A name disambiguation module for intelligent robotic consultant in industrial internet of things," Mechanical Systems and Signal Processing, vol. 136, article 106413, 2020.