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Mobile application for early detection of Malaria in children: case of Western Kenya.

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Mobile Application for Early Detection of Malaria in Children: Case of Western Kenya

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Abstract

Malaria is the most infectious disease and continues to be a major global health problem with part of the world's population being at risk to various degrees of malaria risk. In many endemic countries, the clinical diagnosis has been proven to be the only method used to decide on the correct treatment even though the method is not that accurate and may be limited by the low specificity of the various signs and symptoms of malaria. Some of the challenges affecting the early detection of malaria include and are not limited to severe anemic and respiratory diseases in children and delayed detection of malaria leading to irreversible and fatal complications in children. These challenges led to the implementation of a mobile application for early detection of malaria in children. Several measures have been made in combating malaria, however, the indicators in Africa still do not show any promise for elimination in the future as the infections still result in high mortality and a rise in the high rate of children affected with malaria. Reducing the number of deaths in children affected by malaria would yield huge gains in reducing the overall under five mortality and morbidity rates in malarial dominant areas. The purpose of this research is to be able to detect malaria at an early stage in children in the regions of Western Kenya. The solution proposed, was coming up with a mobile application that will facilitate the most suitable and convenient way of malaria disease detection, especially in rural and remote regions. The camera of the smartphone will act as a microscope and there will be no need to attach it to the eyepiece of the microscope. This enhances mobility and the Remote Health Worker is able to diagnose the patient and offer treatment. This will allow real time treatment and the records will be uploaded to the database for the next visit from the Remote Health Worker. The study used agile software development model to design, develop and test the application since it is iterative. The mobile malaria detection application was developed and tested to be used by the resulting model which had an accuracy level of 94%. The findings from the usability acceptance test showed that the users acknowledged that the application was easy to navigate, use and the instructions were clear to use as a first-time user.

Keywords: Detection, Respiratory Diseases, Mortality, Morbidity

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List of Abbreviations

CDC	Center for Disease Control
CHW	Remote Health Worker
CNN	Convolutional Neural Network
DTI-R	Diagnosis Treatment Investigation Response
GIS	Geographic
IoT	Internet of Things
ITN	Insecticide Treated Net
HIV/AIDS	Human Immunodeficiency Virus Acquired Immunodeficiency Syndrome
KMIS	Kenya Malaria Indicator Survey
MIS	Malaria Indicator Survey
NMCP	National Malaria Control Programme
P. falciparum	Plasmodium falciparum
RDT	Rapid Diagnostic Test
SVM	Support Vector Machine
WHO	World Health Organization

Definition of Terms

Mortality: This is death especially in large numbers (Hernandez & Kim, 2021)

Morbidity: This is the condition of being diseased (Hernandez & Kim, 2021)

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Chapter 1. Introduction

1.1 Background of the Study

Malaria is the most infectious disease and continues to be a major global health problem with over 40% of the world's population being at risk to various degrees of malaria risk (Dhorda et al., 2020a). However, in many endemic countries, the clinical diagnosis has been proven to be the only method used to decide on the correct treatment even though the method is not that accurate and may be limited by the low specificity of the various common malaria signs and symptoms.

There are five types of malaria as shown in table 1.1 below by (Lalremruata et al., 2017). They include Plasmodium malariae (or P. malariae), Plasmodium falciparum (or P. falciparum), Plasmodium ovale (or P. ovale), Plasmodium knowlesi (or P. knowlesi) and Plasmodium vivax (or P. vivax). The most common is Plasmodium falciparum which is life-threatening according to (Lalremruata et al., 2017) report, and may lead to death.

Table 1.1 Characteristics of Malaria Parasite *(Lalremruata et al., 2017)*

Parasite	Characteristics		
	Incubation Period	Fever Period	RBC Affect
P. Falciparum	6-14 days	48 hrs.	All
P. Vivax	12-17 days	48 hrs.	Reticulocytes
P. Malaria	13-40 days	72 hrs.	Matured RBC
P. Ovale	9-18 days	50 hrs.	Reticulocytes

Several measures have been made in combating malaria, however, the indicators in Africa still do not show any promise for elimination in the future as the infections still result in high mortality and a rise in the high rate of children affected by malaria. Children who are under the age of five years are the most vulnerable with most of the mortality occurring in this age group. In Kenya, the transmission patterns are mostly influenced by altitude, varying patterns of rainfall, vector species, as well as the intensity of biting. Malaria in Kenya occurs in most parts of the Coast, Nyanza, and Western counties (Sultana et al., 2017a). In these areas, the transmission rate is very high. Western Kenya was the area of study with regards to the early detection of malaria in children below the age of five years old.

The role of innovative tools becomes crucial in the fight against malaria. Several technologies have been in place in the detection and treatment of malaria such as the rapid diagnostic tests. An example for the same would be the phone based RDT readers. In this case a smartphone is used for quantitative reading of the parasite that is used for both Android and iPhone. The images of the rapid diagnostic test are acquired, in either transmission or reflection and then processed in real time to deliver the test results within 10 minutes(Poostchi et al., 2018). The other form of technology that was used to detect malaria was by use of the microfluidic chip, which was connected to the phone camera which would in turn analyze the parasites and deliver the results in 10 minutes.

Machine learning has been widely used in coming up with detection models for diseases. Some of the machine learning techniques that have been used in the detection of malaria include the use of the Artificial Neural Network. Sometimes it is preferred because of its usefulness in pattern recognition, abstraction, generalization, identification, as well as interpretation of any noisy inputs. Though, it is not fit for image processing because these layers of networks can easily experience overfitting. In addition, it has several trainable parameters which require more powerful processors to process hence making the model not suitable to be used with a mobile device(Taher et al., 2019).

Another form of machine learning that has been used in the detection of malaria, is the use of the Convolutional Neural Network. This model has been used to come up with the mobile application for the detection of malaria due to its advantage and ability to use many similar neuron of the same kind. This allows the CNN model to have numerous neurons which allows the actual parameters that will be learned to be small in number. Most of the related works as discussed in this research have used CNN to model their application sin coming up with a detection tool for malaria(Hussain et al., 2018). This model gives a faster and cheaper method for detecting the malaria parasites.

There have been various control strategies and systems which have been effective but at some point, they have been limited by lack of proper early diagnostic for detection specifically in remote areas. The technologies available include and not limited to Biosensors for detection of malaria according to (Krampa et al., 2020), and malaria screener smart phone based application that works after attaching the mobile phone camera to a microscope by (Yu et al., 2020a).

The main purpose of coming up with this mobile application was to facilitate the most suitable and convenient way of malaria disease detection, especially in rural and remote regions. In this study, we proposed a mobile application to aid in early detection of malaria in children. The camera of the smartphone will act as a microscope and there will be no need to attach it to the eyepiece of the microscope. The classification will be done using Convolutional Neural Network algorithm to find Plasmodium Falciparum and group them.

1.2 Problem Statement

There is lack of timely detection of malaria in children who are five years and below that would lead to fatal implications and irreversible conditions if malaria is detected late. Rapid and effective treatment of malaria is of essence in children as it ensures prompt and accurate early detection of malaria (Amir et al., 2018).Most deaths in children happen within the first twenty-four hours after showing malaria like signs and symptoms after admission to the nearest health facility. This is due to a combination of the following factors, high occurrence of asymptomatic infection in some areas, nonspecific clinical representation of the disease, insufficient access to health facilities and personnel, lack of early detection of signs and symptoms in children as well as multiple misdiagnosis of the disease in children.

Based on these issues there is need to develop a mobile application to facilitate the most suitable and convenient way of malaria disease detection affecting children, especially in rural and remote regions. This will allow real time treatment and the records will be uploaded to the database for the next visit from the remote health worker. This will provide a good forecast period for the necessary interventions by the remote health worker in due time.

Detecting malaria at an early stage in children will greatly reduce the time taken during observation, any analysis projected and inference and will provide a second unbiased consistent opinion.

1.3 Objectives

1.3.1 General Objective

The general objective of this study is to develop a remotely accessible healthcare application which will use machine learning algorithm to classify and find the Plasmodium Falciparum to be used by the medical practitioners for use in early detection of malaria in children.

1.3.2 Specific Objectives

i. To analyze the challenges facing the early detection of malaria in children.
ii. To evaluate the techniques used in the approaches for the detection of malaria in children.
iii. To design and develop a mobile application tool kit for early detection of malaria in children.
iv. To validate the mobile application tool kit.

1.4 Research Questions

i. What are the challenges faced in the early detection of malaria in children?
ii. What are the techniques used in the early detection of malaria in children?
iii. How will the mobile application tool kit be designed and developed?
iv. How will the mobile application tool kit be validated?

1.5 Justification

Rapid and effective treatment of malaria is of essence in children as it ensures prompt and accurate early detection of malaria. Children who are five years and below are thought to be the most vulnerable to malaria since most deaths happen within the first twenty-four hours after showing malaria like signs and symptoms after admission to the nearest health facility.

The objective of this study is to develop a mobile application that will help detect malaria at an early stage in order to reduce the morbidity and mortality rate in children affected by malaria using machine learning algorithm to remove any form of misdetection by training the inference model with image dataset to find Plasmodium Falciparum accurately.

This will reduce the time of observation, reduce and mitigate against the rapid emergence and spread of drug resistance in children whose immunity is still developing, any analysis to be done and inference and will provide a second unbiased consistent opinion hence reduce the mortality and morbidity rate in children. It will be able to provide a good forecast period for the necessary interventions which will be put in place to address the epidemic. In return there will be accurate detection of malaria in children and proper administration of treatment in due time.

The mobile tool kit is expected to be helpful to the ministry of health and other entities involved in the management of malaria.

1.6 Scope

The study mainly focused on developing a mobile application that will be integrated in the users' mobile phone. The classification was done using the convolutional neural network to find Plasmodium falciparum. The data used to train and test the model was collected from secondary data sources. The assumptions made were that the variables chosen for the detection of malaria were ultimate and true inputs. The system will be used by the remote health workers who will perform the registration and detection process.

1.7 Limitation

The proposed mobile application will be developed using the android platform and thus will disregard other application development platforms such as the iOS.The researcher wished to develop a fully functional system. Due to time limitations and other resources, the final product was a prototype covering only the basic functionalities and variable.

Chapter 2. Literature Review

2.1 Introduction

The spatial and temporal patterns of malaria are expected to change in Africa due to several factors. These factors include transmission and incidence, climatic factors which include the high and lows of temperature, rainfall and relative humidity is a spatial pattern which has made the malaria vector to spread to new areas that have become warm. Non climatic factors which include the multiple spread of the malaria vectors, increase in the malaria parasite, water development projects such as the irrigation channels, dams and ponds. Urbanization has also played a major role as one of the leading factors in the increase of the malaria disease, population movement, deforestation, human host factors, interruption to control and preventive measures, insecticide resistance in vectors as well as drug resistance in malaria parasite cite as per chapter 1 factors. This highlights the need for early detection of malaria in children.

This section presents a literature review for early detection of malaria and machine learning techniques available to find Plasmodium Falciparum. and group them. The study findings will show the relationship between malaria and child development. The review will also discuss some of the studies that touch on the key issues raised in the objectives. The focus will mainly be on children below the age of five years because they are the most exposed and easily susceptible to malaria infections which may lead to irreversible and fatal implications, hence increase in mortality and morbidity rate. Lastly a summary of the gaps that exist in the scholarly literature has been discussed. The review also features a conceptual framework of the proposed model.

2.1.1 Malaria and Child Health

Malaria is a severe disease that can easily lead to death if detected late. Malaria is a global major public health issue that mostly affects infants, children below the age of five, pregnant women, patients with HIV/AIDS and the elderly, due to their specific circumstances. According to the World Health Organization report (World Malaria Report 2020: 20 Years of Global Progress and Challenges, 2020) in 2020, there was an estimate of two hundred and twenty-eight million cases of malaria worldwide, compared with two hundred and fifty-one million cases in 2010 and two hundred and thirty-one million cases in 2017 which were mainly in Africa. The most susceptible group is children below the age of five years who reported 67% (272,000) of all malaria deaths worldwide (World Malaria Report 2020: 20 Years of Global Progress and Challenges, 2020).

Malaria has five types which include Plasmodium vivax (P. vivax), Plasmodium ovale (P. ovale), Plasmodium falciparum (P. falciparum), Plasmodium malariae (P. malariae) and Plasmodium knowlesi (P. knowlesi). The most common is Plasmodium falciparum which is life threatening according to (Lalremruata et al., 2017) and may lead to death. Infections caused by Plasmodium falciparum led to the highest morbidity and mortality rate in children. This is because Plasmodium falciparum is fully dependent on the status of the body's defenses of the infected person. The body's defenses for children is always susceptible to diseases and infection since it is not that strong compared to adults.

Mothers are the first source of treatment for their children. In most times they tend to give their children with over-the-counter drugs to suppress the symptoms. In order for them to be accurate during diagnosis, there is need to know the general various aspects that lead to malaria in children as well as how treatment can be administered on time. These aspects range from environmental factors for instance the climatical conditions, the high and lows of temperature and altitude, human factors such as the economic status, the social status, access to health facilities, migration, gender and not using insecticide treated net (ITN), biological factors which are related to the Anopheles vector, the parasite as well as the human host and lastly the use of land such as urbanization, irrigation, fish farming, swamp drainage, deforestation and living near the mosquitos breeding sites (Roberts & Matthews, 2016). Malaria is highest among the poorest of the country since they cannot afford prevention and protection of malaria through improved housing, not living near breeding sites especially near lakes, rivers and swampy areas as well as maintaining a clean environment which leads to ineffective early detection of malaria.

Most factors that lead to morbidity and mortality rate in children is due to resistance of drugs, having to rely on over-the-counter drugs, noncompliance with treatment, difficulties in administering bitter medications. There are various types of malaria diseases that affect children. They include respiratory distress, cerebral malaria, hypoglycemia, black water fever as well as algid malaria(Mutsigiri-Murewanhema et al., 2017).

Most parents have less knowledge on the signs and symptoms. This would range from simple and severe malaria that affects the children and in result when they take their children to the hospital, they don’t get full medical attention from the health professionals. The most common signs and symptoms of malaria in children below the age of five years include and are not limited to high fevers which in most cases is normally accompanied by chills, rigors, sweats, and headaches, other symptoms include generalized body weakness, backache, myalgias, vomiting, and pallor. In most cases these symptoms in children tend to be similar to viral syndrome, acute gastroenteritis, cholera, typhoid and any other epidemic diseases which are frequently mistaken for(Al-Dhaibani et al., 2019).

There have been various measures which have been implemented in order to curb malaria infections in children. These include the use of indoor residual spraying, proper treated mosquito net, use of proper diagnostic tools, proper use and administration of antimalarial drugs, effective resource delivery which will then prevent the transmission of malaria parasites from one human to another (Gachelin et al., 2018). Creating awareness and knowledge of proper management and early detection of malaria is important especially to children below the age of five since malaria is a life threating disease to this age group. This will greatly reduce the morbidity and mortality rate in children.

2.1.2 Malaria and Child Health in Kenya

In Kenya, malaria is the major cause of the high rate of mortality and morbidity rate in children below the age of five years and pregnant women around the Western Kenya region and the Coastal regions remains the major cause. Around the world and more so in Kenya, key factors have been focused on in order to eliminate and reduce malaria in the region. United Nations' Sustainable Development Goals have come up with various objectives in combatting the disease. Kenya is in line with these objectives as part of the Vision 2030 (Bashir et al., 2019).

In Kenya, the Ministry of Health through the National Malaria Control Programme (NMCP), has come up with evidence-based strategies and policies in order to fight malaria. Some of the important factors introduced by NMCP include prompt detection and early diagnosis of malaria, treatment of all malaria cases, the provision of insecticidal nets, improvement of the capacity of health providers as well as handling the supply chain from various health suppliers in order for them to deliver diagnostic tests kit and assured and verified by the Ministry of Health medicines at all levels of the health facilities system (Alegana et al., 2021).

In order for NMCP to be able to form policies and programs they engage in routine monitoring and periodic evaluations (Alegana et al., 2021a). The use of health information systems as well as surveillance in regularly checking up the status updates of malaria is routine monitoring. This information reported becomes the assessment on performance against the set targets and offers guidance on immediate actions to be taken. In order to have long term view of trends and progress against malaria, periodic evaluations are conducted through remote surveys and health facilities (Alegana et al., 2021).

An example of the periodic evaluation conducted in Kenya in 2015 is the Kenya Malaria Indicator Survey (KMIS) which is normally done at the remote level. At the time, KMIS main goal was to determine the impact of malaria with regards to reducing the morbidity and the mortality rate of children, to assess the occurrence of malaria among children below the age of five years and lastly to determine the progress established by the Kenya Malaria Strategy between 2009 and 2018 on malaria interventions KMIS recognizes strategic communication as an essential component in achieving the vision of a malaria free Kenya(Jenkins et al., 2015). There is a huge risk of the diversity of malaria infection as the level of endemicity in Kenya tends to differ from counties to counties. This is contributed due to the following factors, environmental factors such as the climate, temperature and altitude, human factors as well as land use.

The Kenyan counties as shown in figure 2.1 below according to (*Kenya | History, Map, Flag, Climate, Capital, & Facts*, 2019.) are categorized in to classes of ecosystems based on the risk of malaria infection such as the areas close to the lake or ocean from the coastal region where the rate of transmission of malaria is high the entire year, Lake Victoria and its environment which have similar characteristics as the lakeside areas and the malaria transmission are seasonal, highlands areas where the occurrence of the malaria parasite tends to be low in these regions (Tamari et al., 2020). The other ecosystem is the seasonal arid region such as the western and north eastern regions who live near water bodies and lastly the regions that have low risk of malaria such as the Nairobi and the central highlands region.

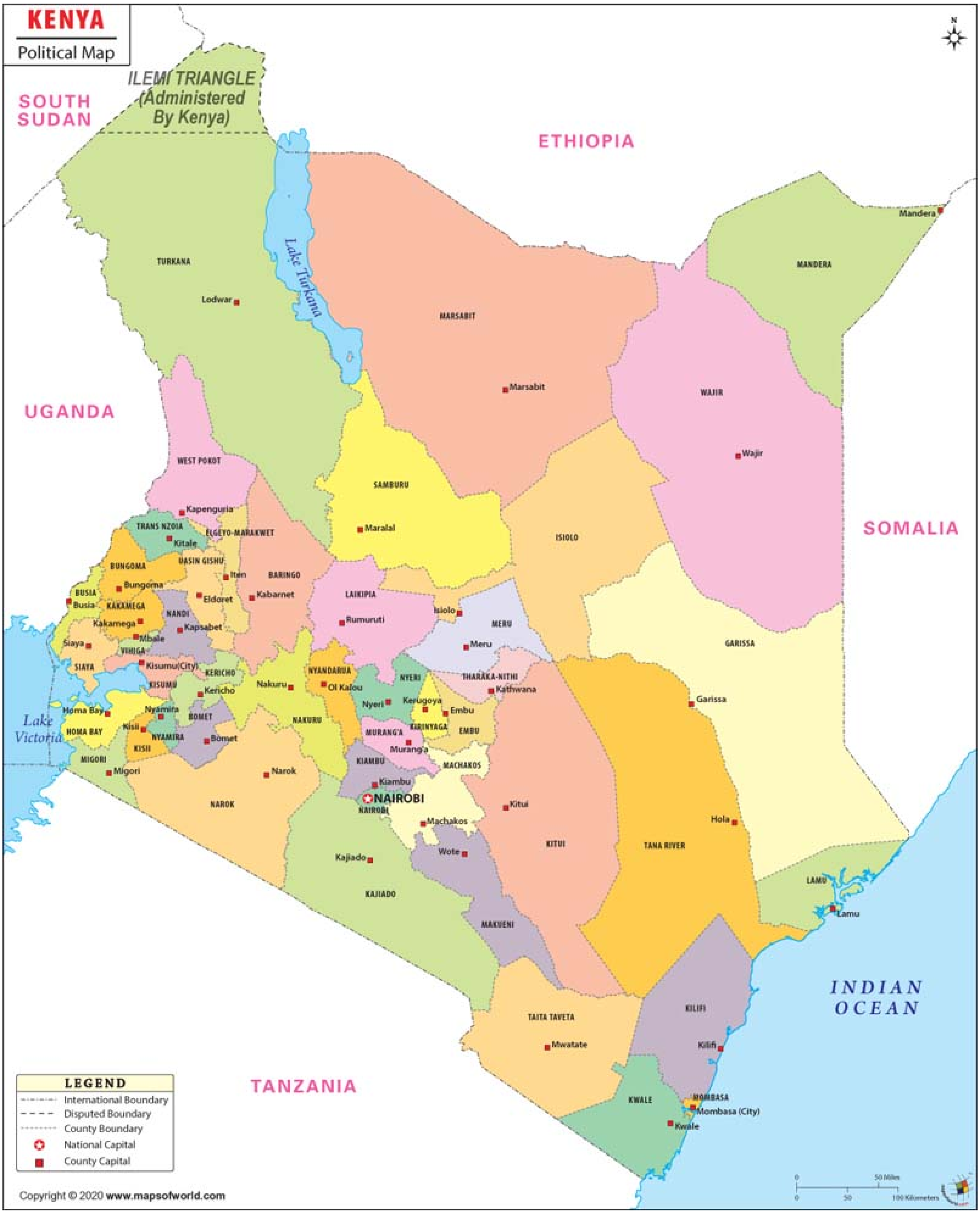


Figure 2.1 : Map of Public of Kenya (Kenya | History, Map, Flag, Climate, Capital, & Facts, 2019.)

2.1.3 Malaria and Child Health in Western Kenya

Malaria occurrence in the Western region especially in areas along Lake Victoria is still high as per the Malaria Indicator Survey (MIS) (Bashir et al., 2019). There have been several proven risk factors with similar settings such as Kenya that are associated with the malaria parasitemia such as the social status, the age of the child, the economic status of the country, the various housing conditions, the level of education for all age groups in the country, how land has been used and the various residency options such as rural or urban (Mugwagwa et al., 2015). It is quite undefined how these factors have contributed to the increase and decrease of malaria in these regions. If this information is captured correctly, the Ministry of Health would analyze and understand what are the causes of parasitemia and would come up with specific control measures in order to be able to reduce the occurrence of malaria and consecutively work on the pre-elimination of malaria (Bashir et al., 2019).

The Western region of Kenya is made up of counties such as Homabay, Busia, Migori, Kisii, Nyamira, Kericho, Bomet, Bungoma, Kakamega, Kisumu, Migori, Siaya and Vihiga county. The counties in this region with the exemption of Kisii, Bungoma, Nyamira, Vihiga, all have one thing in common in that they share Lake Victoria which is a fresh water lake in Africa (Bashir et al., 2019). In this area, they experience at least consistent annual rainfall patterns, the climatical temperatures range between 19℃ to 27℃ and the altitude above sea level fall between 1200m to 1700m hence the population of the mosquito vector is very high and due to the suitable climatical conditions in the region the transmission of malaria is strong leading to stable malaria transmissions throughout the year.

In most cases the child illnesses are first perceived, defined and treated at home by mothers before taking their children to the nearest health facility. The mothers would seek health care treatment as the last options due to the various reasons such as culture, where they do not believe in artificial medicines, the distance of the healthcare, financial constraint in getting the treatment, the availability of drugs in the health facilities as well as how quick the patient is attended to at the health facility(Al-Dhaibani et al., 2019).

Malaria infection is an important health concern among the children below the age of five-year-old residing from Western side of Kenya. It's of importance to have working intervention measures which include the early detection of malaria, prompt and accurate diagnosis and treatment of malaria in children especially those with malaria like signs and symptoms, reduction of malaria transmission in the society and use anti malaria drugs as prescribed by the health practitioner in order to prevent drug resistance of the anti-malaria drugs (Alegana et al., 2021b). In order to put in to use the targeted strategies, control and manage in these regions, assessment of malaria risks at all levels should be observed so as to be able to know the most susceptible areas and be able to implement the various specific prevention strategies in the occurrence of the disease. The understanding of the important malaria risk factors that lead to the increase of malaria in the area will assist in having appropriate steps in order to mitigate malaria risk factors.

2.1.4 Problems and Challenges Faced in Early Detection of Malaria in Children

One of the tools used for malaria prevention strategies is remote awareness which is not the most effective in preventing malaria cases in the African region. There are various problems and challenges that affect early detection of malaria in children below the age of five. Some of the factors leading to these problems include environmental factors such as the climate, temperature and altitude, human factors such as the economic status, the social status, access to health facilities, migration, gender and not using insecticide treated net (ITN) (Binka & Akweongo, 2006), biological factors which are related to the Anopheles vector, the malaria parasite, the human being the host as well as the use of land such as urbanization, irrigation, fish farming, swamp drainage, deforestation and living near the mosquitos breeding sites. Malaria is highest among the poorest of the country. This is because they cannot afford prevention and protection of malaria through improved housing, not living near breeding sites especially near lakes, rivers and swampy areas as well as maintaining a clean environment which leads to ineffective early detection of malaria (Mordecai et al., 2020).

Some of the challenges affecting early detection of malaria include and are not limited to (Oguonu & Edelu, 2016) HIV/AIDs, malnutrition, respiratory diseases in children, anemia, and respiratory diseases in children, blood transfusion especially to children who have severe malaria anemia who often sometimes do not make it alive to the referred centers due to either financial constraints from the parents or guardians in purchasing the blood among other chronic diseases. Another challenge includes delayed presentation and detection of malaria in children hence leading to inadequate treatment. This may be because of poverty, inadequate home treatment, over usage of over-the-counter drugs leading to resistance of the antimalaria drugs and minimal to no access of the health facility. Another challenge is due to the strong belief of both religions based healing and herbal medications which in result may bring about delayed affirmation of presence of malaria. Hospital personnel and lack of enough health facilities is also a challenge experienced during early detection of malaria. In rural and remote areas there are fewer qualified health personnel making it difficult for those patients with severe malaria to travel in search of the nearest health facility(Kamau et al., 2020).

Economic development has suffered a major constraint due to the measurable direct and indirect costs from these patients. Personal and public expenditure on treatment and the prevention of malaria is an indirect cost. The personal expenditures such as buying of insecticides, buying treated mosquito nets, buying the antimalarial medicine, transport from their place to the health facility, fees for the health personnel, support for the patient which includes having to stay in the hospital with the child is a strain to the family or the individual. Public expenditures such as carrying out education and research, having to maintain the health facilities as well as the health care infrastructure provided by the government, may not be enough for equal distribution in all counties. Lack to loss of income or productivity may be due to factor of the total cost of the expected individual working in a formal employment is a form of indirect cost while taking care of the child's illness or death (Sultana et al., 2017b).

There has been a major restraint in the economic progress due to the measurable direct and indirect costs. The direct costs of malaria include a combination of both personal and public expenditures on both treatment and prevention of malaria. Some of the personal expenditures include individual or family spending on buying insecticides, mosquito treated nets, the doctors' fees, antimalarial drugs, transport to the health facilities, support for the patient and sometimes having to stay in the hospital with the child (Sultana et al., 2017b) . The public expenditures include maintenance of the health facilities and health care infrastructure by the government, research and education. The indirect costs of malaria include lost productivity or income associated with illness or death of the child. This can be represented by the cost of lost workdays from their formal employment.

Active practices, attitudes, research and development that leads to greater knowledge of malaria should be implemented as an effective control measure.

2.2 Theoretical Framework

There are various theoretical frameworks that have been applied for the understanding of malaria.

2.2.1 Landscape Epidemiology Framework

Early studies adopt a landscape epidemiological approach based on Pavlosky's theory of natural focality of disease. This means that the foci of infectious diseases are analyzed by delimiting vector habitats through the examination of vegetation, climate and other elements of the physical environment and natural landscapes and linking them to vectoral risk indices and malaria transmission patterns but contain the aspect of culture (Onyeahialam, 2015).

The temporal dynamics of a vector, pathogen populations and a host is a description of landscape epidemiology that interact spatially within an environment that is accommodating in order to carry out transmission. Climate, latitude, elevation, vegetation and geology are some of the spatially defined transmission characteristics for malaria. In order to determine the ecological complexity, temporal stability as well as the dimensions, vector bionomics and knowing the pathogen natural history is used (Onyeahialam, 2015). Transmission efficiency, pathogen intensification and host populations can be used to define a heterogenous surface by use of remote sensing and statistical tools.

Landscape epidemiology is used for the spatial delineations of the vector borne diseases which are transmitted to humans from an infection. The vector borne diseases comprise of malaria (protozoan) which is an anopheles species of mosquito, dengue and yellow fever. The evolution of vector borne diseases in humans is triggered by their penetration into a disease system contained naturally amongst wild animals (Beard et al., 2016). However, when humans intrude into this region, this destabilizes the equilibrium and the vectors that ordinarily feed on animals tend to change their feeding patterns to human, and in the process infect them (Onyeahialam, 2015). Human beings must have taken habitat of the said disease or penetrated the “foci” in order for them to acquire a disease associated with the physical environments such that they become the host to the parasites,

This theory has a shortcoming of lacking the socio-culturalism in consideration of the individual and society, perceived exposure and cultural aspects. The determinants of the disease risk and the geographical distribution should not be used in decision making on matters of health. This requires the consideration of complex factors of malaria. The definition of vector habitats and supposed human intrusion might be criticized for environmental determinism. On the brighter side many of the landscape epidemiology concepts such as disease regions and pathogens distribution, have been integrated in to the human ecology of disease framework to regionalize vector habitats as well as human interactions in to these environments (Onyeahialam, 2015).

These studies utilize GIS and remote sensing techniques to regionalize and come up with geographic profiles of vector and malaria transmission risk. Figure 2.2 shows the model for landscape epidemiological analysis for disease transmission (Ziegler, 2016).

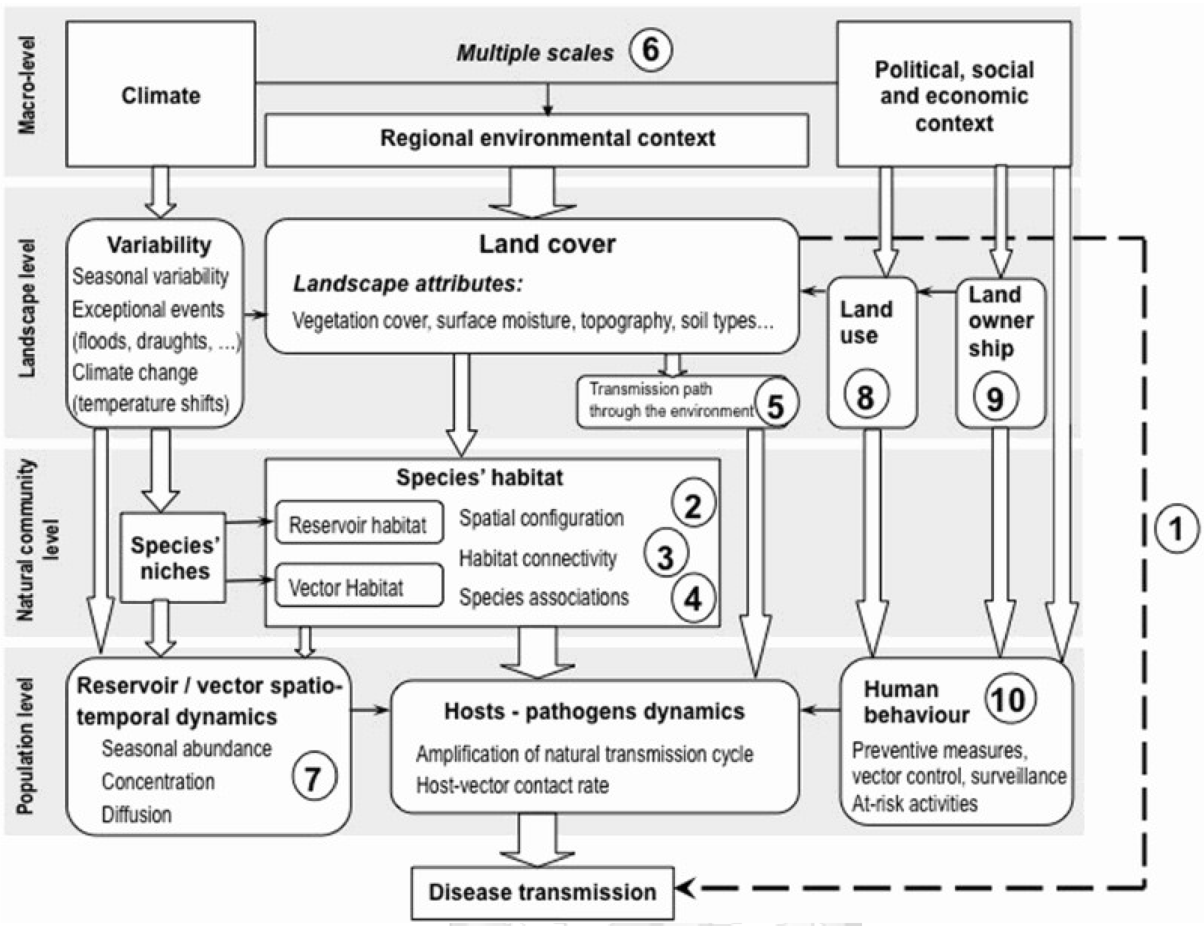


Figure 2.2: Model for landscape epidemiological analysis of disease transmission (Ziegler, 2016)

2.3 Current Malaria Detection Techniques

2.3.1 Microscopy

Microscopic examination of either thin or thick blood film is carried out in order to be able to tell whether the malaria parasitemia is present or not hence guiding to appropriate treatment. The patient's blood is collected by pricking their finger or by taking their blood from the vein for the purpose of intense laboratory testing commonly known as venipuncture. For this type of laboratory testing, it is advisable that the blood collected be spread immediately on to a slide so as to prevent exposure of the blood (Mathison & Pritt, 2017). Since the most sensitive type of smear is the thick smear, two or three drops of the thick blood is placed on a slide. At this stage the malaria parasite blood stages are shown such as the gametocytes, trophozoites and schizonts are exposed from the red blood cells whereas the thin blood smears under the slide contains a single layer of cells (Mbanefo & Kumar, 2020).

One of the limitations of microscopy is that it needs trained health personnel since the process is ill-suited and difficult for large data output and since the collection of blood is specific and sensitive and may vary based on the skill of the health personnel. Delay in treatment is another limitation since it takes time for one to be able to detect the parasitemia. For those patients with low parasitemia with asymptomatic signs, still remain untreated and undiagnosed due to the low detection limit hence the occurrence of malaria transmission continues in the society (Mbanefo & Kumar, 2020).This method may not be a guarantee as a measure to detect and diagnose malaria especially in rural and remote areas especially those health facilities that have no resources such as electricity, laboratories and tools and equipment.

In remote rural areas especially those that are peripheral medical clinic with no access to electricity and nor health facility resources, this method may not be guaranteed as a measure to detect and diagnose malaria.

2.3.2 The Rapid Diagnostic Tests

RDT helps by detecting and diagnosing the presence of malaria parasitemia in the body. This tool is useful in remote and rural areas with limited to no access of laboratories as well as the health personnel as it is the most consistent method of early detection of malaria (Mbanefo & Kumar, 2020)

One of its main advantage in resource and scarce poor setting is that it is not expensive. They take about 5 to 30 minutes to process and can be performed by an individual with minimal training. Compared to manual microscopy the detection sensitivity of RDT is lower and does not require any special equipment whatsoever. One of the disadvantages of using RDT's is that it does not provide quantification of the result. This is evident in the fact that RDT does not allow any identification of asymptomatic carrier and the difference in the brands may lead to decrease in the efficiency and reliability of the method hence having microscopy method and RDTs method of malaria detection complement one another (Poostchi et al., 2018).

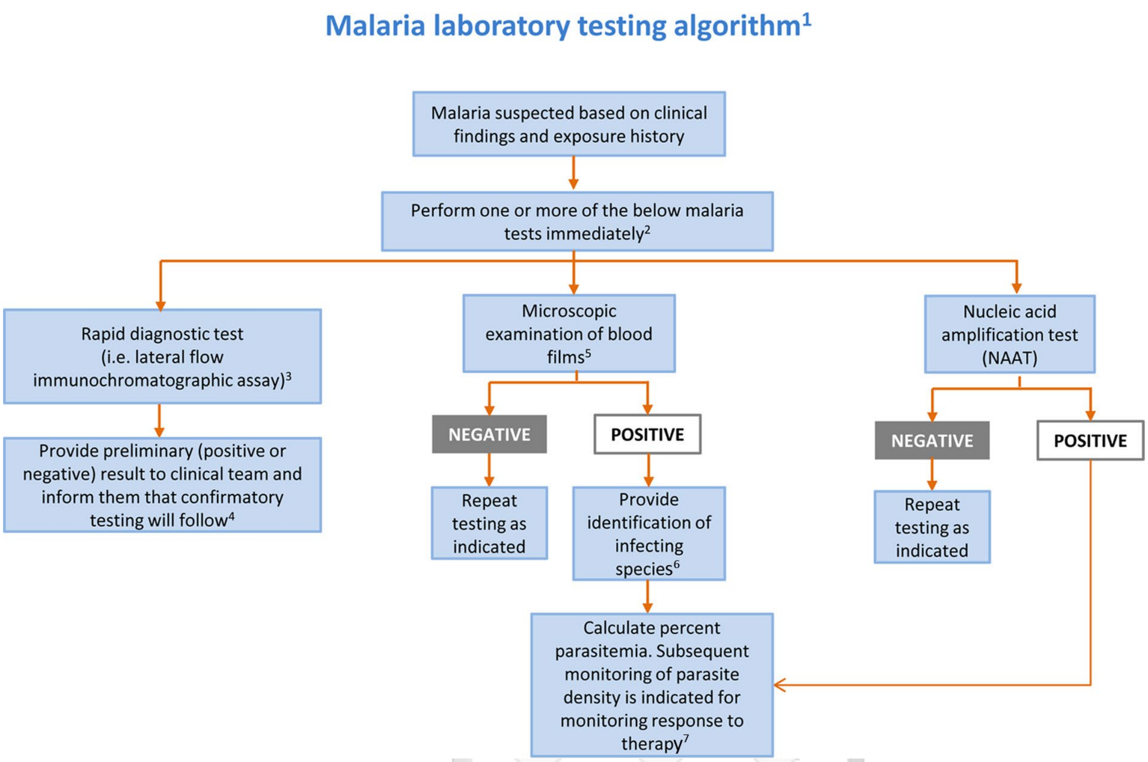


Figure 2.3: Malaria Laboratory Testing Algorithm (Mathison and Pritt, 2017)

2.4 Machine Learning

The science involved in ensuring that computers act like human and learn is Machine Learning. Feeding the computer with information and data over time improves their capacity to learn in various forms such as world interactions and observations (Ahmad et al., 2018). Learning that is involved in this stage is the process of conversion of that information and data collected to usable knowledge. This comes from the person who comes up with a program that the machine can easily recognize as patterns or learn from what is being feed as the input. The more the models are exposed to the new data, they can flexibly adapt independently as one of the iterative features of machine learning. Once the computers learn from the various computations, the output is reliable (Ahmad et al., 2018).

Machine learning has been used in healthcare due to its capability in helping the health personnel plan and make better decisions while providing care to the patients by its capability of been able to handle and process the huge datasets that are beyond the knowledge of human capability, then later converting the analysis of the data in to meaningful clinical perceptions hence having low cost of care and better medical report outcomes (Ahmad et al., 2018). The various applications of Machine Learning in the healthcare field include artificial assisted radiology and pathology, physical robots for surgery assistance, prediction of vector borne diseases, the discovery of drugs with the aid of machine learning, precision medicine, diagnosis in medical imaging as well as disease diagnosis (Sarkar, 2020).

2.4.1 Machine Learning Techniques

In machine learning in the medicine world early detection and diagnosis of terminal disease like cancer has been modelled in order to be able to save the person's life before it is too late. It is an area of artificial intelligence and is applied in the available data sets and the output obtained. The model from the algorithms is created from the mathematical computations alongside some training data as inputs which then the model is used to come up with various decisions and predictions. With the model in place one can map the input to various outputs depending on a given set of rules or conditions.

2.4.2 Machine Learning Algorithm Structure

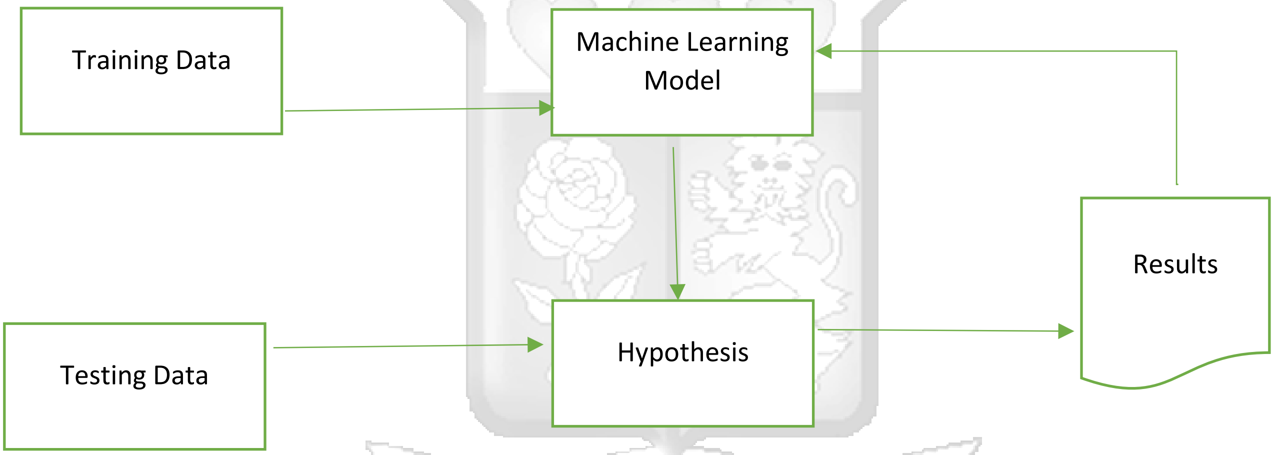


Figure 2.4: Algorithm Structure for Machine Learning

The goal of machine learning is to be able to train the models from the algorithms that will perform and learn without any human intervention. The algorithms will be constructed with the capacity to be able to learn data which means that the model will be created based on the data provided by the computer.

2.5 Machine Learning Approach to Early Detection of Malaria

Malaria which is a parasitic disease leads to death of children. The disease arises because of the damaging of the red blood cells in the blood and lack of early detection. Many methods and science have been found to detect the malaria disease. One of the challenges towards low mortality and morbidity rate has been due to inadequate malaria detection (Poostchi et al., 2018). There are several methods which can be used for early malaria detection using machine learning. They include the use of Artificial Neural Network, Support Vector Machine and Convolutional Neural Network.

2.5.1 The Artificial Neural Network

This algorithm replicates the learning system of the brain of a human and is inspired by the functionality of how the human brain works in machine. ANN goes through a training stage where it learns to identify patterns in data in various formats. It is also known as a multilayer perceptron and can be used to model complex nonlinear functions. It is made up of several layers such as either one or more hidden layers, the input and output layers the figure below. It compares the actual output given with what is expected to give which is the desired output (Taher et al., 2019).

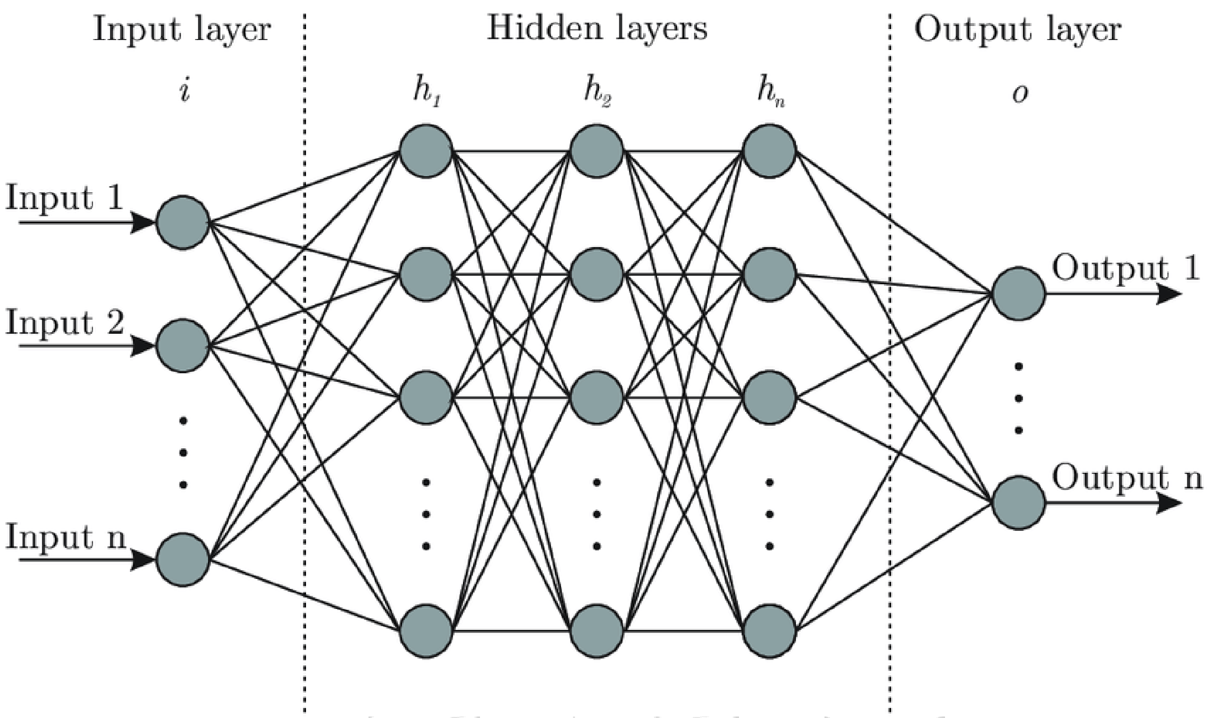


Figure 2.5: Structure of ANN (Bre et al., 2017)

To adjust the outcome with the expected result techniques such as Back propagation, feed-forward and the feedback are used by ANN. It has interconnected layers and they include the input layer, the hidden layer and the output layer and is made up of several nodes that receives entries (X1, X2, …, Xn) and give (Y) as an output. The nodes are interrelated with a weight (W1, W2, …, Wn) which in most cases it is adjusted until a desired output for the training data set is met (Taher et al., 2019).

Artificial Neural Network is preferred because of its usefulness in pattern recognition, abstraction, generalization, identification, as well as interpretation of any noisy inputs. Though, it is not fit for image processing because these layers of networks can easily experience overfitting. This means that the network fails to generalize the training data and correctly carry out classification of the unseen data. In addition, it has several trainable parameters which require more powerful processors to process hence making the model not suitable to be used with a mobile device.

2.5.2 Convolutional Neural Network

This is a form of deep learning algorithm takes an image as an input, then allocate biases and weights to the objects and views in the given image and then have the capability to distinguish amongst them (Pan et al., 2018). It is used for classification in image processing by ways of classification, clustering of the images, identification of the objects as well as naming. Due to its advantage and ability to use many similar neuron of the same kind, CNN allows the model to have numerous neurons which allows the actual parameters that will be learned to be small in number. CNN has some shortcomings whereby it requires the use of large amounts of images as the preferred training set and it takes quite some time for CNN to achieve the level of accuracy desired hence the need to use transfer learning as use for pre-trained model to perform large classification on the images that may no be in the domain of the model (Hussain et al., 2018).

The convolutional neural network has been designed to distinguish between uninfected and parasitized blood samples. The proposed model consists of three convolutional layers and fully connected layers each. The neural network presented is a cascade of several convolutional layers having multiple filters present in layers, which yields the exceptionally good accuracy as per the available resources. The model is trained and later several blood sample images are fed to test the accuracy of the designed system.

Extraction of automatic features is performed by the convolutional layer in the CNN model. The important and hidden features will be extracted which will then perform classification on the given images by ensuring maximization of the scores of the probability.

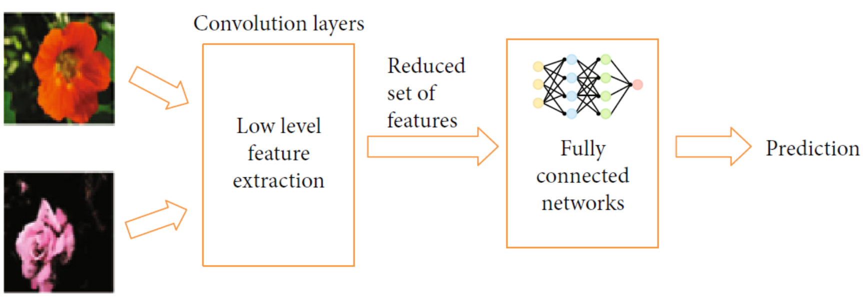


Figure 2.6: A General Convolutional Neural Network Model (Masud et al., 2020)

2.5.3 Components of the Convolutional Neural Network

The CNN is made up for the flowing layers:

i. Convolutional layer

In this layer the various features will be extracted from the input images. The input images become the feature indictor which results to a matrix after performing convolutional operation. This means that if the input of the image size is 6 by 6 and th filter size provided is a 3 by 3 then the convolution operation performed will be a 4 by 4 matrix as long as the stride value results to 1.

ii. Pooling Layer

The aim of this layer is to decrease the size of the convolved feature map. This is achieved by decreasing the connections between the layers and operates on each feature map provided independently. This process aides in ensuring that the model is stable. In this case, a mx pooing layer will be used since the maximum value is chosen from the region that is covered by the filter as its output.

iii. Dense Layer

This is used for the output layers after the pooling layer has been flattened and fed in to the first dense layer. At this point, if the predicted value is 0 the input images will be classified as parasitized and if the value that is predicted is 1, the input images are classified by the model as uninfected.

In this case we will have sample images of infected malaria blood sample and a non-infected blood malaria sample which will be used against the blood sample collected from the patient (child)to check whether malaria is present or not.

CNN can be used in diagnosing malaria from the microscopic blood smear images. The CNN uses images inputs for the datasets and the layers have the capability of learning several objects using the images from the datasets.

2.5.4 Tensorflow Framework

For the training and inference of the CNN, TensorFlow framework was used. TensorFlow allows for flexibility and it supports a variety of applications (Abadi et al., 2016). The study used the tensorboard, which is a visualization toolkit of TensorFlow for the convolutional neural network in the Colaboratory (Colab) cloud environment.

2.6 Related works in early detection of malaria

This section has reviewed some of the existing research and studies related to the study problem. These describes the current studies that have been adopted in the early detection of malaria in children using the various machine learning techniques. At the moment there are various research that has been conducted on the advancement of machine learning techniques in health especially in curbing the impact of malaria in pursuit to solving the growing challenges of malaria affecting children. The machine learning techniques that have been commonly used include the Artificial Neural Network (ANN), Support Vector Machine (SVM) and Deep Learning techniques such as Convolutional Neural Network.

2.6.1 Malaria Screener: a smartphone application for automated malaria screening

In this research, the authors Hang Yu and others (Yu et al., 2020), proposed a semi-automated method of detecting malaria by implementing feature extractors that used CNN model for the classification of infected and uninfected blood cell to enable the identification of the disease. For the feature input, they used both thin and thick blood smears. The smartphone is used with a microscope adapter. The author expounds more on the image acquisition, image screening and management of the acquired data. This study however did not address the mobility and the availability of the light microscope to the health practitioners in remote regions hence posing a challenge in having a robust automatic malaria detection that can be used in real time. In addition, this technique was dependent on a light microscope to make inference of the parasites.

2.6.2 Smart phone based malaria parasite detection for thick blood smears

In this study (Yang et al., 2020), proposed a deep learning for smart phone based malaria parasite detection for thick blood smears. The system is implemented as a smartphone app for the Android mobile operating system and then the camera of the smartphone is attached to the eyepiece of the microscope. The user tends to adjust the microscope to find the target field in the blood smear and then the user takes pictures with the app. The study did not address the practicability of the detection promptly as the user has to take several images until they have collected enough data to meet the requirements of their local protocols. This is time consuming and efficient, since the user has to carry out multiple tests to determine the presence of Plasmodium Falciparum.

2.6.3 The Malaria System Microapp: A new, mobile device-based tool for malaria detection.

The malaria system micro app by (Oliveira et al., 2017) for malaria diagnosis, was aimed at developing a mobile device based diagnostic system that combined with light microscopy to identify the Plasmodium falciparum species. The system uses artificial intelligence techniques and image processing and a face detection algorithm for the identification of the Plasmodium parasites. The algorithm that was used was based on the integral image and haar-like feature concepts and uses the weak classifies with adaptive boosting learning and not training learning. The shortcoming of this application was that it depended on a light microscope, attached to the mobile phone camera to make inference.

In summary, there has been no study that has been done so far to detect malaria in real time. The attaching of the light microscope under the mobile phone camera is not an efficient and effective way of conducting real time detection of Plasmodium Falciparum. This process is time consuming. The user will always have to carry the microscope with them or carry the samples to the nearest health facility to carry out detection.

2.7 Research Gap

As discussed from the studies in this chapter, malaria is a global threat to children under the age of five. There has been several researches and projects that have been tailored towards finding a solution, hence implying that malaria in children has been given a lot of attention.

There have been some research gaps in trying to understand the various pathways that link malaria transmission and infection as well as poor child development leading to irreversible and fatal implications hence lowering the mortality rate and preventing the morbidity rate in children. In addition, there has been a gap in trying to evaluate the impact of malaria on the growth and development of children below the age of five years as well as quantify the risks involved in cases of mild malaria.

Existing works understand and implement the detection problem differently by comparing it to prevention or diagnosis of malaria in children hence not offering a suitable solution as discussed in this chapter. The current techniques of detecting the presence of malaria do not offer timely responses. For instance, Rapid Diagnostic Test does not detect these parasites in the body after infection up to an approximate period of around one month and the parasite load cannot be quantifiable. This in return makes it difficult to predict how far the malaria parasites have led to non-irreversible infection and the ability to know when the child was infected by malaria. The other technique, Manual Microscopy is prone to human error and time consuming. The duration that it takes from the moment the blood is collected from the child to the laboratory for further diagnosing may lead to early deaths.

The mobile application that has been used to detect the real time presence of malaria in blood smears for android mobile operating systems. The camera of the smartphone acts as a microscope and there will be no need to attach the mobile phone camera to the eyepiece of the microscope. The classification will be done using a machine-learning algorithm to find Plasmodium falciparum and group them. The main purpose of coming up with this device is to facilitate the most suitable and convenient way of real time malaria disease detection, especially in rural and remote regions.

During the vulnerable stages of development in children, malaria is associated with this and may lead to death at an early period in their life. Therefore, early detection of malaria, leads to immediate treatment and is important for the optimal development in children especially since Kenya and Africa are susceptible to high transmission of malaria, by using the correct detection tool and machine learning techniques, hence lowering the mortality rate and preventing morbidity rate of the children.

2.8 Conceptual Framework

Detection of malaria using manual systems is time consuming and, in most cases, prone to human error. The standard test of malaria based on the guidelines from WHO, the procedure involves intensive examination of the blood smear at roughly 100X magnification. This stage is where health practitioners manually count the Red Blood Cells that contain the parasites out of 5,00 cells (Rajaraman et al., 2018). The conceptual framework below links the literature reviewed together with the research problem and objectives that will aide in the detection of malaria.

The sample will be previewed by the smartphone camera of the remote health worker mobile phone. The image previewed will be pre-processed by the application of various filters and removal of any noise, image segmentation, feature calculation approaches, image analysis and Feature extraction will be used (Yang et al., 2020b). Classification will be done in order to identify the Plasmodium Falciparum and then cluster them together. The app will then detect and count the parasites while recording the number of parasites to a child's record and then later through the interface using the algorithm, the user will be able to see the results for the presence of malaria or not based on its features.

After this process the remote health worker will be required to fill information for the patient whose sample was collected and they will fill the signs and symptoms that the child has. The child's record and data will be accessed and monitored by the remote health worker before and after diagnosis.

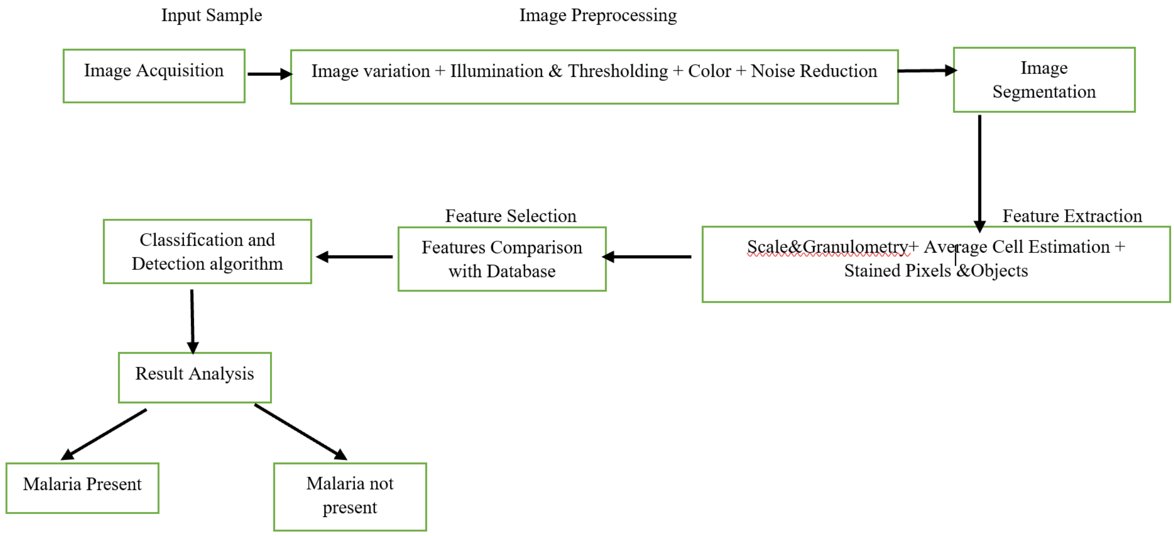


Figure 2.7: Malaria Parasite Detection System

Chapter 3. : Research Methodology

3.1 Introduction

This chapter included the system development of the convolutional neural network model that was used, the research design as well as data collection which was secondary data that was used for analysis obtained from the various verified publications on data relevant to malaria infection statistics. The methodology used was agile since the methodology allows easy building and testing of application features and quickly adopting feedback to enhance the features being built over time. This aided in better outcomes as opposed to building the application and testing it later in the development cycle and finding out gaps in delivered solution. Lastly, the research methodology chapter explored the ethical considerations involved for the research.

3.2 System Development Methodology

The Agile Development Methodology has been implemented. In agile development the different stages in the life cycle are normally revisited every now and then hence iterative and incremental process of agile development (Alsaqqa et al., 2020). The iterative approach gives room for quick prototyping of solutions that can continuously be improved as more and more related requirements are identified. This will ensure early customer involvement, iterative development, self-organizing as well as adaptation to change during the phases. Due to time constraint this was the most appropriate methodology as opposed to adopting the waterfall model and software development lifecycle, which they assume the existence of unlimited adequate resources and eventual success of a project.

The advantages of using the Agile Development methodology is that it allows easy building and testing of applications effectively while adopting feedback in order to improve the features being built over time. This helped the researcher in having real time outcomes as opposed to building the application and then testing the application later in the development cycle and finding out irreversible gaps in the delivered solution.

The mobile application and the convolutional neural network were implemented using agile methodology. This was important in putting together the CNN because some hyper parameters such as the number of training steps to be carried out were experimental. The mobile application had the following steps which were iterative until the desired features of the final product were achieved.

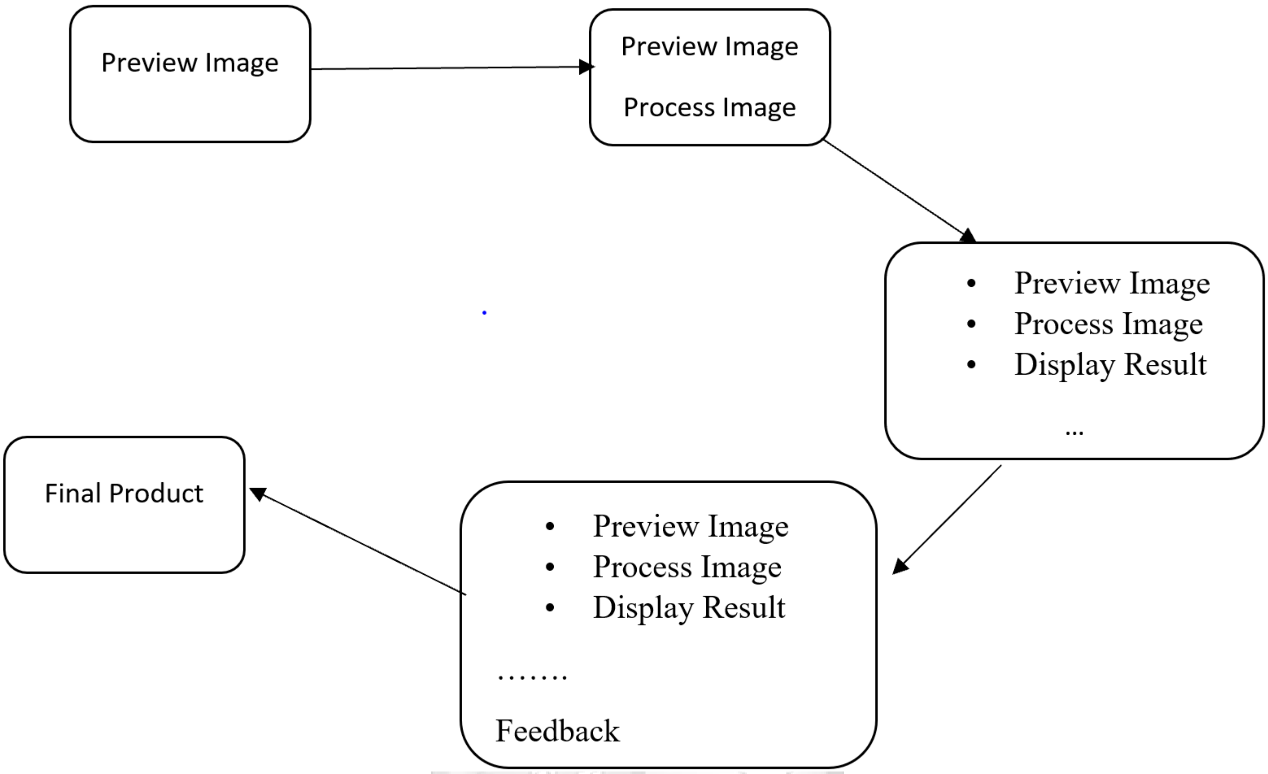


Figure 3.8 Agile Development Methodology for the Mobile Application

3.3 Research design

The study used applied research design which is designed to address specific questions that is aimed at solving practical problems (Mello & Wood Jr, 2019).It included coming up with a feature that would meet the need(s) of the user and lastly come up with a prototype and test whether the application meets the desired functions of the research. Through this research the mobile application was based on the android mobile operating system that had the following steps: the image was the input, then the image was processed and then after the presence of Plasmodium Falciparum was determined.

3.4 Target Population

This research was based in Western Kenya. Western Kenya regions are known to be malaria endemic zone. Malaria in Kenya is said to be the leading cause of mortality in the country in 2017, according to (Omondi et al., 2019). Currently some areas in the western Kenya regions are experiencing some major changing dynamics of the malaria transmission despite the increase in use of the insecticides, the treated nets and other interventions that have been put in place. The regions include Kakamega, Kisumu, Homabay, Migori, Siaya, Vihiga, Bungoma and Busia. In Kenya, one in twelve children (84 per 1000 live births) dies before their fifth birthday (Amek et al., 2018) contributing to the global malaria burden hence increase in malaria morbidity and mortality. The target population was composed of children between 0 and 5 years.

3.5 Data Collection

This is the method of measuring and gathering information on the various variables of interest (Kabir, 2016). The study used secondary data by reviewing the existing data from books, journals and online.

3.5.1 Secondary Data

This form of data collection comes from secondary sources that include published documents such as newspapers, journals, books, articles as well as internal records which is quick and easy when it comes to data collection (Prada-Ramallal et al., 2018). It is information that has already been collected by other people for a different use other than the current problem. The secondary data was used in order to gain insight in the early detection of malaria using datasets from the Lister Hill National Center for Biomedical Communications (LHNCBC), part of National Library of Medicine (NLM) (Rajaraman et al., 2019) and will address what has been done so far in detection of malaria using the Convolutional Neural Network.

This involved document reviewing, the study of various architectures, frameworks, tools, technologies and collection of data which was in form of images. This helped in coming up with development tools and technologies. This came from the various secondary sources:

3.5.2 Document Reviewing

In order to get the secondary data, some of the documents from the National Health database and the internet were used. The malaria image dataset is obtained from the National Library of Medicine hosted by Lister Hill National Center for Biomedical Communications, USA (Rajaraman et al., 2019). The training dataset consists of 27,558 images in total, equally divided into classes 'parasitized' and 'uninfected'. The test dataset consists of 8,268 images in total, equally divided into classes 'parasitized' and 'uninfected'. All the images are less than 20 KB in size and are of varied dimensions. Both the parasitized and uninfected classes have 17,361 images each in the training data set.

Data Analysis

This involved the breakdown of the data collected to further smaller parts which can be easily understood. The data was analyzed by the use of Microsoft Excel which allowed the researcher to carry out statistical analysis functionalities and non-functionalities. The information obtained was demonstrated using graphs and charts which provided the representation for proper analysis and interpretation of the same of the results obtained after the user acceptance and validation testing.

3.6 Research Quality

To measure the quality of the study we use validity and reliability of data. The results have been expounded more as below.

3.6.1 Data Reliability

Data reliability is a measure of the stability or consistency of the results gathered. It reflects consistency and replicability over time. The output data of the model was tested on several occasions on the training phase of the agile development. In return, by doing so there was reduced error rate and the inputs for each variable at this point was optimal. The measures of performance was computed for the evaluation of the model. Users of this system will be trained in its use, and all aspects of performance was tested.

3.6.2 Data Validity

The variable inputs that will be used for the model will be used to observe the detection of malaria in children and the output will be compared to the actual blood sample collected. Data validity in this research was achieved by using an automated model testing. The use of tensor board was implemented to track the CNN model's learning or loss rate which in return made it easier to carry out debugging and the optimization of the model.

3.7 Ethical Issues

The previous works from various researchers were acknowledged and cited accordingly. The researcher also used images that were used in this study from the various public sources online with permission to use during the educational research.

Chapter 4. System Analysis, Design and Architectures

4.1 Introduction

The chapter involves the analysis and design of the mobile application system that can aide in the detection of malaria in children at an early stage based on the conceptual model presented in figure 2.11. This includes diagrams such as use cases, sequence diagram, entity relationship diagram, class diagram as well as a wireframe of the mobile application that will aide in providing details of the various components while illustrating the interactions between the components of the system and the user. For the modelling of the diagrams discussed above, Unified Modelling Language was used (UML) in illustrating the interactions.

4.2 System Analysis

System analysis involves diagnosing problems, gathering and interpreting facts and using the information to recommend various improvements to the system (Nwakanma et al., 2018).The system analysis will establish the users of the system, give an overview of what the system will do and at what point will the system be used in the early detection of malaria in children. It will also review the user expectancy of the proposed system. The system analysis addresses the system requirement specifications, system hardware analysis, system software analysis, requirement gathering of the research as we discuss how data was collected and analyzed, the functional requirements of the system and the non-functional requirements of the system.

4.2.1 Requirement Gathering

The malaria image dataset is obtained from the National Library of Medicine hosted by Lister Hill National Center for Biomedical Communications, USA (Rajaraman et al., 2019). The training dataset consists of 27,558 images in total, equally divided into classes ‘parasitized’ and ‘uninfected’. The test dataset consists of 8,268 images in total, equally divided into classes ‘parasitized’ and ‘uninfected’. All the images are less than 20 KB in size and are of varied dimensions. The selection of the training data set was carried out using the 60/20/20 rule. The training data set in this case takes 60 of the total sample data set, while the remaining 20/20 is set aside for the testing and validation. Both the parasitized and uninfected classes have 17,361 images each in the training data set.

4.2.2 Functional Requirements

This specifies what the implemented system should do in regard to behavior, function and input or output which are meant to support the goals, tasks and activities of the remote health worker. The functional requirements include:

i. The system should allow the remote health worker to register and login
ii. The system should be able to preview the image and make an inference
iii. The system should accurately classify the images as either positive or negative in detecting the presence of malaria in children.
iv. The system should give the results of the detection of the Plasmodium Falciparum
v. The system should allow the remote health worker to offer recommendations to the patient based on the results.

4.2.3 Nonfunctional Requirements

The accuracy, appearance and the speed of the system are the most common non functional requirements as the properties of the proposed system which describe the overall attributes of the system. The non-functional requirements include:

i. The system should be reliable, secure and efficient.
ii. The system should be accurate in giving the output.
iii. The system should be easy to use to allow the user to perform the required functions under the given conditions.
iv. The system should be scalable to allow customization and the addition of the functionalities.
v. The system's response time should be in real time to allow quick and informed decision making.

4.3 System Architecture

The use of the system architecture is a guide to how the different system components will support the achievement of the system functionality. The main input for the malaria mobile application is the patient's blood, which is fed in to a converted lite format of CNN for embedding in to the application. All the data that is written and read by the remote health worker will be saved on the database.

The malaria detection process begins with remote health worker downloading and installing the application on any android based phone. The remote health worker then registers on the system before they can be able to log in. The information that is required for registration includes the user's name, email address and password. Once they have registered a verification email is sent to their email address and upon approval, the remote health worker can then login into the application. Once the remote health worker is logged in they can access the identify module for the malaria detection, treatment, the patients profile as well as the overall feedback.

After smearing the blood on a slider, the remote health worker will launch the application and go to the identify module. From this module, the remote health worker will see the smear background functionality. The smear background represents the blood sample on the slider and the more the remote health worker focuses the mobile phone, the inference changes. At this point they are able to get results of whether the blood sample is uninfected or parasitized.

Figure 4.1 below shows an illustration of the system architecture.

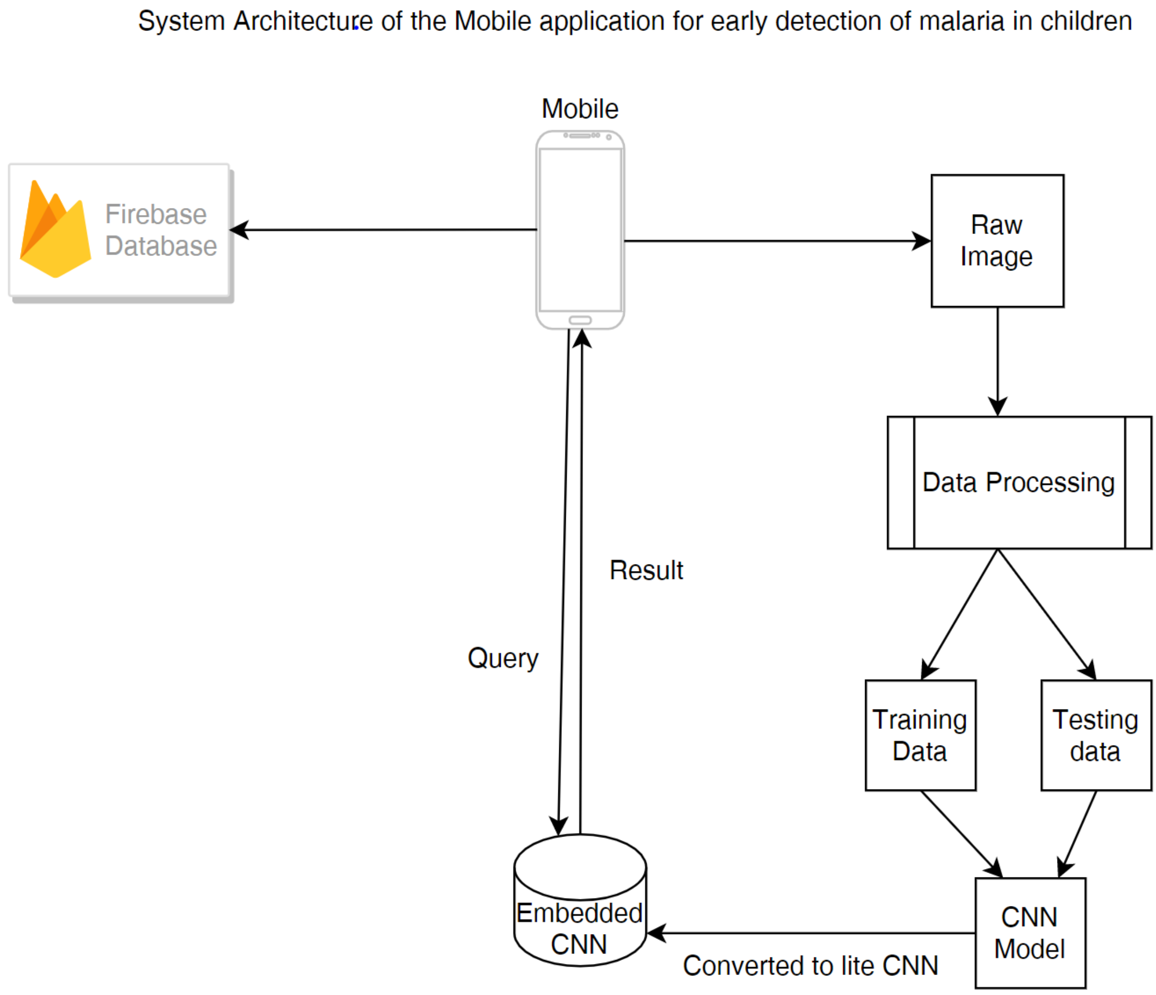


Figure 4.9 System Architecture of the Mobile application for the early detection of malaria in children

4.4 System Designs

This is involves coming up with a design of the various elements of a system such as the components, the architecture and the modules, the data that is passed through this system as well as the various interfaces of the system components derived from the specified functional requirements (Odhiambo, 2019). These diagrams include the sequence diagram, use case diagram, entity relationship and the application wireframe. The objects in the system are a combination of the processes and data which translates to users.

4.4.1 Use case

A Use case is used to explain and document the interactions of the system that is required between the user's environment and the system in order to achieve the user's task. They represent what a system does and can be used to come up with more functional requirements.

The remote health worker registers in the system. After registration, they are able to login and access the system. The remote health worker can view the cumulative reports. Through the malaria system, the remote health worker is able to make an inference from the blood sample collected. The administrator on the other hand is able to validate the remote health workers as well as manage the users.

Figure 4.2 shows Use Case Diagram for Early Detection Model of Malaria in Children in Western Kenya.

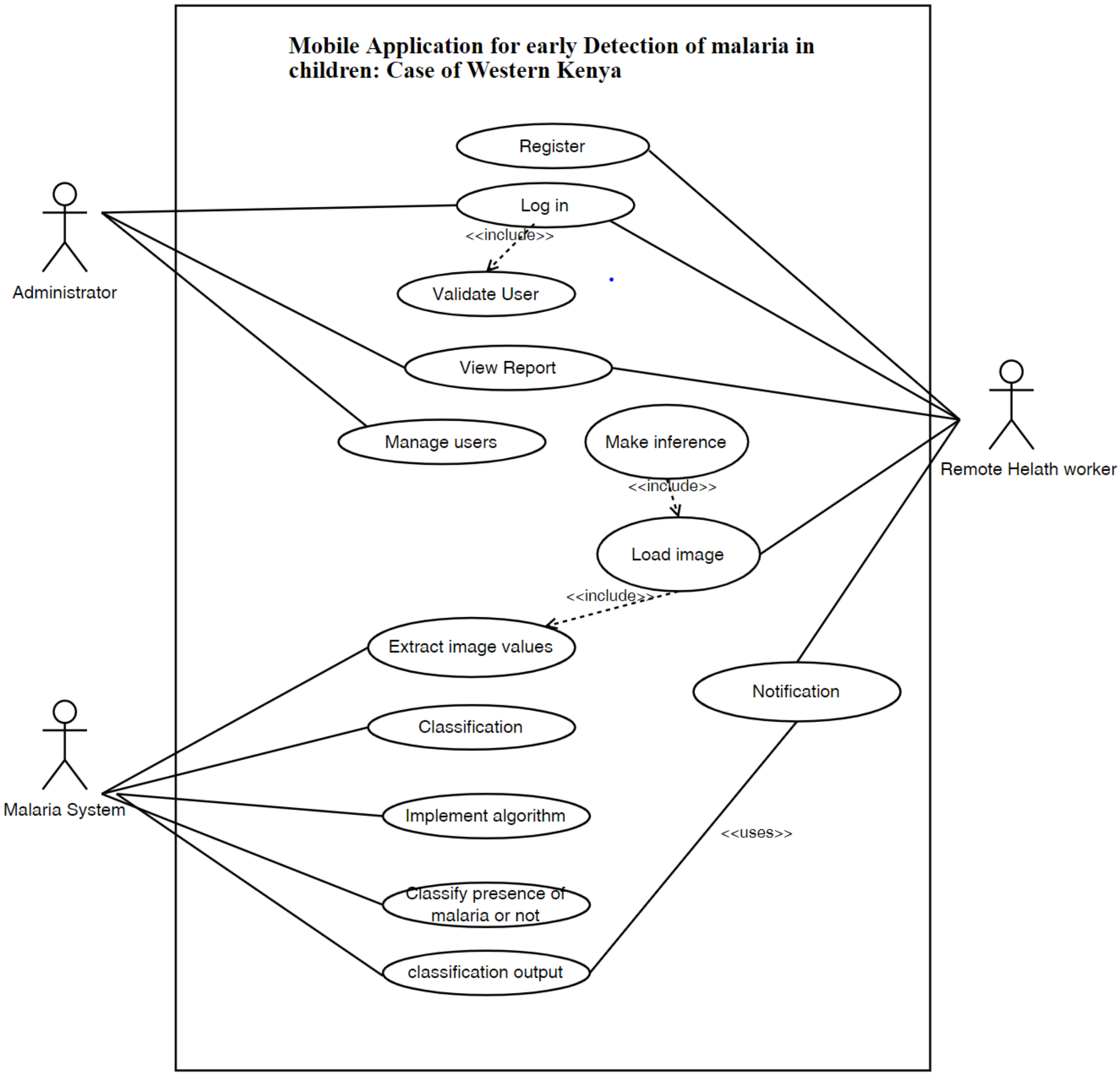


Figure 4.10 Use Case

Use Case Description:

Table 4.2 Get Image and Make Inference

Use Case UC1	Make inference of the loaded image
Primary Actors	The Remote Health Worker
Brief Description	This use case defines how the remote health worker loads the image in to the system for classification.
Pre-condition	Remote health Worker is identified and authenticated Trained CNN Model for classification
Post-condition	Image that is classified and results generated
Main Success Scenario	
Actor Action	**System responsibility**
RHW prepares the camera settings and loads the image	
	System loads image as input to the lite embedded CNN model
	System performs classification
	Systems returns classification result
User views the percentage and accuracy level of the Plasmodium Falciparum	
Exit camera mode	
Extensions At any time that the system fails to capture the image: 1. The RHW restarts the camera 2. Confirm the camera settings are correct	

Table 4.3 Receive Notification

Use Case UC2	Receive Notification
Primary Actors	The Remote Health Worker

Brief Description	This use case describes how the user receives a notification on the status of the presence of malaria
Pre-condition	Successful classification of the presence of malaria or not by the system
Post-condition	Recommended course of action
Main Success Scenario	
Actor Action	**System responsibility**
User	
	Return the output of classification
View Feedback and course of action	
	Display time taken and the level of accuracy
Exit system	
Extensions At any time, the notification status is requested and not obtained: 1. Retry the request for notification 2. Send email notification request to admin	

Table 4.4 Register and Login

Use Case UC3	Register and Login
Primary Actors	The Remote Health Worker
Brief Description	This use case describes the registration and login of the user
Pre-condition	Registration information
Post-condition	User registered, Verification of the user
Main Success Scenario	
Actor Action	**System responsibility**
User fills in the registration information	

	Systems verifies and save registration details
	System sends verification link to the user
User fills in login details	
	System authenticates the user
Extensions At any time, the user forgets their password: 1. Click on the reset password and user will be able to reset their account details	

Table 4.5 Manage Users

Use Case UC4	Manage Users
Primary Actors	Administrator
Brief Description	The administrator managers the remote health worker(Users)
Pre-condition	Manage users account
Post-condition	Activate and Deactivate users Updated Database
Main Success Scenario	
Actor Action	**System responsibility**
Activate user	
Deactivate user	
	System updates the database

4.4.2 Sequence Diagram

The sequence diagram depicts the interactions of the various processes and how they will operate with one another in the system following a particular order. The sequence diagrams show the message flow between the objects, the behavior of the system and the detailed order of the objects. In this case the sequence diagram provides a visual representation during the detection process of malaria.

This included the actor who is the remote health worker and the objects throughout the detection process.

Figure 4.3 shows the sequence of activities which took part in the system. The remote health worker initiates the process by loading the image, the image values are extracted and normalization takes place. The normalized data is then used as the input and data set test for the algorithm. The classification of the detection of malaria based on the input values is provided and the remote health worker is able to see the inferences made showing the presence of malaria or not in the patient and administer treatment.

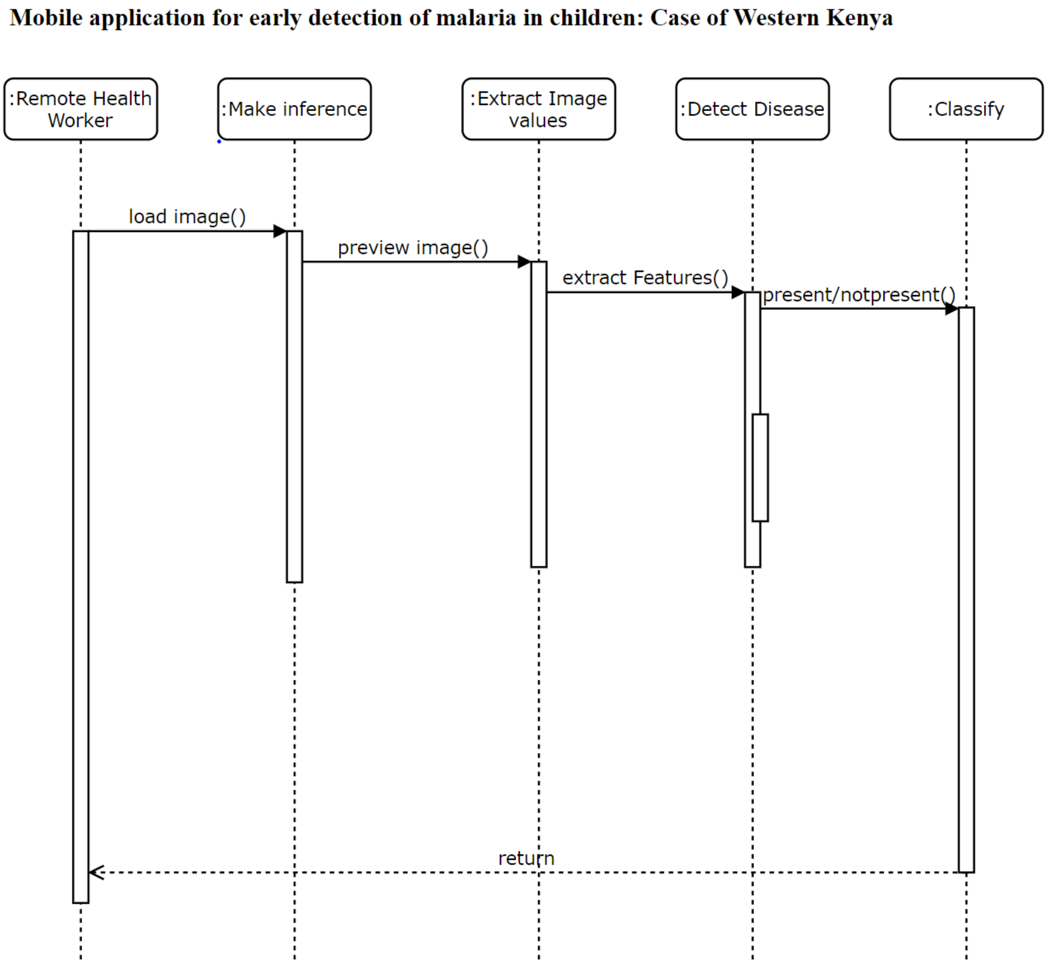


Figure 4.11 Sequence Diagram

4.4.3 Entity Relationship Diagram

The Entity Relationship Diagram describes the structure of the database with the help of a diagram which shows the relationship among the different entities for instance the relationship between the patient and the remote health worker (“Entity Relationship Diagram - ER Diagram in DBMS,” 2015).

This has been illustrated in figure 4.4 of the ERD diagram

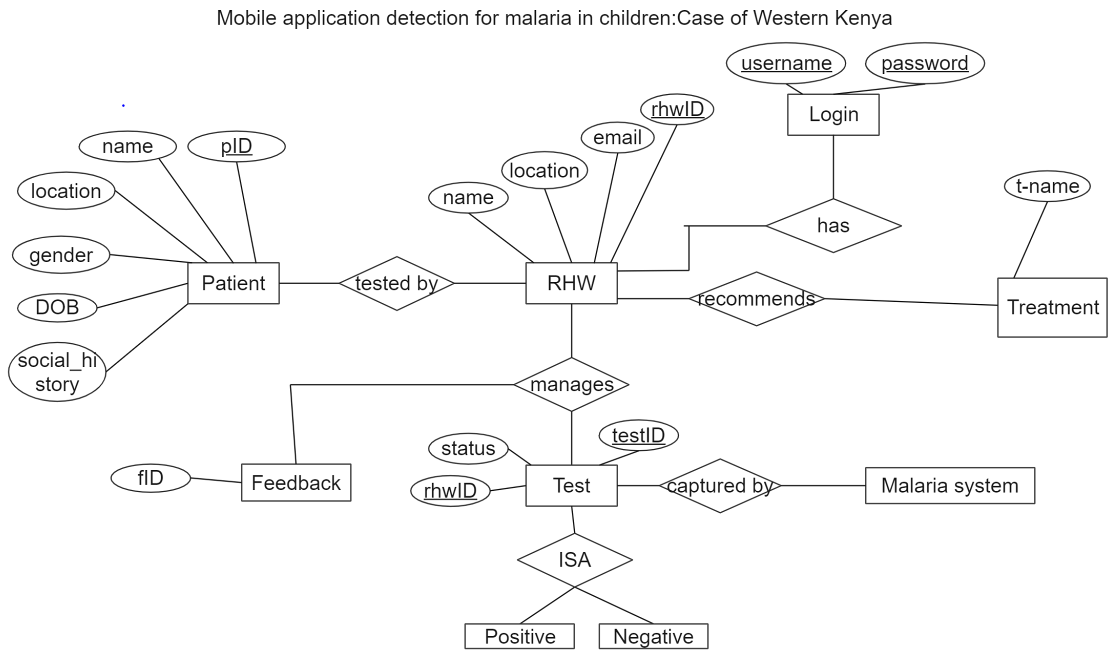


Figure 4.12 Entity Relationship Diagram

4.4.4 Class Diagram

The class diagram includes the principles of the relationships such as their inheritances, interactions, methods, attributes and connections that are in the system and all objects that are most important in the specification of the UML (el Alami & Bahaj, 2018)

The Remote Health Worker can login to the system, modify their details and log out. The RHW and the system administrator are authorized user who inherit attributes. The figure 4.5 illustrates the relationship between the classes.

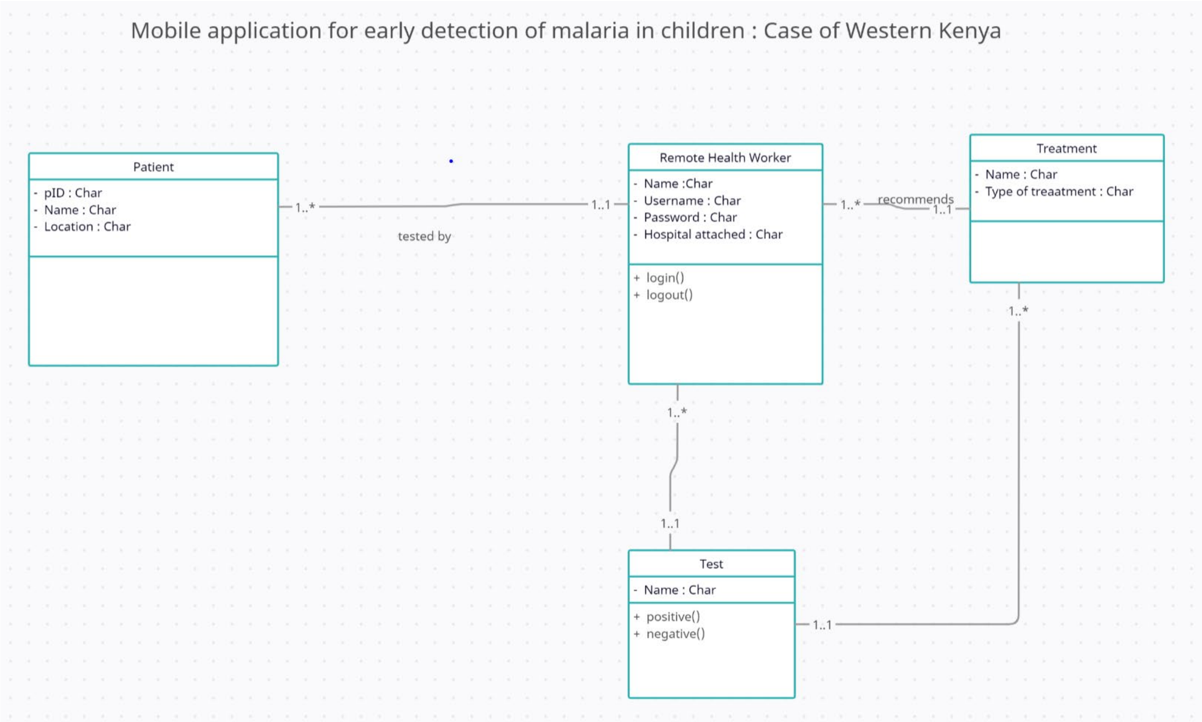


Figure 4.13 Class Diagram

4.4.5 Wireframe

The figures below show the mobile application's wireframes as a visual representation of the proposed system. The design of the user interface has been made simple hence saves time during navigation.

Figure 4.6 illustrates the Homepage for the Detection app in the system. The user can create their account to access the platform.

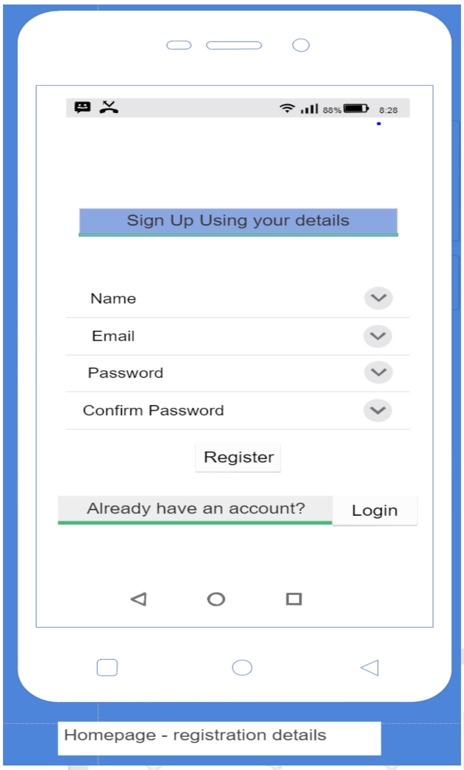


Figure 4.14 Homepage for the detection application

Figure 4.7 represents the RHW dashboard after successful login to the application. They can access and make changes to the modules in the system.

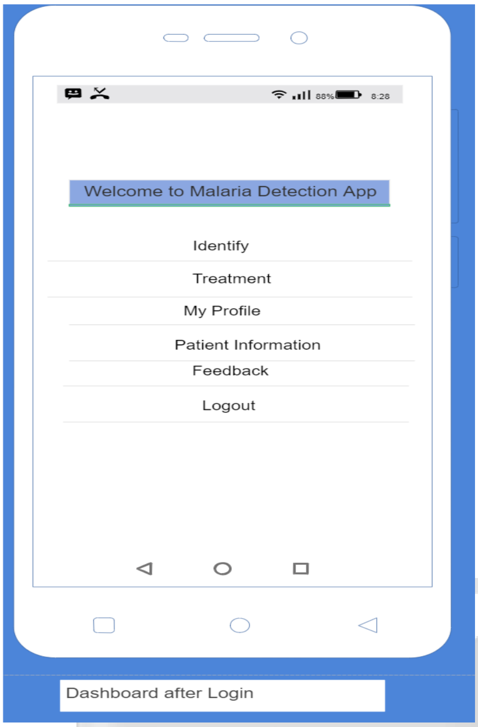


Figure 4.15 RHW Dashboard

Figure 4.8 represents the real time identification of the plasmodium falciparum parasites

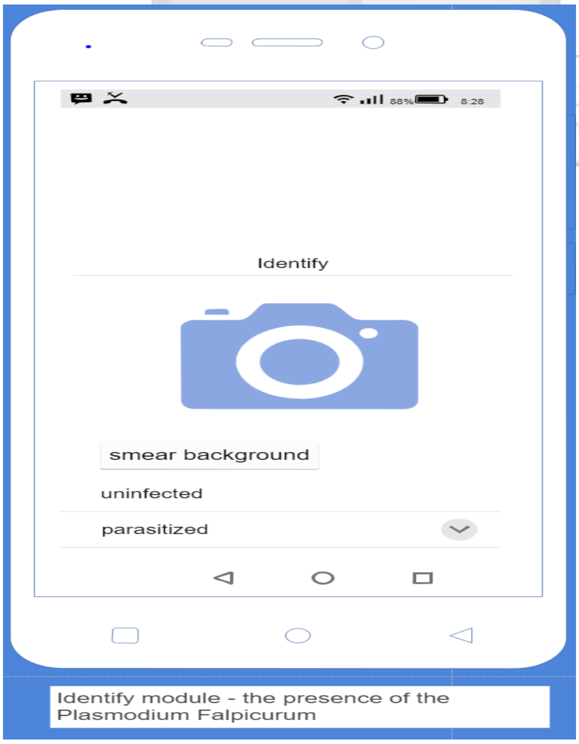


Figure 4.16 Identify Module

Figure 4.9 illustrates the Update profile option for the Remote Health Worker

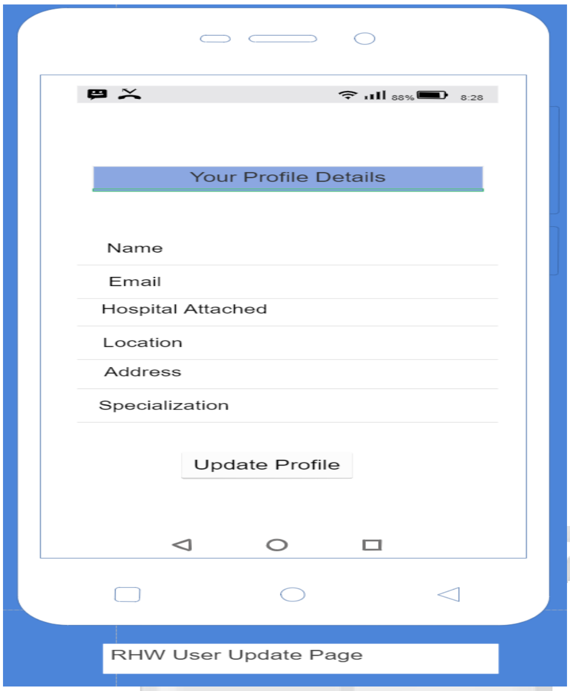


Figure 4.17 Update RHW Profile

Chapter 5. System Implementation And Testing

5.1 Introduction

This chapter gives an overview of how the proposed system was implemented, tested and validated. It describes the implementation of the CNN model, the testing of the model against the test data set and the level of accuracy. The CNN model was used to implement the detection of the disease using real time images previewed by the remote health worker using the mobile application installed on their mobile phones. Firebase was used as the database of choice since it is a NoSQL database that will store and sync the data in real time. Once the detection has been made, the remote health worker is able to see the results then based on the results they can offer treatment to the child.

5.2 System Implementation

The Agile Prototyping methodology as discussed in chapter 3 was used to design and develop the malaria detection system.

5.2.1 System Hardware Environment

The model was developed using a Huawei Matebook Pro, core i7 laptop which has 16GB Ram and 1TB HDD and 512 SSD. These were used in the design and implementation of the system.

5.2.2 System Software Environment

The model was developed using the Convolutional Neural Network algorithm as a form of supervised learning for classification and detection of malaria. The advantage of using the CNN model is that it is cheaper and faster to have accurate detection. In comping up with the mobile application, the platform used Android Studio 2020.3.1 for Windows 64-bit, jupyter notebook for the model and lastly for the conversion of the model, the platform used was tensorflow lite framework and Google Colab.

5.2.3 Network Environment

The network environment that was required was by the use of WIFI and Local Area Network.

5.2.4 Mobile Application Prototype

In coming up with the mobile application, the system used Java for the Android platform which was used to come up with the source codes which was then complied and tested using the android software development kit as the testing emulator. This platform was selected as the implementing language for the prototype as it has various advantages such as having a pool of online developer forums who were readily available for technological support, in addition the software development kit is flexible to use with other platforms and the availability of the diverse android development tools make it worthwhile to interact with.

The mobile application was implemented and the remote health worker was able to preview the image of the sample collected with the identify module. When the application was initiated after login, the identify module was able to detect the smeared background and make inference as to whether the sample is parasitized or uninfected with Plasmodium Falciparum. Once the detection is complete, the results were displayed on the screen. Then the remote health worker would go back to the other modules and if the child has malaria, the remote health worker would recommend treatment under the treatment module and fill the patients details for purpose during the next visit. For the mobile application the development environment used included:

- Android Studio
- Java
- Windows 10
- Firebase Database
- Mobile phone camera

The resulting APK file was installed and tested on the various android mobile platforms.

5.2.5 Mobile Application Modules

Below are the Mobile application modules implemented in the system

Registration Module

This module allows the remote health worker to register in to the system pending verification after confirming their email. Figure 5.1 shows the registration module of the user and Figure 5.2 shows the login module of the application.

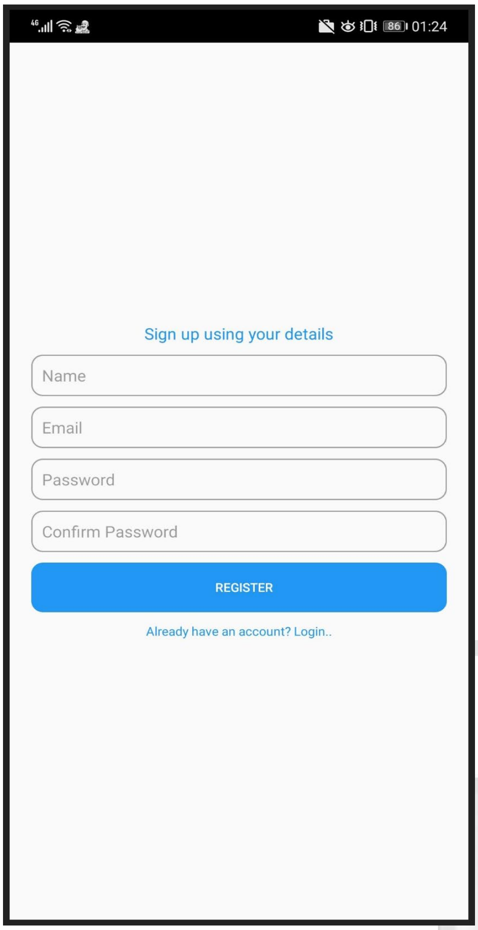


Figure 5.18: Registration Module

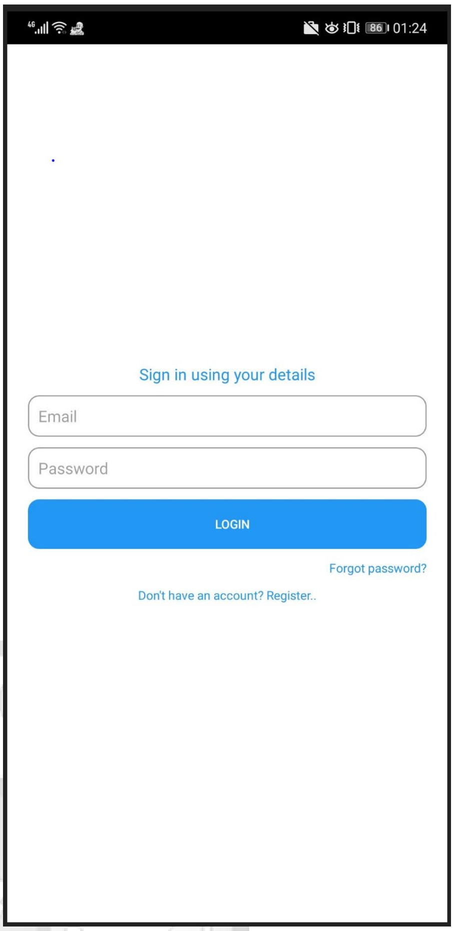


Figure 5.19: Login Module

Dashboard Module

After the remote health worker has successfully logged in, the system presents the RHW with several options of all the modules that will help them. This serves as the home page of the application. Figure 5.3 shows the dashboard module with the list of all the other modules

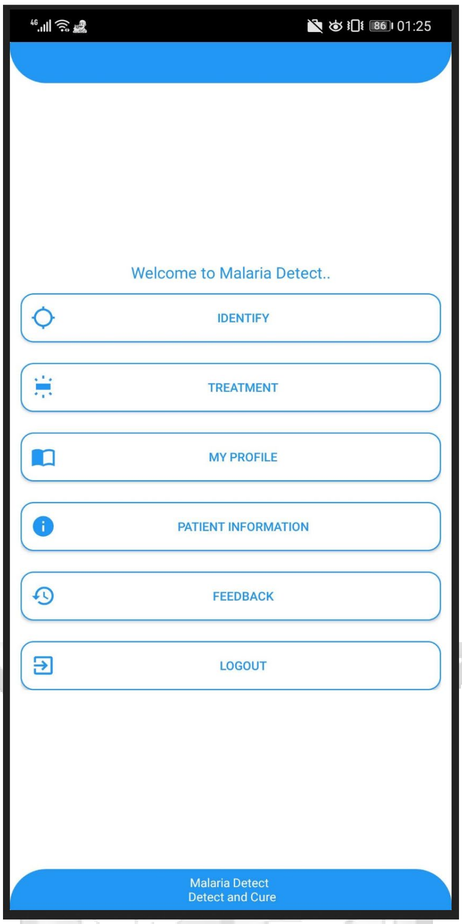


Figure 5.20: Dashboard Menu

Identify Module

This module allows the remote health worker to make inference of the previewed sample. It includes the smear background and the level of accuracy, the percentage level of the parasitized and uninfected analysis of the detection of the Plasmodium Falciparum. Figure 5.4 shows the identify module.

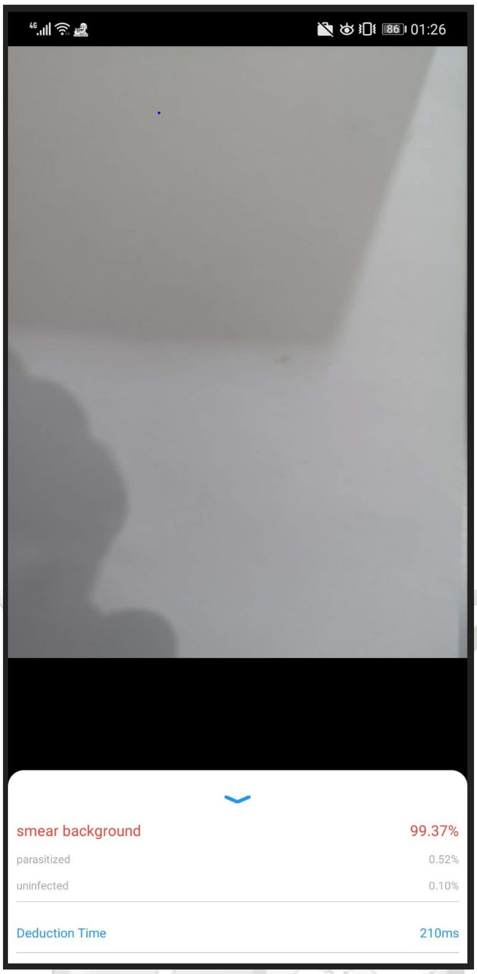


Figure 5.21: Identify Module

Treatment Module

This module provides the remote health worker with the treatment details they can administer as first aid to the child. The remote health worker can also include other forms of treatment for future administration as shown in Figure 5.5, Figure 5.6 and Figure 5.7 that includes the treatment dashboard.

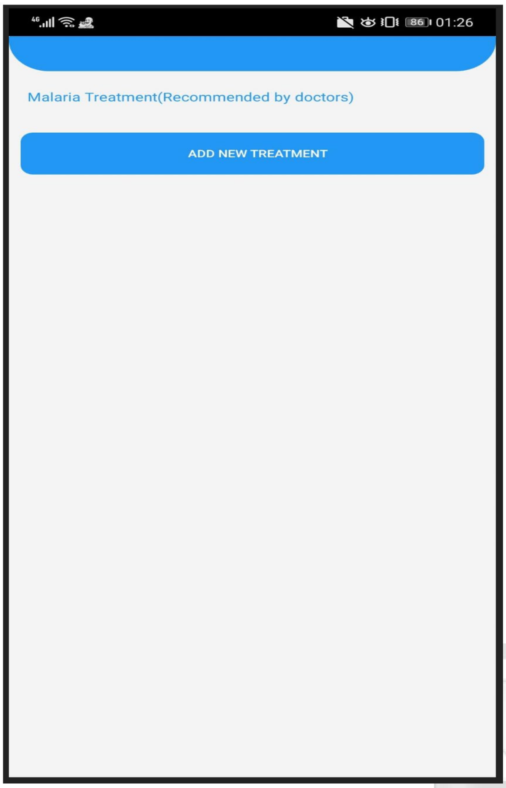


Figure 5.22: Add new treatment

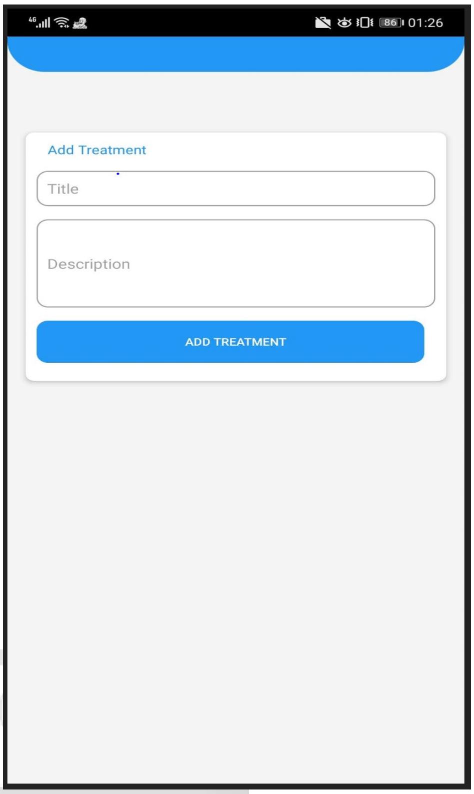


Figure 5.23: Add Treatment (b)

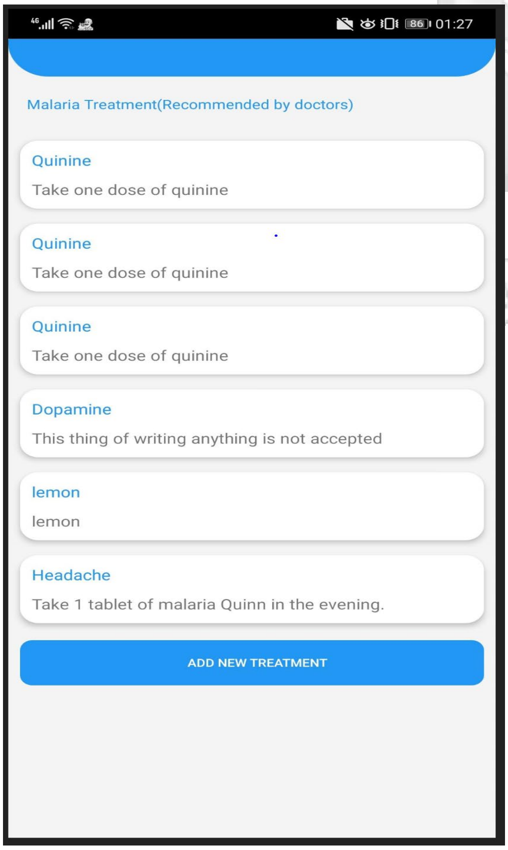


Figure 5.24: Treatment dashboard

Profile Details module for the Remote Health Worker

After the remote health worker has successfully logged in, they can update their profile details in the profile details module as shown in FIG, this includes the name, hospital attached, experiences among the rest of the required information.

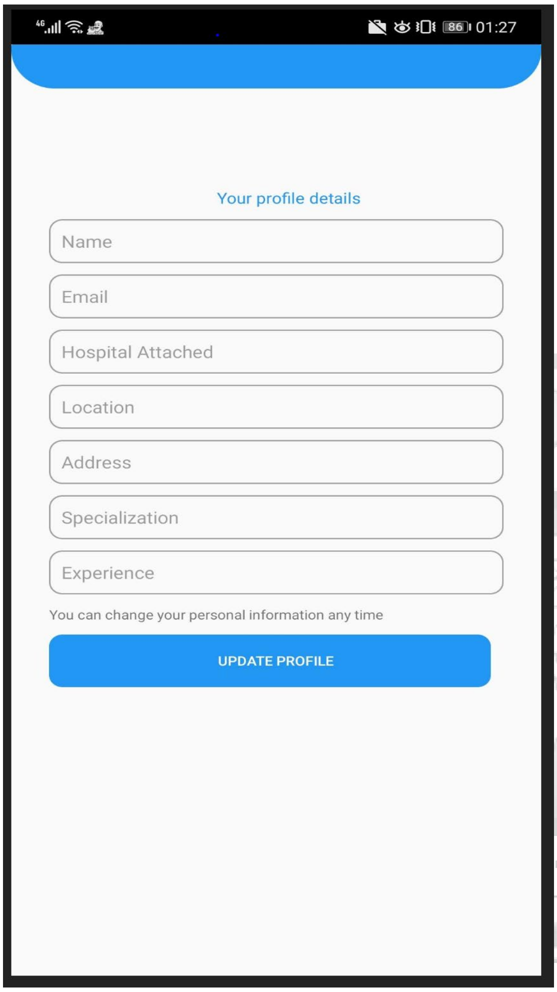


Figure 5.25: CHW Profile details (a)

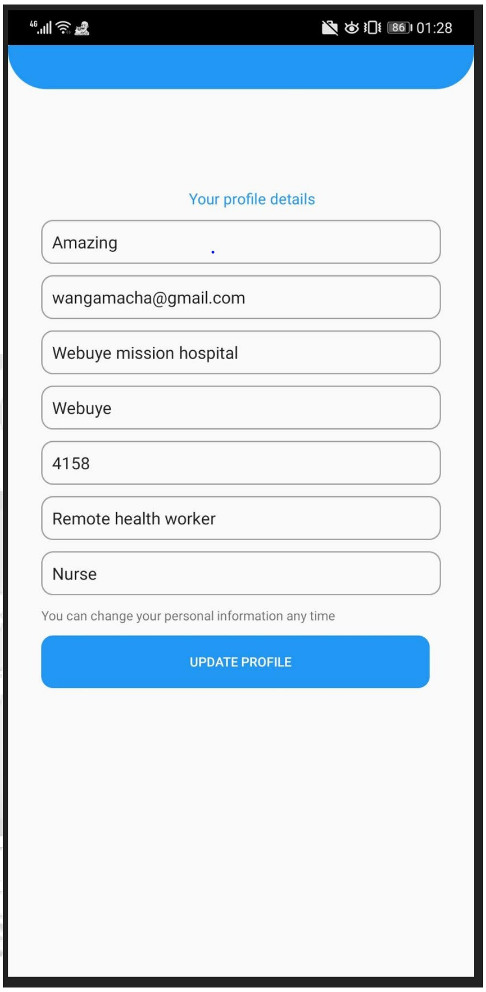


Figure 5.26: Updated profile details for the remote health worker

Patient Profile Module

After identifying the presence of the parasitized or uninfected, the remote health worker fills in the patient details and included in the module are the various signs and symptoms as shown in figure 5.10 and figure 5.11.

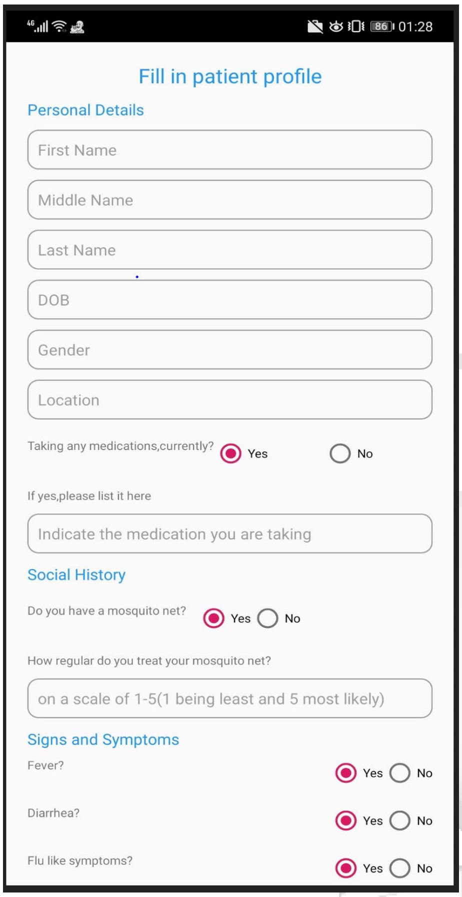


Figure 5.27: Patient Profile (a)

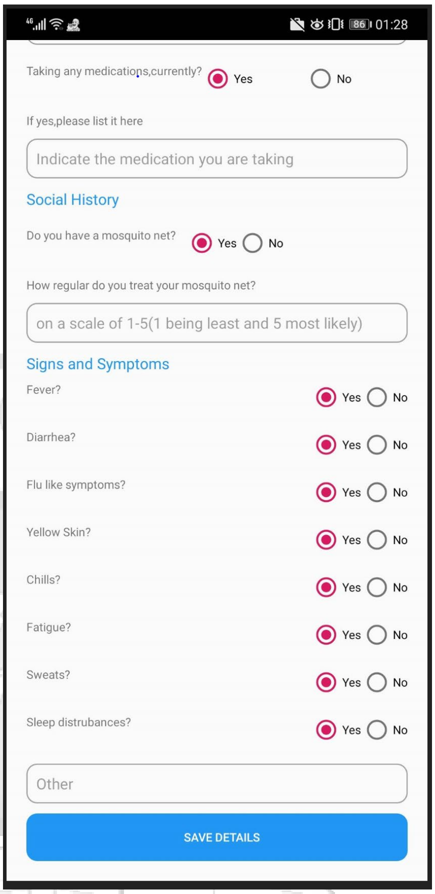


Figure 5.28: Patient Profile (b)

Feedback module

The remote health worker can share feedback on the usage of the detection app, recommend checkup and recommend the nearest health facility if the patient is critical, figure 5.12 shows this.

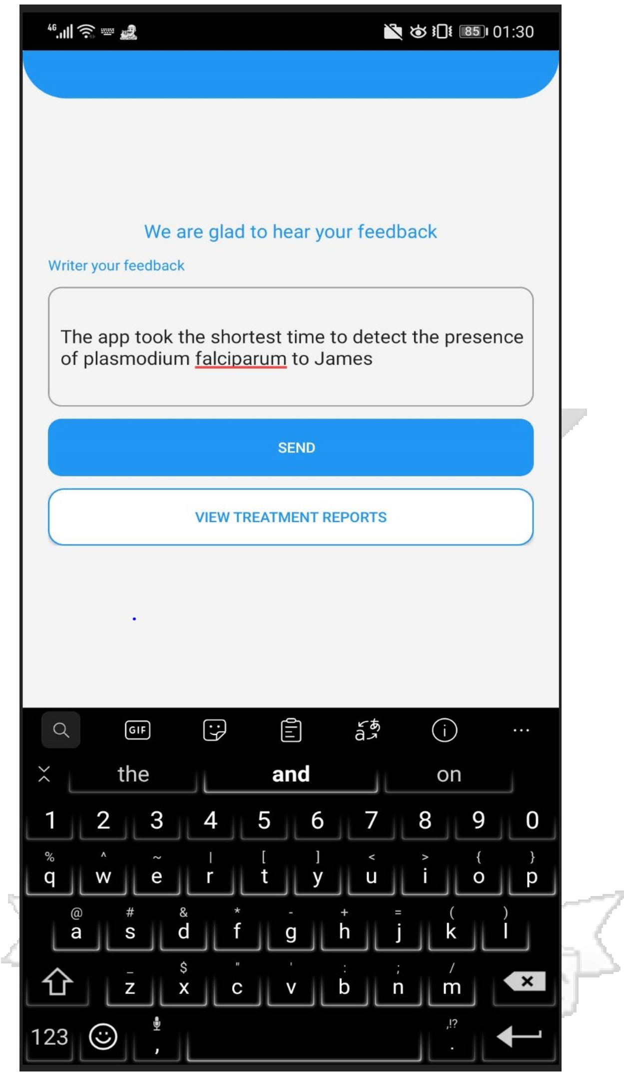


Figure 5.29: Feedback Module

5.2.6 Implementing the CNN algorithm

The algorithm comprised of the data collection, data preprocessing, training of the CNN model, validation of the CNN model and lastly testing of the CNN model. In data collection, the data set that was used was from Lister Hill National Center for Biomedical Communications (LHNCBC), part of National Library of Medicine (NLM) (Rajaraman et al., 2019). The Data set was downloaded as a cell_images.zip which contains the parasitized and uninfected images. The cell mapping for the Patient-ID to cell mappings for the parasitized and the uninfected classes were downloaded under patientid_cellmapping_parasitized.csv and patientid_cellmapping_uninfected.csv.

The CNN algorithm was implemented and the data set pre-processed for the data collection. The dataset used had 27,558 segmented cell images that had uninfected and parasitized occurrences. The presence of Plasmodium Falciparum is found in theparasitized cell images and those that are free from the parasites are under the uninfected cell images.

```
from pandas import np
from sklearn.model_selection import train_test_split
from collections import Counter


def files_df(args):
    pass


train_files, test_files, train_labels, test_labels = train_test_split(files_df['filename'].values,
                                                                      files_df['label'].values,
                                                                      test_size=0.3, random_state=42)
train_files, val_files, train_labels, val_labels = train_test_split(train_files,
                                                                    train_labels,
                                                                    test_size=0.1, random_state=42)

print(train_files.shape, val_files.shape, test_files.shape)
print('Train:', Counter(train_labels), '\nVal:', Counter(val_labels), '\nTest:', Counter(test_labels))

# Output
# (17361,) (1929,) (8268,)
# Train: Counter({'healthy': 8734, 'malaria': 8627})
# Val: Counter({'healthy': 970, 'malaria': 959})
# Test: Counter({'malaria': 4193, 'healthy': 4075})
```

Figure 5.30: Implementing the CNN algorithm

The dataset images were not of equal sizes, hence resized them to 125*125 pixels, which would allow for faster model convergence as per the code in figure 5.14 and figure 5.15.

```python
IMG_DIMS = (125, 125)

def get_img_data_parallel(idx, img, total_imgs):
    if idx % 5000 == 0 or idx == (total_imgs - 1):
        print('{}: working on img num: {}'.format(threading.current_thread().name,
                                                   idx))
    img = cv2.imread(img)
    img = cv2.resize(img, dsize=IMG_DIMS,
                     interpolation=cv2.INTER_CUBIC)
    img = np.array(img, dtype=np.float32)
    return img

ex = futures.ThreadPoolExecutor(max_workers=None)
train_data_inp = [(idx, img, len(train_files)) for idx, img in enumerate(train_files)]
val_data_inp = [(idx, img, len(val_files)) for idx, img in enumerate(val_files)]
test_data_inp = [(idx, img, len(test_files)) for idx, img in enumerate(test_files)]

print('Loading Train Images:')
train_data_map = ex.map(get_img_data_parallel,
                        [record[0] for record in train_data_inp],
                        [record[1] for record in train_data_inp],
                        [record[2] for record in train_data_inp])
train_data = np.array(list(train_data_map))

print('\nLoading Validation Images:')
val_data_map = ex.map(get_img_data_parallel,
                        [record[0] for record in val_data_inp],
                        [record[1] for record in val_data_inp],
```

Figure 5.31: Image Resizing

```python
                        [record[0] for record in train_data_inp],
                        [record[1] for record in train_data_inp],
                        [record[2] for record in train_data_inp])
train_data = np.array(list(train_data_map))

print('\nLoading Validation Images:')
val_data_map = ex.map(get_img_data_parallel,
                        [record[0] for record in val_data_inp],
                        [record[1] for record in val_data_inp],
                        [record[2] for record in val_data_inp])
val_data = np.array(list(val_data_map))

print('\nLoading Test Images:')
test_data_map = ex.map(get_img_data_parallel,
                        [record[0] for record in test_data_inp],
                        [record[1] for record in test_data_inp],
                        [record[2] for record in test_data_inp])
test_data = np.array(list(test_data_map))

train_data.shape, val_data.shape, test_data.shape
```

Figure 5.32: Image Resizing

For the parasitized cells, they contain some red globular structures. In figure 5.16 and figure 5.17 shows the sample images for the parasitized cell images.

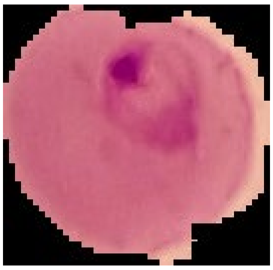


Figure 5.33: Parasitized Cell Image

Figure 5.34: Parasitized Cell Image (b)

In figure 5.18 and figure 5.19 shows the uninfected cell images sample image

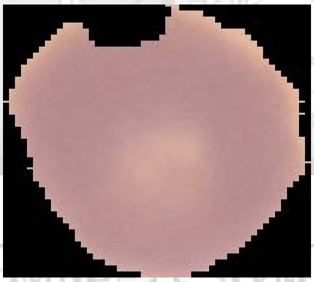


Figure 5.35: Uninfected Cell image

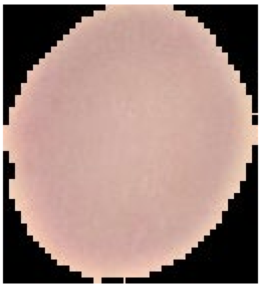


Figure 5.36: Uninfected Cell image(b)

5.2.7 Data Preprocessing

The acquired images go through several preprocessing techniques. The preprocessing is done to make images more suitable for the subsequent process. Pre-processing techniques involve resizing reduction in noise, and image contrast. Image size normalization is essential for maintaining the spatial resolution of images from multiple sources.

The training of the convolutional neural network was carried out in the cloud utilizing Google Colab. It provides a CPU runtime environment having Intel processor with a base clock speed of 3.0GHz. The graphics processing unit (GPU) runtime environment provided by Colab has a Tesla K80 GPU. For training and evaluation of the deep learning models, data scaling was performed for normalization of data by rescaling the original data points that are in the images to a range that is between 0 and1. The data was split in to training, validation and testing with the percentage of 60%,20%and 20%respectively. The training set has 17361 images, 1929 images for validation and 8268 images for testing. The average training time in seconds taken per epoch in the Colab environment. The average time taken by CPU for training is 898 seconds and by GPU is 179 seconds. GPU's are specialized processors which can perform computations in parallel with ease. A GPU which possesses more number of cores than a CPU can easily perform the neural network training as the training process is a parallel task.

Figure 5.20 below shows the data split of the dataset.

```python
from pandas import np
from sklearn.model_selection import train_test_split
from collections import Counter


def files_df(args):
    pass


train_files, test_files, train_labels, test_labels = train_test_split(files_df['filename'].values,
                                                                      files_df['label'].values,
                                                                      test_size=0.3, random_state=42)
train_files, val_files, train_labels, val_labels = train_test_split(train_files,
                                                                    train_labels,
                                                                    test_size=0.1, random_state=42)

print(train_files.shape, val_files.shape, test_files.shape)
print('Train:', Counter(train_labels), '\nVal:', Counter(val_labels), '\nTest:', Counter(test_labels))

# Output
# (17361,) (1929,) (8268,)
# Train: Counter({'healthy': 8734, 'malaria': 8627})
# Val: Counter({'healthy': 970, 'malaria': 959})
# Test: Counter({'malaria': 4193, 'healthy': 4075})
```

Figure 5.37: Training, Validation and Testing of the dataset

5.2.8 Converting Tensorflow Model to TensorFlow lite for mobile development

In order to enable the mobile application to detect malaria fast, TensorFlow model was converted to TensorFlow lite framework which supports the acceleration of the hardware and the improvement of the inference made by improving the model loading times. The tflite from python API which has simplified the model conversion as part of the deployment of the model. Once the tflite model has been converted, it then loaded to the android device for the detection of malaria.

```
import datetime

logdir = os.path.join('/home/dipanzan_sarkar/projects/tensorboard_logs',
                      datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback = tf.keras.callbacks.TensorBoard(logdir, histogram_freq=1)
reduce_lr = tf.keras.callbacks.ReduceLROnPlateau(monitor='val_loss', factor=0.5,
                              patience=2, min_lr=0.000001)
callbacks = [reduce_lr, tensorboard_callback]

history = model.fit(x=train_imgs_scaled, y=train_labels_enc,
                    batch_size=BATCH_SIZE,
                    epochs=EPOCHS,
                    validation_data=(val_imgs_scaled, val_labels_enc),
                    callbacks=callbacks,
                    verbose=1)
# # Output
# Train on 17361 samples, validate on 1929 samples
# Epoch 1/25
# 17361/17361 [====] - 32s 2ms/sample - loss: 0.4373 - accuracy: 0.7814 - val_loss: 0.1834 - val_accuracy: 0.9393
# Epoch 2/25
# 17361/17361 [====] - 30s 2ms/sample - loss: 0.1725 - accuracy: 0.9434 - val_loss: 0.1567 - val_accuracy: 0.9513
# ...
# ...
# Epoch 24/25
# 17361/17361 [====] - 30s 2ms/sample - loss: 0.0036 - accuracy: 0.9993 - val_loss: 0.3693 - val_accuracy: 0.9565
# Epoch 25/25
# 17361/17361 [====] - 30s 2ms/sample - loss: 0.0034 - accuracy: 0.9994 - val_loss: 0.3699 - val_accuracy: 0.9559
```

Figure 5.38: Tensorflow Model

The instances where the model predicted positive and the actual result was positive are true positives (TP). The cases in which the model predicted positive but actual result was negative are false positives (FP). False-negative (FN) are the instances in which the model predicted negative but it was positive. And finally, the cases in which the model predicted negative and the actual result was also negative are true negatives (TN). A good prediction model is supposed to have higher instances of TP and TN but lower instances of FP and FN simultaneously (Prakash et al., 2020). The standard formula for getting the accuracy levels include getting the percentage of the correctly classified instance of(TP + TN)/(TP + TN +FP +FN). The TP,FN,FP and TN represents the number of true positives, false positives, false negatives and true negatives. And for the detection rates this will be the number of outliers detected divided by the total number of outliers in the data udes.

In order to get the accuracy of the model, the research used 5 images from each parasitized and uninfected sample. The TN total was 2 out of 5 and the TP was 3 out of 5. The detection rate for the model was high and could detect any abnormality on the data. In conclusion, the accuracy of the model was at 92%.

5.2.9 Model Implementation

Using transfer learning, the CNN model was created to see the results that would be achieved from the dataset with the help of TensorFlow which aided in building the model.

5.3 System Testing

To ensure that the system designed met the user expectation the researcher undertook various test. This involved testing the reliability, the functionality and the compatibility of the proposed application.

5.3.1 Functionality testing

The functionality test was carried out to check that the user requirements were met as projected during the system functionalities analysis. The mobile application modules were tested extensively with the results obtained recorded in the table as shown in Table 5.1. This was essential as it guided the researcher to confirm that objectives of the study were met by ensuring that the mobile application was error free from various software bugs.

Table 5.6 Functional Testing results

Test Case	Test Carried out	Test Results	Remark	Error
Does the application allow the remote health worker to register?	Registration of the remote health worker	Successful registration details of the remote health worker by the mobile application	Executed as projected	None
Does the application allow the remote health worker to login?	Remote health worker logs in	The remote health worker can successfully login to the system	Executed as projected	None
Does the remote health worker manage to update their profile?	Successfully update the RHW profile	Successful update of the remote health worker details.	Executed as projected	None
Does the application successfully carry out real time identification and	Identify Module – make inference	Real time inference of the sample made by the identify module of the	Executed as projected	None

detection of the presence of the Plasmodium Falciparum?		Plasmodium Falciparum.		
Does the remote health worker manage to update the child's details?	Successful update of the patient's details.	Successful addition of information for the child	Executed as projected	None
Does the system allow the remote health worker access the various report options?	View the feedback report, view the patient report	Remote health worker successfully views the various report option	Executed as projected	None

5.3.2 Compatibility testing

Various devices using Android platform were used to in testing the mobile application so as to confirm if the application was compatible and they include Huawei, Samsung s10 and Nokia.

5.3.3 User Acceptance Testing

The user acceptance test was carried out by randomly selecting users to achieve various functionalities such as the system functionality and system usability and compatibility.

i. System Functionality

This was to get the general functionality of the system and it included the test of the various modules such as the registration and the login module, the detection module, the patient module and the feedback module as shown in figure 5.1. 81% of the users tested the various modules. The other user response based on the system functionality are in Appendix E

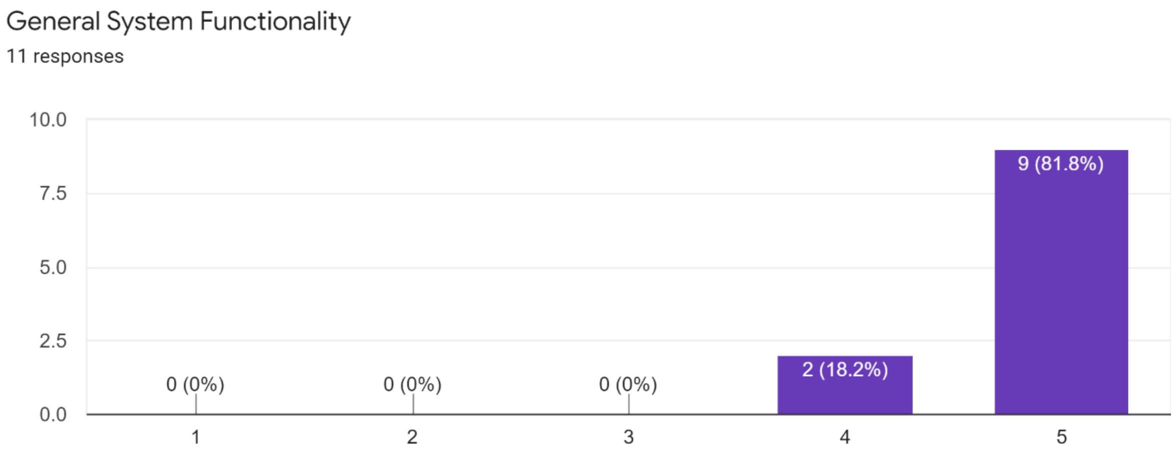


Figure 5.39 General System Functionality

ii. System Usability

This was to determine the level at which the system was user friendly to the user, the ease of navigation as well as level of feedback and instructions provided by the system. Figure 5.14 shows that 100% of the users found the application easy to navigate and fig shows that the feedback and applications provided by the system were clear.

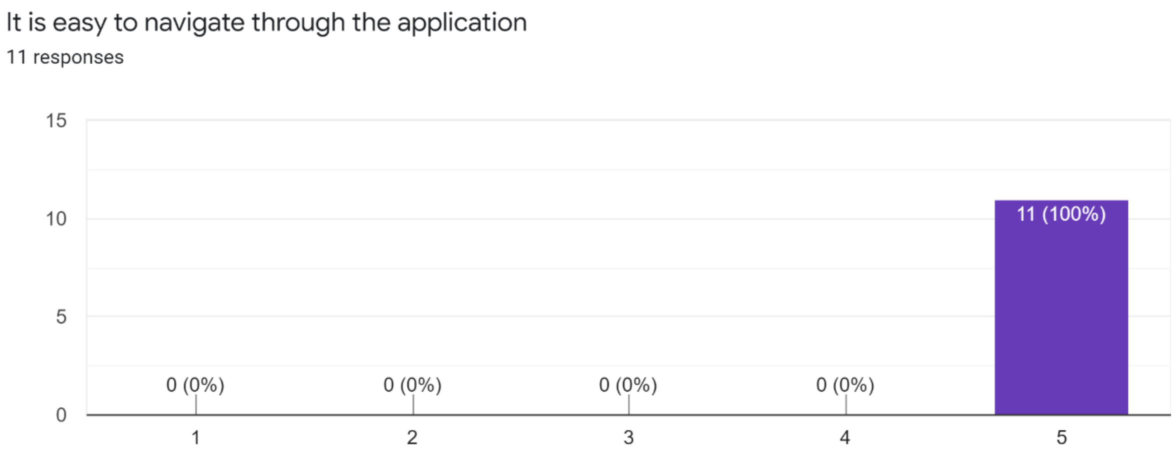


Figure 5.40 Navigation

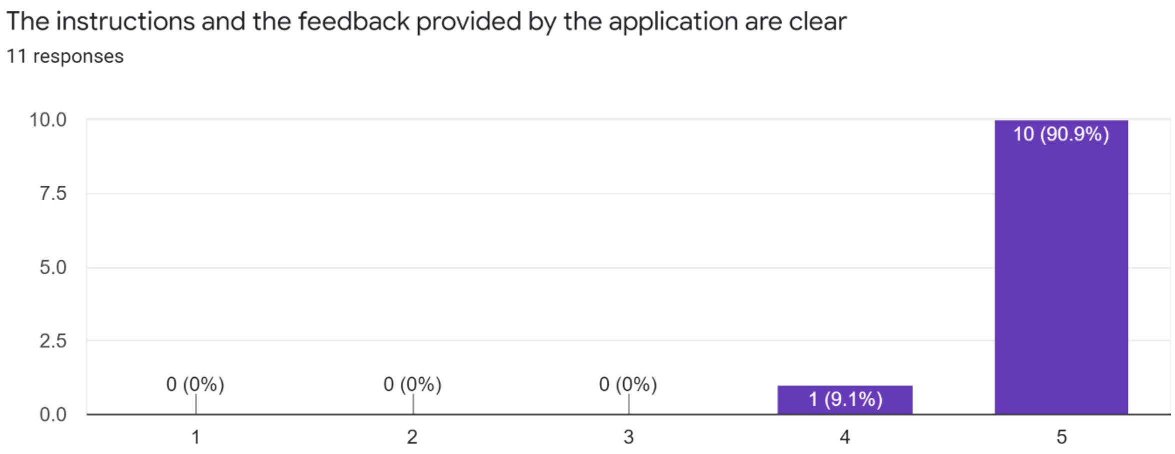


Figure 5.41 Feedback

iii. System Compatibility

This enabled the users to indicate the android platform that they used.

5.4 System Validation

A post survey questionnaire was created as shown in Appendix A and given to the randomly selected end users to give their input on the mobile application. The validation of the mobile application was carried out to determine whether the malaria detection system would assist the remote health workers in the rural and interior regions of the case study.

The users who took part in the user acceptance test were the same users who gave their input on the validation test as shown in figure 5.16 which indicated if the users used the system and 90.9% installed and used the system.

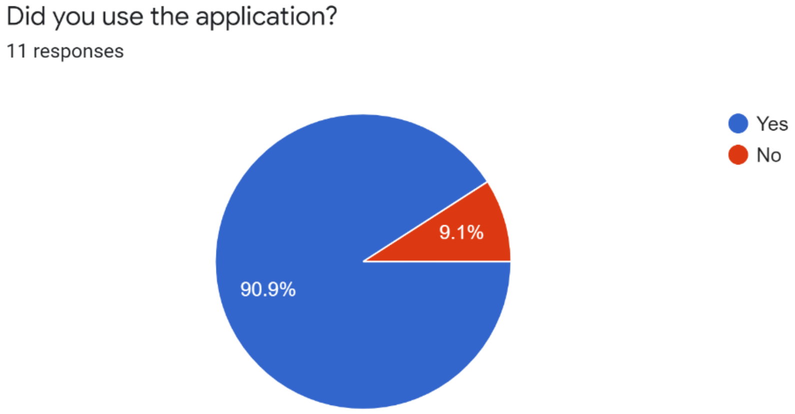


Figure 5.42 Application Use

Fig 5.17 below shows whether the functionalities of the system were being addressed by the tool kit . 100% of the users found the tool kit easy to use.

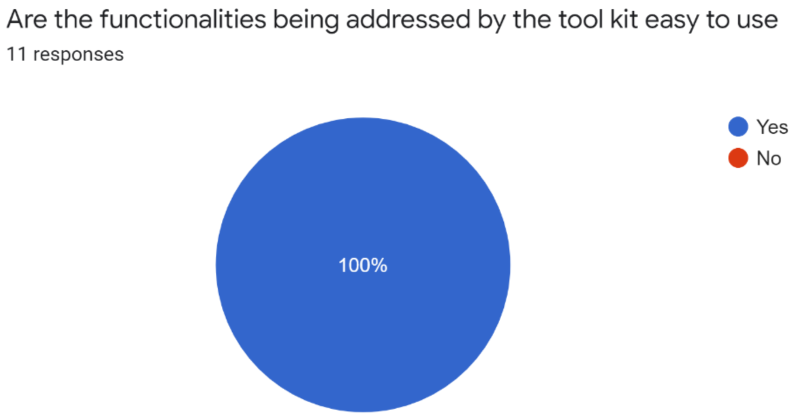


Figure 5.43 Functionality

Figure 5.18 shows that 100% of the users would recommend the mobile application tool kit

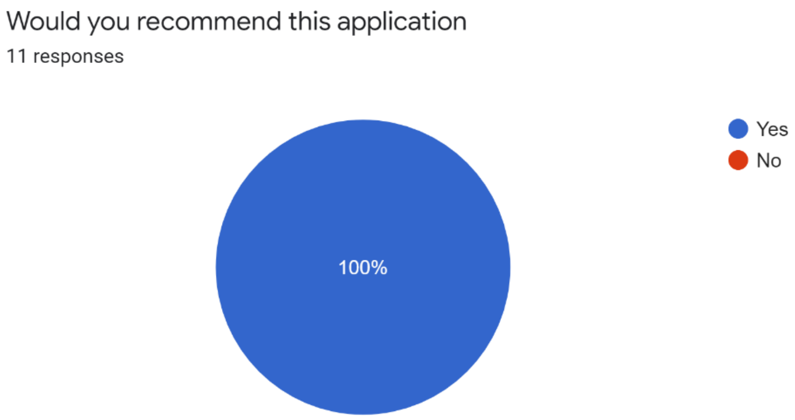


Figure 5.44 Recommendation

Chapter 6. Discussion

6.1 Introduction

This chapter addressed the research questions and how they complemented the set objectives while making comparisons between the existing systems and the developed system for malaria detection. The technology that was used to come up with the application has been established and the steps taken to achieve this have been explained based on the methodology and the system designs. To achieve these objectives, the research made use of secondary data. This data was used as an evaluation tool for the various proposed malaria detection systems architectures and framework that have been deployed and find the most suitable technology.

6.2 Objective One Review

The first objective was to assess the prevailing problems and challenges that are faced in the early detection of malaria in children. There was an even distribution of challenges faced in the detection of malaria in children where lack timely detection of malaria would lead to irreversible and fatal complications to children under the age of five whose immune system is still growing and developing. It was important for the health worker to accurately and promptly detect the presence of the Plasmodium Falciparum to ensure the low prevalence of the mortality and morbidity rate of malaria in children This was an important objective especially in validating the need for the proposed solution.

6.3 Objective Two Review

The second objective of the research was to assess the current practices and perceptions about the detection of malaria in children This aim of this objective was to establish the information and the data that was necessary for determining the detection of malaria in children. This objective was achieved by carrying out extensive research of scholarly materials as well as from the initial study that was conducted in this research. This was to check if there have been solutions that have been implemented around these areas.

The research illustrated that most of the proposed solutions were not easy to use and required the use of a third-party device to detect the presence of the Plasmodium Falciparum. This required the user to attach their mobile phone camera to a microscope. Therefore, for prompt detection of malaria, this must be conducted in real time. This in turn became the basis of the information and data that was important in detecting the presence of Plasmodium Falciparum in children as illustrated in the Literature Review of Chapter 2 of this report.

6.4 Objective Three Review

The fourth objective was to design and develop as illustrated in the System Analysis, Design and Architecture in Chapter 4 of the document, a real time mobile application for the detection of malaria in children so as to meet this objective. The design tools that were used were the Use Case Diagram, the Sequence Diagram, Entity Relationship, Class diagram and lastly the Wireframes. This was achieved by developing the Malaria Detection Application as discussed. Due to time constraints the objective was not fully meet, but the researcher developed the proposed prototype to proof the concept.

6.5 Objective Four Review

The last objective was to test and validate the mobile application that helps in the detection of malaria and the performance and results were documented as part of the research study in the Implementation and Testing in Chapter 5. A pre-test section and a post-section survey was conducted as part of the validation as seen in Appendix A so that the user could voice their satisfaction based on the functionalities of the system. The pre-test focused on getting the user's input in their experience with the functionality, usability and compatibility of the mobile application while the post-test focused on the users' experience with the Malaria Detection mobile application.

Chapter 7. Conclusion and Recommendation

7.1 Introduction

This chapter includes the conclusions derived by the researcher based on the research, a summary of the recommendations and future work for this particular area of study. With the mobile application in place, the remote health workers could easily carry out the detection of malaria in children as outlined from the beginning of the research.

7.2 Conclusions

Malaria is the most infectious disease and continues to be a major global health problem with over 40% of the world's population being at risk to various degrees of malaria risk (Dhorda et al., 2020b). Delayed detection of malaria is one of the challenges leading to high mortality and morbidity rate in children under the age of five years. Through this research, the proposed system has demonstrated that we can have a real time mobile application for the detection of malaria which initially required one to have a microscope or carry out the test in a hospital laboratory and this would take hours.

The Mobile application for Malaria Detection has many benefits such as carrying out real time detection of the Plasmodium Falciparum and further updating the patient's information with ease for future reference by the remote health worker. If this application is implemented by the rest of the health practitioners, malaria detection will be managed to ensure that irreversible and fatal implications to the children has reduced hence low mortality and morbidity rate in children under the age of five affected by malaria in Western Kenya.

The Mobile application was tested and it was established that it functioned as required and the recommendations made by the users would assist in illustrating the future implementation.

7.3 Recommendations

The recommendations drawn from the research results include:

i. Conduct training to the remote health worker to assist them in navigating and understanding the application.
ii. The research recommends using the application for other patients affected by malaria and not just focusing on the children under the age of five.
iii. Testing the application outside the Western region of Kenya.

iv. Technology enhancements and improvements on the features.

7.4 Future works

The future improvements that can be implemented include:

i. This research was carried out in the Western region of Kenya and these requires the need for deeper research work to be done in the different environments in the country to aid in the detection of malaria by the use of diverse models and both android and iOS applications for the users.
ii. There is need to add more features to the Malaria Detection Mobile Application and explore the emerging technologies in CNN and how they can be implemented to improve the application.
iii. The mobile application developed uses data enabled android phones and the detection must be carried out using the internet. Research can be carried out to have other options of access especially in areas where connectivity of mobile phones is limited with unstable internet connection
iv. Integration with other health systems for epidemic control in the country
v. Include other mobile platforms such as the Windows phone and iOS

REFERENCES

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., & Zhang, X. (2016). *TensorFlow: A system for large-scale machine learning*.

Ahmad, M. A., Teredesai, A., & Eckert, C. (2018). Interpretable Machine Learning in Healthcare. *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, 447–447. https://doi.org/10.1109/ICHI.2018.00095

Al-Dhaibani, R., Bamatraf, M. A. M., & Sha'Afal, Khalid. Q. (2019). Data Benchmark Collection of Patients with Malaria for Machine Learning: A study in Hadhramout- Yemen. *2019 First International Conference of Intelligent Computing and Engineering (ICOICE)*, 1–3. https://doi.org/10.1109/ICOICE48418.2019.9035166

Alegana, V. A., Suiyanka, L., Macharia, P. M., Ikahu-Muchangi, G., & Snow, R. W. (2021a). Malaria micro-stratification using routine surveillance data in Western Kenya. *Malaria Journal*, *20*(1), 22. https://doi.org/10.1186/s12936-020-03529-6

Alegana, V. A., Suiyanka, L., Macharia, P. M., Ikahu-Muchangi, G., & Snow, R. W. (2021b). Malaria micro-stratification using routine surveillance data in Western Kenya. *Malaria Journal*, *20*(1), 22. https://doi.org/10.1186/s12936-020-03529-6

Alsaqqa, S., Sawalha, S., & Abdel-Nabi, H. (2020). Agile Software Development: Methodologies and Trends. *International Journal of Interactive Mobile Technologies (IJIM)*, *14*, 246. https://doi.org/10.3991/ijim.v14i11.13269

Amek, N. O., Van Eijk, A., Lindblade, K. A., Hamel, M., Bayoh, N., Gimnig, J., Laserson, K. F., Slutsker, L., Smith, T., & Vounatsou, P. (2018). Infant and child mortality in relation to malaria transmission in KEMRI/CDC HDSS, Western Kenya: Validation of verbal autopsy. *Malaria Journal*, *17*(1), 1–11. https://doi.org/10.1186/s12936-018-2184-x

Amir, A., Cheong, F.-W., De Silva, J. R., & Lau, Y.-L. (2018). Diagnostic tools in childhood malaria. *Parasites & Vectors*, *11*(1), 53. https://doi.org/10.1186/s13071-018-2617-y

Binka, F., & Akweongo, P. (2006). Prevention of malaria using ITNs: Potential for achieving the millennium development goals. *Current Molecular Medicine*, *6*(2), 261–267. https://doi.org/10.2174/156652406776055203

Bre, F., Gimenez, J., & Fachinotti, V. (2017). Prediction of wind pressure coefficients on building surfaces using Artificial Neural Networks. *Energy and Buildings*, *158*. https://doi.org/10.1016/j.enbuild.2017.11.045

Dhorda, M., Ba, E. H., Kevin Baird, J., Barnwell, J., Bell, D., Carter, J. Y., Dondorp, A., Ekawati, L., Gatton, M., González, I., Guérin, P. J., Incardona, S., Lilley, K., Menard, D., Nosten, F., Obare, P., Ogutu, B., Olliaro, P. L., Price, R. N., … Research Malaria Microscopy Working Group. (2020a). Towards harmonization of microscopy methods for malaria clinical research studies. *Malaria Journal*, *19*(1), 324. https://doi.org/10.1186/s12936-020-03352-z

Dhorda, M., Ba, E. H., Kevin Baird, J., Barnwell, J., Bell, D., Carter, J. Y., Dondorp, A., Ekawati, L., Gatton, M., González, I., Guérin, P. J., Incardona, S., Lilley, K., Menard, D., Nosten, F., Obare, P., Ogutu, B., Olliaro, P. L., Price, R. N., … Research Malaria Microscopy Working Group. (2020b). Towards harmonization of microscopy methods for malaria clinical research studies. *Malaria Journal*, *19*(1), 324. https://doi.org/10.1186/s12936-020-03352-z

el Alami, A., & Bahaj, M. (2018). *The Migration of a Conceptual Object Model COM (Conceptual Data Model CDM, Unified Modeling Language UML class diagram ...) to the Object Relational Database ORDB*.

Entity Relationship Diagram—ER Diagram in DBMS. (2015, April 20). *Beginnersbook.Com*. https://beginnersbook.com/2015/04/e-r-model-in-dbms/

Hernandez, J. B. R., & Kim, P. Y. (2021). Epidemiology Morbidity And Mortality. In *StatPearls*. StatPearls Publishing. http://www.ncbi.nlm.nih.gov/books/NBK547668/

Hussain, M., Bird, J., & Faria, D. (2018). *A Study on CNN Transfer Learning for Image Classification*.

Jenkins, R., Omollo, R., Ongecha, M., Sifuna, P., Othieno, C., Ongeri, L., Kingora, J., & Ogutu, B. (2015). Prevalence of malaria parasites in adults and its determinants in malaria endemic area of Kisumu County, Kenya. *Malaria Journal*, *14*(1), 263. https://doi.org/10.1186/s12936-015-0781-5

Kabir, S. M. (2016). *METHODS OF DATA COLLECTION* (pp. 201–275).

Kamau, A., Mtanje, G., Mataza, C., Mwambingu, G., Mturi, N., Mohammed, S., Ong'ayo, G., Nyutu, G., Nyaguara, A., Bejon, P., & Snow, R. W. (2020). Malaria infection, disease and mortality among children and adults on the coast of Kenya. *Malaria Journal*, *19*(1), 210. https://doi.org/10.1186/s12936-020-03286-6

Kenya | History, Map, Flag, Climate, Capital, & Facts. (n.d.). Encyclopedia Britannica. Retrieved September 7, 2021, from https://www.britannica.com/place/Kenya

Krampa, F. D., Aniweh, Y., Kanyong, P., & Awandare, G. A. (2020). Recent Advances in the Development of Biosensors for Malaria Diagnosis. *Sensors*, *20*(3). https://doi.org/10.3390/s20030799

Lalremruata, A., Jeyaraj, S., Engleitner, T., Joanny, F., Lang, A., Bélard, S., Mombo-Ngoma, G., Ramharter, M., Kremsner, P. G., Mordmüller, B., & Held, J. (2017). Species and genotype diversity of Plasmodium in malaria patients from Gabon analysed by next generation sequencing. *Malaria Journal*, *16*(1), 398. https://doi.org/10.1186/s12936-017-2044-0

Masud, M., Alhumyani, H., Alshamrani, S. S., Cheikhrouhou, O., Ibrahim, S., Muhammad, G., Hossain, M. S., & Shorfuzzaman, M. (2020, July 8). *Leveraging Deep Learning Techniques for Malaria Parasite Detection Using Mobile Application* [Research Article]. Wireless Communications and Mobile Computing; Hindawi. https://doi.org/10.1155/2020/8895429

Mathison, B. A., & Pritt, B. S. (2017). Update on Malaria Diagnostics and Test Utilization. *Journal of Clinical Microbiology*, *55*(7), 2009–2017. https://doi.org/10.1128/JCM.02562-16

Mbanefo, A., & Kumar, N. (2020). Evaluation of Malaria Diagnostic Methods as a Key for Successful Control and Elimination Programs. *Tropical Medicine and Infectious Disease*, *5*(2), 102. https://doi.org/10.3390/tropicalmed5020102

Mello, A., & Wood Jr, T. (2019). What is applied research anyway? *Revista de Gestão*, *26*, 338–339. https://doi.org/10.1108/REGE-10-2019-128

Mordecai, E. A., Ryan, S. J., Caldwell, J. M., Shah, M. M., & LaBeaud, A. D. (2020). Climate change could shift disease burden from malaria to arboviruses in Africa. *The Lancet Planetary Health*, *4*(9), e416–e423. https://doi.org/10.1016/S2542-5196(20)30178-9

Mutsigiri-Murewanhema, F., Mafaune, P. T., Shambira, G., Juru, T., Bangure, D., Mungati, M., Gombe, N. T., & Tshimanga, M. (2017). Factors associated with severe malaria among children below ten years in Mutasa and Nyanga districts, Zimbabwe, 2014-2015. *The Pan African Medical Journal*, *27*, 23. https://doi.org/10.11604/pamj.2017.27.23.10957

Nwakanma, I., Folashade, A., Jeremiah, O., Ikechukwu, A., & Cletus, A. (2018). Transitions in System Analysis and Design Methodology. *American Journal of Information Science and Technology*, *2*. https://doi.org/10.11648/j.ajist.20180202.14

Odhiambo, D. (2019, May 9). *System Design in Software Development*. Medium. https://medium.com/the-andela-way/system-design-in-software-development-f360ce6fcbb9

Oliveira, A. D., Prats, C., Espasa, M., Serrat, F. Z., Sales, C. M., Silgado, A., Codina, D. L., Arruda, M. E., Prat, J. G. i, & Albuquerque, J. (2017). The Malaria System MicroApp: A New, Mobile Device-Based Tool for Malaria Diagnosis. *JMIR Research Protocols*, *6*(4). https://doi.org/10.2196/resprot.6758

Pan, W. D., Dong, Y., & Wu, D. (2018). Classification of Malaria-Infected Cells Using Deep Convolutional Neural Networks. *Machine Learning - Advanced Techniques and Emerging Applications*. https://doi.org/10.5772/intechopen.72426

Poostchi, M., Silamut, K., Maude, R. J., Jaeger, S., & Thoma, G. (2018). Image analysis and machine learning for detecting malaria. *Translational Research*, *194*, 36–55. https://doi.org/10.1016/j.trsl.2017.12.004

Prada-Ramallal, G., Roque, F., Herdeiro, M. T., Takkouche, B., & Figueiras, A. (2018). Primary versus secondary source of data in observational studies and heterogeneity in meta-analyses of drug effects: A survey of major medical journals. *BMC Medical Research Methodology*, *18*(1), 97. https://doi.org/10.1186/s12874-018-0561-3

Prakash, S. S., Kovoor, B. C., & Visakha, K. (2020). Convolutional Neural Network Based Malaria Parasite Infection Detection Using Thin Microscopic Blood Smear Samples. *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, 308–313. https://doi.org/10.1109/ICIRCA48905.2020.9182944

Rajaraman, S., Antani, S. K., Poostchi, M., Silamut, K., Hossain, M. A., Maude, R. J., Jaeger, S., & Thoma, G. R. (2018). Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images. *PeerJ*, *6*, e4568. https://doi.org/10.7717/peerj.4568

Rajaraman, S., Jaeger, S., & Antani, S. K. (2019). Performance evaluation of deep neural ensembles toward malaria parasite detection in thin-blood smear images. *PeerJ*, *7*, e6977. https://doi.org/10.7717/peerj.6977

Roberts, D., & Matthews, G. (2016). Risk factors of malaria in children under the age of five years old in Uganda. *Malaria Journal*, *15*(1), 246. https://doi.org/10.1186/s12936-016-1290-x

Sarkar, T. (2020, April 30). *AI and machine learning for healthcare*. Medium. https://towardsdatascience.com/ai-and-machine-learning-for-healthcare-7a70fb3acb67

Sultana, M., Sheikh, N., Mahumud, R. A., Jahir, T., Islam, Z., & Sarker, A. R. (2017a). Prevalence and associated determinants of malaria parasites among Kenyan children. *Tropical Medicine and Health*, *45*, 25–25. PubMed. https://doi.org/10.1186/s41182-017-0066-5

Sultana, M., Sheikh, N., Mahumud, R. A., Jahir, T., Islam, Z., & Sarker, A. R. (2017b). Prevalence and associated determinants of malaria parasites among Kenyan children. *Tropical Medicine and Health*, *45*, 25. https://doi.org/10.1186/s41182-017-0066-5

Taher, K. A., Mohammed Yasin Jisan, B., & Rahman, Md. M. (2019). Network Intrusion Detection using Supervised Machine Learning Technique with Feature Selection. *2019 International Conference on Robotics,Electrical and Signal Processing Techniques (ICREST)*, 643–646. https://doi.org/10.1109/ICREST.2019.8644161

Tamari, N., Minakawa, N., Sonye, G. O., Awuor, B., Kongere, J. O., Hashimoto, M., Kataoka, M., & Munga, S. (2020). Protective effects of Olyset® Net on Plasmodium falciparum infection after three years of distribution in western Kenya. *Malaria Journal*, *19*(1), 1–11. https://doi.org/10.1186/s12936-020-03444-w

Yang, F., Poostchi, M., Yu, H., Zhou, Z., Silamut, K., Yu, J., Maude, R. J., Jaeger, S., & Antani, S. (2020a). Deep Learning for Smartphone-Based Malaria Parasite Detection in Thick Blood Smears. *IEEE Journal of Biomedical and Health Informatics*, *24*(5), 1427–1438. https://doi.org/10.1109/JBHI.2019.2939121

Yang, F., Poostchi, M., Yu, H., Zhou, Z., Silamut, K., Yu, J., Maude, R. J., Jaeger, S., & Antani, S. (2020b). Deep Learning for Smartphone-Based Malaria Parasite Detection in Thick Blood Smears. *IEEE Journal of Biomedical and Health Informatics*, *24*(5), 1427–1438. https://doi.org/10.1109/JBHI.2019.2939121

Yu, H., Yang, F., Rajaraman, S., Ersoy, I., Moallem, G., Poostchi, M., Palaniappan, K., Antani, S., Maude, R. J., & Jaeger, S. (2020a). Malaria Screener: A smartphone application for automated malaria screening. *BMC Infectious Diseases*, *20*(1), 825. https://doi.org/10.1186/s12879-020-05453-1

Yu, H., Yang, F., Rajaraman, S., Ersoy, I., Moallem, G., Poostchi, M., Palaniappan, K., Antani, S., Maude, R. J., & Jaeger, S. (2020b). Malaria Screener: A smartphone application for automated malaria screening. *BMC Infectious Diseases*, *20*(1), 825. https://doi.org/10.1186/s12879-020-05453-1

Ziegler, M. (2016). Landscapes of Disease. *Landscapes*, *17*(2), 99–107. https://doi.org/10.1080/14662035.2016.1251100

Appendices

Appendix A: Originality Report

The Ouriginal Report Summary

Ouriginal

Document Information

Analyzed document	Final Documentation.docx (D103362752)
Submitted	4/30/2021 9:41:00 AM
Submitted by	
Submitter email	gmacharia993@gmail.com
Similarity	4%
Analysis address	library.strath@analysis.urkund.com

Sources included in the report

Appendix B: Post Survey Questionnaire

Mobile Application for Malaria DetectionPost Survey

This survey will be used for academic purpose to assess the users' experience for the Malaria Mobile Tool Kit.

Kindly provide your honest opinion on the same on the above. Please note that your response will be treated as private and confidential.

We would get hear your feedback and know any areas of improvement.

* Required

1. Email address *

2. Select Gender *

   Mark only one oval.

   - Male
   - Female
   - Prefer not to say

System Functionality

This section is to get the practicality of the application

3. General System Functionality *

   Mark only one oval.

	1	2	3	4	5	
Very Hard						Very Easy

4. Registration/Login *

Mark only one oval.

	1	2	3	4	5	
Very Hard	⬭	⬭	⬭	⬭	⬭	Very Easy

5. Identification/Detection Module *

Mark only one oval.

	1	2	3	4	5	
Very Hard	⬭	⬭	⬭	⬭	⬭	Very Easy

6. Recommend Treatment/Update Treatment *

Mark only one oval.

	1	2	3	4	5	
Very Hard	⬭	⬭	⬭	⬭	⬭	Very Easy

7. Filling out the Patient Information Details *

Mark only one oval.

	1	2	3	4	5	
Very Hard	⬭	⬭	⬭	⬭	⬭	Very Easy

8. Updating User Profile *

Mark only one oval.

	1	2	3	4	5	
Very Hard	◯	◯	◯	◯	◯	Very Easy

System Usability

This section is to test your ease of navigating through the application.

9. General System Usability *

Mark only one oval.

	1	2	3	4	5	
Very Hard	◯	◯	◯	◯	◯	Very Easy

10. It is easy to navigate through the application *

Mark only one oval.

	1	2	3	4	5	
Very Hard	◯	◯	◯	◯	◯	Very Easy

11. The instructions and the feedback provided by the application are clear *

Mark only one oval.

	1	2	3	4	5	
Very Hard	◯	◯	◯	◯	◯	Very Easy

12. The response was prompt *

Mark only one oval.

	1	2	3	4	5	
Very Hard	◯	◯	◯	◯	◯	Very Easy

System Compatibility

This section is use to test whether the tool kit works with your mobile device.

13. The application was easy to install *

Mark only one oval.

Yes ◯

No ◯

14. Model of your mobile device *

____

System

This involves the confirmation on the alignment of the system to real business environment.

Validation

15. Did you use the application? *

Mark only one oval.

Yes ⬭

No ⬭

16. Are the functionalities being addressed by the tool kit easy to use *

Mark only one oval.

Yes ⬭

No ⬭

17. Does the tool kit meet your satisfaction for testing early malaria detection in children? *

Mark only one oval.

Yes ⬭

No ⬭

Recommendation

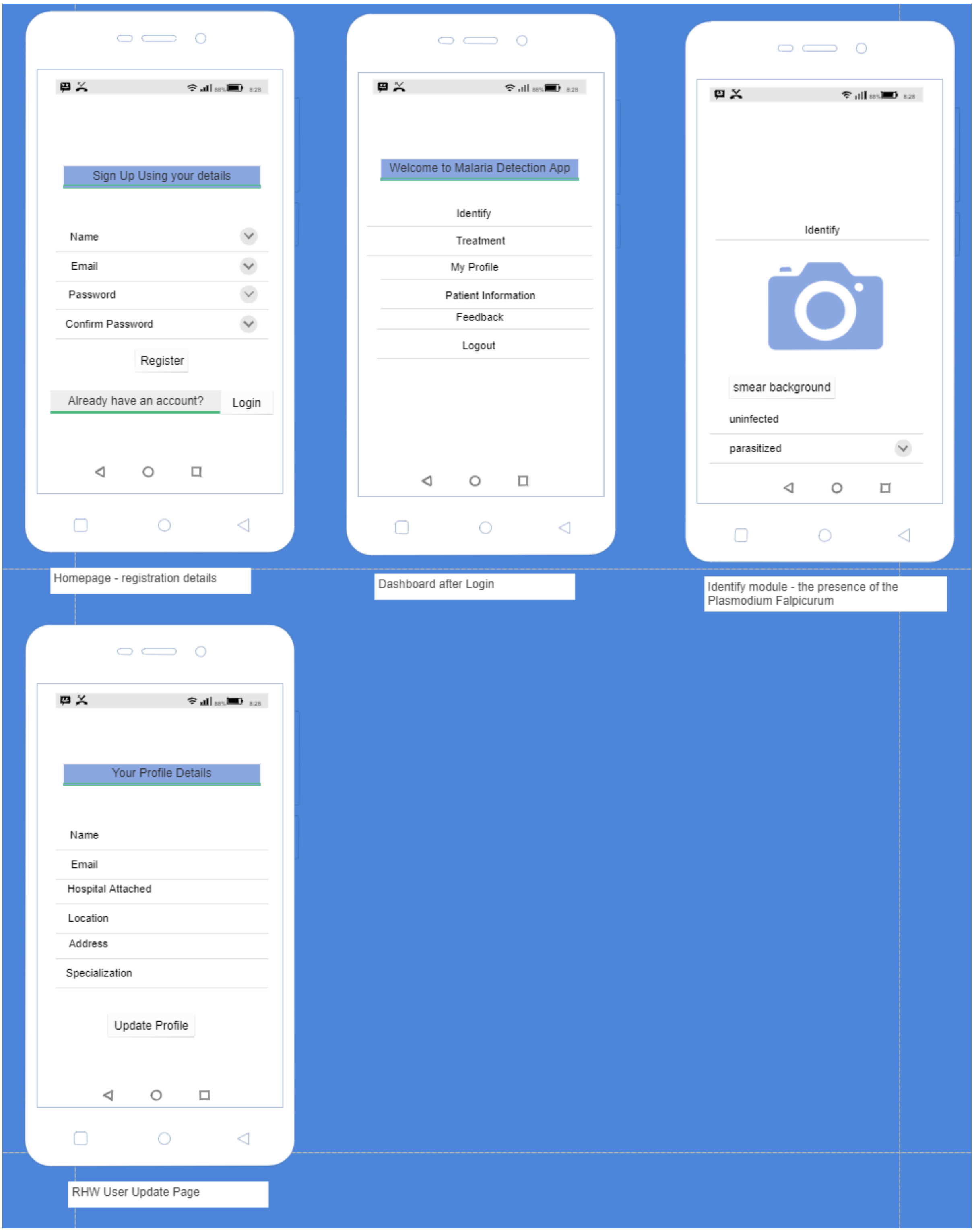
18. Would you recommend this application *

Mark only one oval.

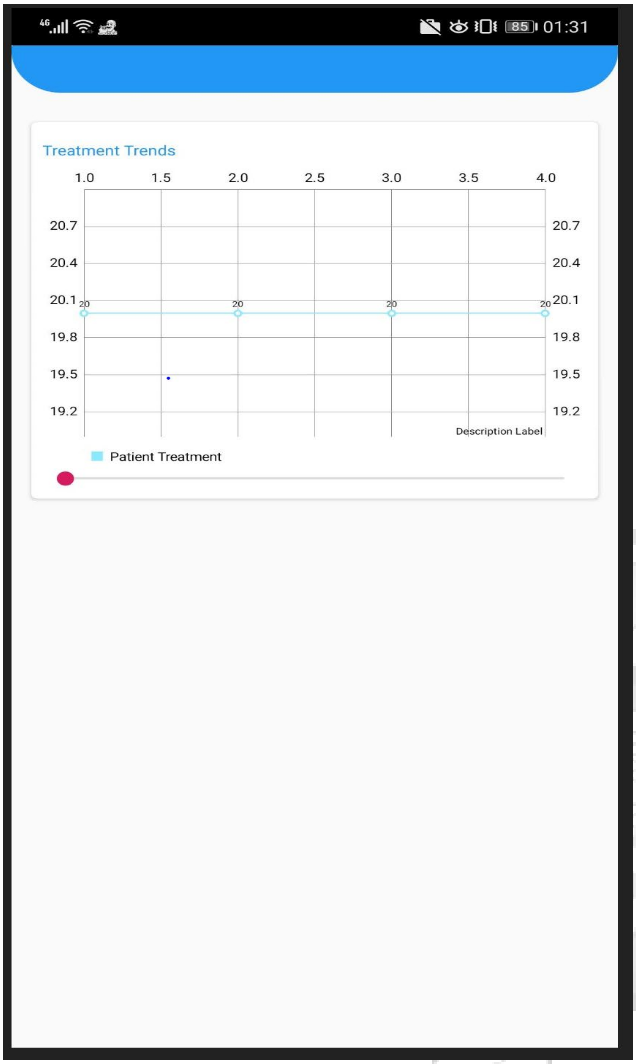
Yes ⬭

No ⬭

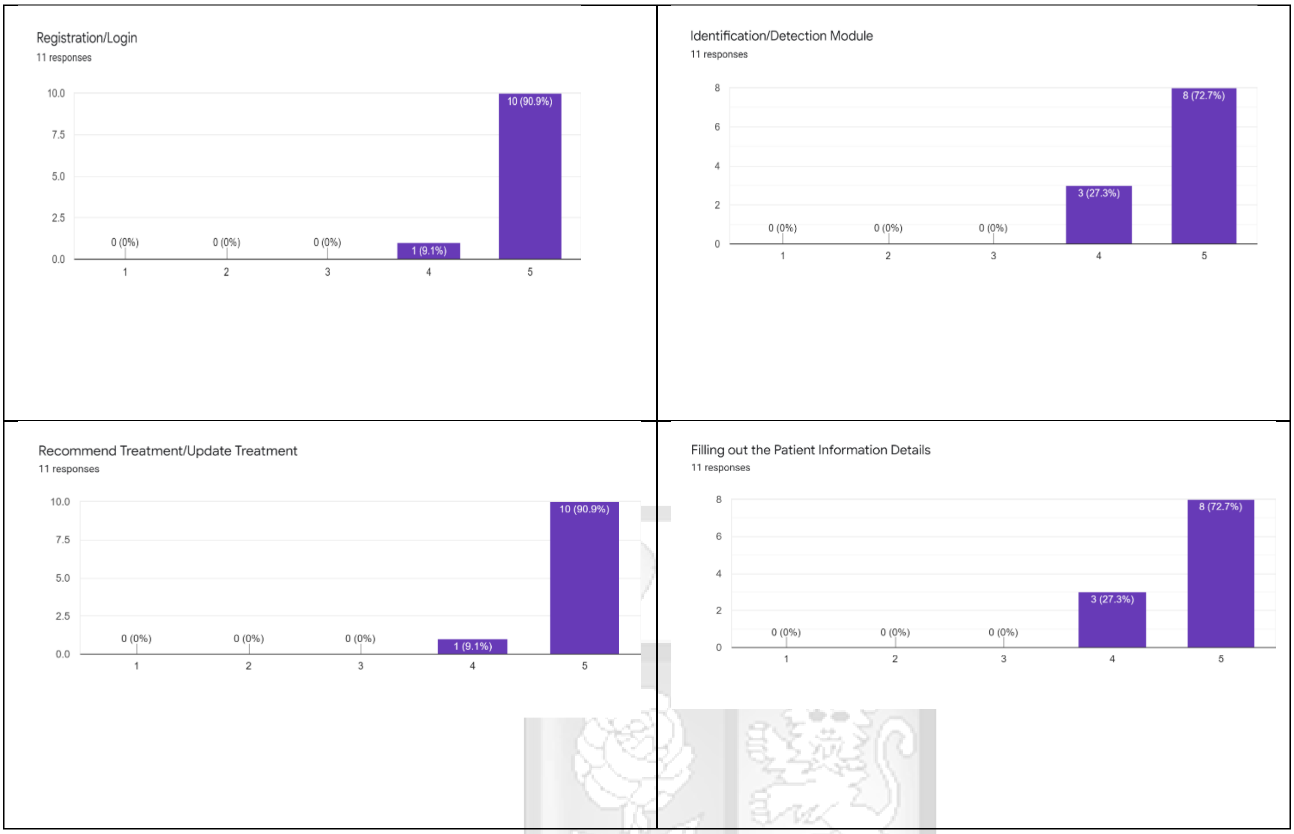
Appendix C: Additional Wireframe Designs



Appendix D: Report module



Appendix E: System Functionality



Appendix F: Importing the Tensorflow Model

```python
import tensorflow as tf

# Load the TensorBoard notebook extension (optional)
%load_ext tensorboard.notebook

tf.random.set_seed(42)
tf.__version__

inp = tf.keras.layers.Input(shape=INPUT_SHAPE)

conv1 = tf.keras.layers.Conv2D(32, kernel_size=(3, 3),
                               activation='relu', padding='same')(inp)
pool1 = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(conv1)
conv2 = tf.keras.layers.Conv2D(64, kernel_size=(3, 3),
                               activation='relu', padding='same')(pool1)
pool2 = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(conv2)
conv3 = tf.keras.layers.Conv2D(128, kernel_size=(3, 3),
                               activation='relu', padding='same')(pool2)
pool3 = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(conv3)

flat = tf.keras.layers.Flatten()(pool3)

hidden1 = tf.keras.layers.Dense(512, activation='relu')(flat)
drop1 = tf.keras.layers.Dropout(rate=0.3)(hidden1)
hidden2 = tf.keras.layers.Dense(512, activation='relu')(drop1)
drop2 = tf.keras.layers.Dropout(rate=0.3)(hidden2)

out = tf.keras.layers.Dense(1, activation='sigmoid')(drop2)

model = tf.keras.Model(inputs=inp, outputs=out)
```