2.1 Background

An image recognition problem undergoes the following sequence of steps:

1. Image acquisition.
2. Image pre-processing.
3. Image segmentation.
4. Feature extraction.
5. Individual object recognition.
6. Image understanding.

Image acquisition involves formation of an image in an image-capturing device such as a camera. Image pre-processing makes the image more suitable for subsequent processing. Image segmentation can be defined as the process of assigning a label to every pixel in an image. The next step is extraction of suitable features from an image by use of appropriate image processing techniques. Based on features extracted, a classification of individual objects present in an image is undertaken using a classifier. The last step in an image recognition process is image understanding or 'making sense' of an ensemble of recognized objects. Here a decision is made of what the image scene is all about based on the recognized objects in the image.

2.1.1 Concept of image acquisition

An image is formed when light from a source is either reflected or transmitted by a scene (object) and then received by an imaging device. An image therefore, has two components namely, the amount of source illumination present on the scene being viewed, and the amount of illumination reflected by the object in the scene. These are called the illumination and the reflectance components and are denoted by $i(x, y)$ and $r(x, y)$, respectively.

The two components combine as a product to form an image. The indices x and y are the 2-D spatial coordinates of the image scene.

$$(x,y) = i(x,y)r(x,y) \quad (2.1)$$

$$\text{Where } 0 < i(x,y) < \infty \quad (2.2)$$

$$\text{And } 0 < r(x,y) < 1 \quad (2.3)$$

Equation 2.3 as a boundary condition indicates that reflectance is when absorption is total and 1 when reflectance is total. The nature of $i(x,y)$ is determined by the illumination source, and $r(x,y)$ is determined by the characteristics of the objects [4].

2.1.2 Concept of image pre-processing

The ultimate goal of image pre-processing is to make an image more suitable for subsequent computer processing. There are three main image pre-processing tasks namely: image rescaling, image restoration, and image enhancement. Image rescaling involves either reducing the image size in order to speed up processing and occupy less memory space or increasing the image size for purposes of magnifying some image details. Image restoration involves reducing or eliminating noise from an image while image enhancement is concerned with improving the visual quality of an image [4].

2.1.2.1 Concept of median filtering

Median filter is used for removing noise while preserving useful features in an image. The filtering process is implemented by replacing each pixel value in an image by the median value of the image neighborhood. The median value is computed by first sorting all pixel values of the image neighborhood in numerical order. The middle value is then chosen as the median. In so doing random noise is eliminated from an image without creating a new

unrealistic pixel value as may be the case for mean filtering. Therefore sharp transitions in an image such as edges are preserved in this type of filtering [4].

2.1.2.2 Concept of image enhancement

The goal of image enhancement is to make an image visually appealing to a human observer. This is a subjective area since the viewer is the ultimate judge of how well a particular method works. A number of image enhancement techniques exist. These include intensity transformation, histogram matching, and histogram equalization amongst others [4], [5].

2.1.3 Concept of image segmentation

Image segmentation involves partitioning a digital image into its constituent regions. The goal of image segmentation is to locate objects and boundaries (lines and curves) in an image. Each of the pixels in a given object in an image share similar characteristics with other pixels belonging to the same object (set). These characteristics include; color, texture, size, orientation, intensity, connectivity etc.

Several image segmentation algorithms and techniques exist. The most commonly used include; morphological image segmentation methods, thresholding based on image histograms, edge detection methods, region growing, and split-and-merge methods [6].

2.1.3.1 Binary images: foreground and background

A binary image is an image in which each of the pixels assumes one of the only two possible discrete, logical values, 1 or 0. Pixels in binary images having local value 1 are referred to as the image foreground pixels, while those pixels having logical value 0 are called image background pixels. An object in a binary image consists of any group of connected pixels. Two definitions of connections are commonly used. If it is required that the

foreground pixel must have at least one neighboring foreground pixel to the north, south, east, or west of itself to be considered as part of the same object, then we are using 4-connection. If however, a neighboring foreground pixel to the north-east, north-west, south-east, or south-west is significant for it to be considered as part of the same object, then we are using 8-connection.

Binary images have no textural content. Thus, the only property of interest in binary images is shape, size and location of the objects in the image. The effect of morphological image processing in binary images reduces simply to the determination of which foreground pixels becomes background and which background pixels become foreground [7].

2.1.3.2 Concept of edge detection

Edges of an image are considered a type of vital information that can be extracted by applying detectors with different methodology [8], [9]. Edge detection is a type of image segmentation techniques that determines the presence of an edge or line in an image and outlines them in an appropriate way. The main purpose of edge detection is to simplify the image data in order to minimize the amount of data to be processed [10], [11]. Generally, an edge is defined as the boundary pixels that connect two separate regions with changing image amplitude attributes such as different constant luminance and tristimulus values in an image [12]–[15]. The detection operation begins with the examination of the local discontinuity at each pixel element in an image. Amplitude, orientation, and location of a particular subarea in the image that is of interest are essentially important characteristics of possible edges [16]–[18]. Based on these characteristics, the detector has to decide whether each of the examined pixels is an edge or not.

2.1.4 Concept of feature extraction

After an image has been segmented, the resulting aggregate of segmented pixels usually is represented and described in a form suitable for further computer processing. Representing and describing regions involves two choices. An object can be represented and described in terms of its external characteristics (its boundary) or in terms of its internal characteristics (the pixels comprising the region). After a representation scheme has been chosen, useful data is extracted from the object based on the chosen representation. For example, an object can be represented in terms of its boundary and the boundary described by features such as length, orientation, boundary signature, etc.

An external representation is chosen when the primary focus is on shape characteristics. An internal representation is chosen when the primary focus is on the regional properties, such as color and texture. Sometimes both internal and external descriptors are used for more accurate description of an object. The features selected as descriptors should be as insensitive as possible to variation in size, translation, and rotation [6].

2.1.5 Object recognition

One of the objectives of image processing is recognition of objects present in an image. The key to successful object recognition lies in selection of appropriate descriptive features of an image. Pattern recognition can be categorized into two principal areas: decision-theoretic and structural. The first category deals with patterns described using quantitative descriptors, such as length, area and texture. The second category deals with patterns best described by qualitative descriptors such as chains, trees, nets and other structural primitives [6].

2.1.5.1 Artificial neural networks (ANNs)

An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron as shown in figure 2-1. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons.

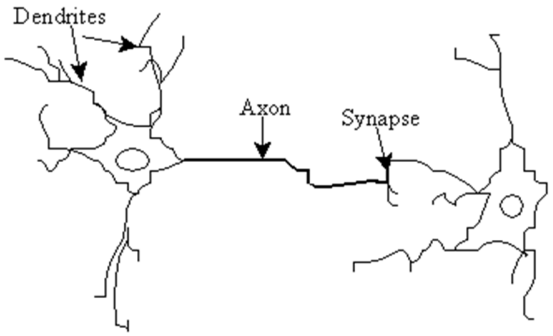

Figure 2-1. Natural neurons.

The complexity of real neurons is highly abstracted when modelling artificial neurons as shown in figure 2-2. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependence of a certain threshold). ANNs combine artificial neurons in order to process information.

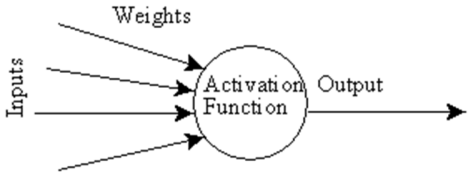

Figure 2-2. An artificial neuron.

An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. Biological nervous systems inspire these elements. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s) as shown in figure 2-3.

The weights in an ANN express the relative strengths (or mathematical values) of the various connections that transfer data from layer to layer. In other words, the weights express the relative importance of each input to a Processing element[19].

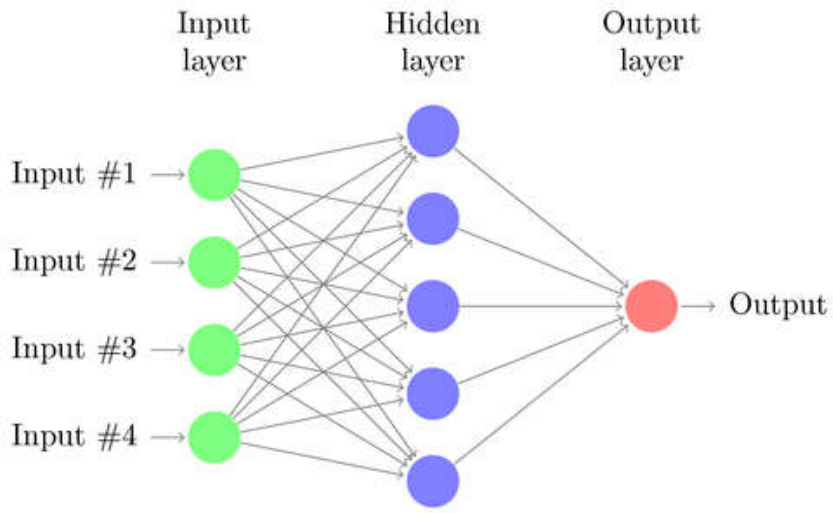

Figure 2-3: Artificial Neural Network.

In situations where statistical properties of pattern class are not known, classification of a decision theoretic problem is best handled by methods that yield the required decision functions directly via training. Neural network is one such approach. It comprises of inter-connections of nonlinear computing elements organized as networks reminiscent of the way neurons are believed to be interconnected in the brain [6].

2.1.6 Malaria

Malaria is a disease caused by a peripheral blood parasite of the genus Plasmodium that has five species that can cause human infection. Four of these - P. falciparum, P. vivax, P. ovale, and P. malariae - are human malaria species that are spread from one person to another via the bite of female mosquitoes of the genus Anopheles. Current information suggests that P. knowlesi malaria is not spread from person to person, but rather occurs in people when an Anopheles mosquito infected by a monkey then bites and infects humans [1]. P. vivax shows the widest distribution and is characterized by reappearances of symptoms after a period of up to five years. With the similar characteristics, P. ovale appears mainly in tropical Africa. P. falciparum is most common in tropical and subtropical areas. It causes the most dangerous and malignant form of malaria without relapses and contributes to the majority of deaths associated with the disease [20]. P. malariae is also widely distributed but much less than P. vivax or P. falciparum. Inside the human body, the parasite undergoes a complex life cycle in which it grows and reproduces. During this process, the red blood cells (RBCs) are used as hosts and are destroyed afterwards [1].

There are three phases of development in the life cycle of most species of plasmodia [21]: exo-erythrocytic stages in the tissues, usually the liver; erythrocytic schizogony (i.e. protozoan asexual reproduction) in the erythrocytes; and the sexual process, beginning with the development of gametocytes in the host and continuing with the development in the mosquito. When an infected mosquito bites humans, several hundred sporozoites (the protozoan cells that develop in the mosquito’s salivary gland and infect new hosts) may be injected directly into the blood stream, where they remain for about 30 min and then disappear. Many are destroyed by the

immune system cells, but some enter the cells in the liver. Here they multiply rapidly by a process referred to as exo-erythrocytic schizogony. When schizogony is completed, the cells produced by asexual reproduction in the liver termed merozoites are released and invade the erythrocytes. In Plasmodium vivax and P. ovale, some injected sporozoites may differentiate into stages termed hypnozoites which may remain dormant in the liver cells for some time before undergoing schizogony causing relapse of the disease.

When the released merozoites enter erythrocytes, the erythrocytic cycle begins. This process is referred to as erythrocytic schizogony. Within an erythrocyte, the parasite is first seen microscopically as a minute speck of chromatin surrounded by scanty protoplasm. The plasmodium gradually becomes ring-shaped and is known as ring or immature trophozoite (Figure.2-4 a-b). It grows at the expense of the erythrocyte and assumes a form differing widely with the species but usually exhibiting active pseudopodia (i.e. projections of the nuclei). Pigment granules appear early in the growth phase and the parasite is known as a mature trophozoite (Figure.2-4 c). As the nucleus begins to divide, the parasite is known as a schizont (Figure.2-4 d-f).

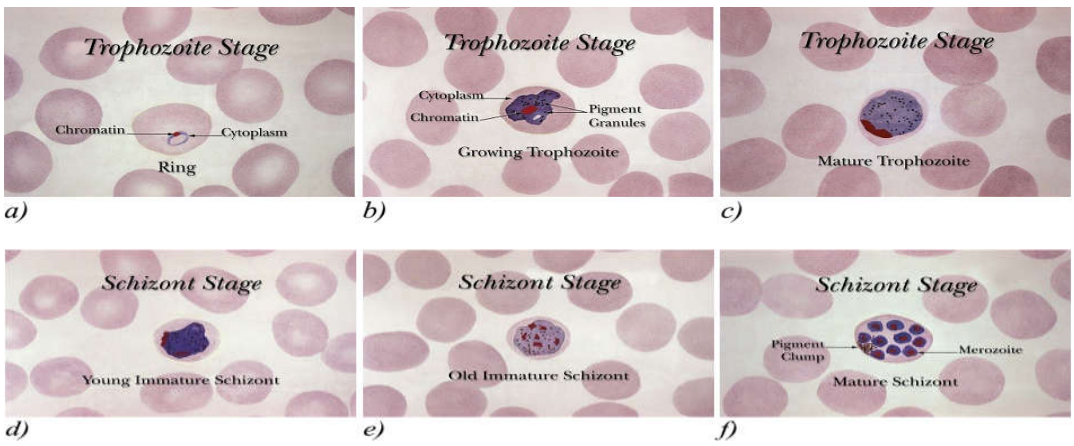

Figure 2-4: Development stages of the Plasmodium parasite. image courtesy of CDC [22].

Dividing nucleus tends to take up peripheral positions and a small portion of cytoplasm gathers around each. The infected erythrocyte ruptures and releases a number of merozoites, which attack new corpuscles, and the cycle of erythrocytic schizogony is repeated. The infection about this time enters the phase in which parasites can be detected in blood smears.

Some merozoites on entering red blood cells become sexual gametocytes, instead of asexual schizonts. When a mosquito ingests gametes, the cells rapidly undergo gamete production. This is the third phase of development in the life of plasmodium, the sexual process of reproduction in a mosquito.

2.1.7 Giemsa stain

Giemsa stain is used to differentiate nuclear and cytoplasmatic morphology of platelets, red blood cells, white blood cells and parasites [23]. Giemsa staining solution stains up nucleic acids and, therefore, parasites, white blood cells, and platelets, which contain DNA, are highlighted in a dark purple color. Red blood cells are usually colored in slight pink colors.

2.1.8 Matlab environment

Millions of engineers and scientists worldwide use Matlab to analyze and design the systems and products transforming our world. Matlab is in automobile active safety systems, interplanetary spacecraft, and health monitoring devices, smart power grids, and LTE cellular networks. It is used for machine learning, signal processing, image processing, computer vision, communications, computational finance, control design, robotics, and much more.

The Matlab platform is optimized for solving engineering and scientific problems. The matrix-based Matlab language is the world's most natural way to express computational mathematics. Built-in graphics make it easy to

visualize and gain insights from data. A vast library of prebuilt toolboxes lets you get started right away with algorithms essential to your domain. The desktop environment invites experimentation, exploration, and discovery. These Matlab tools and capabilities are all rigorously tested and designed to work together. Matlab helps to take ideas beyond the desktop. Analyses can be run on larger data sets and scale up to clusters and clouds. Matlab code can be integrated with other languages, enabling to deploy algorithms and applications within web, enterprise, and production systems.

Information about digital image processing using Matlab and about programming graphics and GUIs with Matlab can be found, for example, in [5] and in [24], respectively. This project, including all functions, segmentation, GUI, image database files, and feature evaluation scripts, have been implemented using Matlab programming environment version R2015. Although we cannot guarantee that, all functions will work properly in older versions of Matlab.

2.1.9 Digital image processing

The influence and impact of digital images on modern society is tremendous, and image processing is now a critical component in science and technology. The rapid progress in computerized medical image reconstruction, and the associated developments in analysis methods and computer-aided diagnosis, has propelled medical imaging into one of the most important sub-fields in scientific imaging [25].

Digital image processing deals with manipulation of digital images through a digital computer. It is a subfield of signals and systems but focus particularly on images. DIP focuses on developing a computer system that is able to perform processing on an image. The input of that system is a digital

image and the system process that image using efficient algorithms, and gives an image as an output. The most common example is Adobe Photoshop. It is one of the widely used application for processing digital images.

A digital remotely sensed image is typically composed of picture elements (pixels) located at the intersection of each row i and column j in each K bands of imagery. Associated with each pixel is a number known as Digital Number (DN) or Brightness Value (BV), which depicts the average radiance of a relatively small area within a scene. A smaller number indicates low average radiance from the area and the high number is an indicator of high radiant properties of the area [26].

The field of digital image processing refers to processing digital images by means of a digital computer, the depiction of a digital image presented in figure 2-5. Once computer has visual information in appropriate format, computer can analyze it, which is called image analysis.

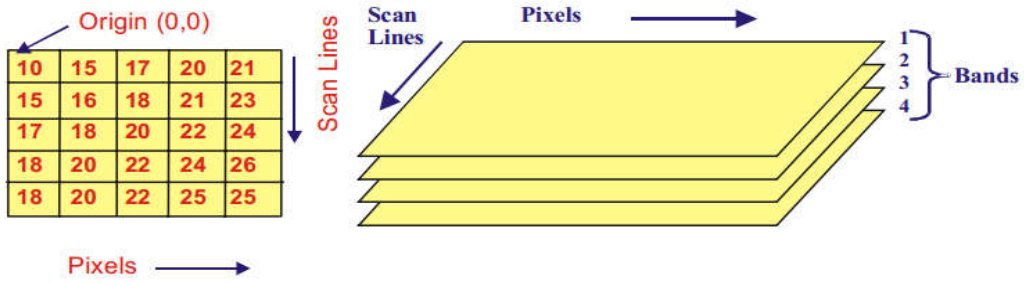

Figure 2-5: Depiction of a digital image.

Digital image processing allows the enhancement of the image's features of interest while attenuating details that are irrelevant in the given context, and then extract or increase the amount of useful information. Such a field of interest with a huge amount of applicability for digital image processing is medicine [4].

The advantages of digital images over analog images are obvious. Digital systems are cheaper, more flexible and information can be shared more easily. The information can be processed and interpreted in most of the cases almost fully automated, and so the speed is highly increased and costs are drastically lowered. Another advantage of digital systems is automatic combination of different acquisitions or/and different techniques in order to obtain more relevant information for human analysis process.

Digital image processing may be subdivided into three groups: preprocessing (low level of processing – preliminary operations used to filter noise, and to eliminate the unnecessary or unwanted details), data reduction (mid-level processing - extraction of useful information, segmentation), feature analysis (high level processing – ensuring semantic meaning extraction) [5].

2.2 Literature Review

A number of confirmatory tests for Plasmodium parasites exist. These techniques can be categorized into two classes depending on their level of detection complexity and cost of installation. These are the low cost, low technology techniques and the high cost, high technology techniques. The low-level techniques include the conventional microscopy and Rapid Diagnostic Tests (RDTs) while the high-level techniques include the Polymerase Chain Reaction (PCR) and Third Harmonic Generation (THG) imaging test [6]. A brief description of these techniques is given below.

2.2.1. Clinical diagnosis of malaria

A clinical diagnosis of malaria is traditional among medical doctors. This method is the less cost and most widely practiced. Clinical diagnosis is based on the patients' signs and symptoms, and on physical findings at examination. The earliest symptoms of malaria are very nonspecific and

variable, and include fever, headache, weakness, myalgia, chills, dizziness, abdominal pain, diarrhea, nausea, vomiting, anorexia, and pruritus [27].

A clinical diagnosis of malaria is still challenging because of the non-specific nature of the signs and symptoms, which overlap considerably with other common, as well as potentially life-threatening diseases, e.g. common viral or bacterial infections, and other febrile illnesses. The overlapping of malaria symptoms with other tropical diseases impairs diagnostic specificity, which can promote the indiscriminate use of anti-malarias and compromise the quality of care for patients with non-malarial fevers in endemic areas [27].

2.2.2 Laboratory diagnosis of malaria

In the laboratory, malaria is diagnosed using different techniques, e.g. conventional microscopic diagnosis by staining thin and thick peripheral blood smears , other concentration techniques, e.g. quantitative buffy coat (QBC) method , rapid diagnostic tests, and molecular diagnostic methods, such as polymerase chain reaction (PCR). Some advantages and shortcomings of these methods have also been described, related to sensitivity, specificity, accuracy, precision, time consumed, cost-effectiveness, labor intensiveness, the need for skilled microscopists, and the problem of inexperienced technicians [27].

2.2.2.1 Conventional microscopy

Microscopic diagnosis of malaria is performed by staining thick and thin blood films on a glass slide to visualize the malaria parasite. Briefly, the patient’s finger is cleaned with alcohol, allowed to dry and then the side of the fingertip is pricked with a sharp sterile lancet or needle and two drops of blood are placed on a glass slide. To prepare a thick blood film, a blood spot is stirred in a circular motion with the corner of the slide, taking care not

make the preparation too thick, and allowed to dry without fixative. As they are unfixed, the red cells lyse when a water based stain is applied. A thin blood film is prepared by immediately placing the smooth edge of a spreader slide in the drop of blood, adjusting the angle between slide and spreader to 45°, and then smearing the blood with a swift and steady sweep along the surface. The film is then allowed to air dry and is fixed with methanol. Because a larger volume of blood is examined the thick film is more sensitive than the thin film (down to around 40 parasites per μL or 1 parasite per 200 white blood cells) although it requires more expertise to read [27].

2.2.2.2 QBC technique

The QBC technique was designed to enhance microscopic detection of parasites and simplify malaria diagnosis. This method involves staining parasite deoxyribonucleic acid (DNA) in micro-hematocrit tubes with fluorescent dyes, e.g. acridine orange, and its subsequent detection by epifluorescent microscopy. Briefly, finger-prick blood is collected in a hematocrit tube containing acridine orange and anticoagulant. The tube is centrifuged at 12,000 g for 5 min and immediately examined using an epi-fluorescent microscope. Parasite nuclei fluoresces bright green, while cytoplasm appears yellow-orange. The QBC technique has been shown to be a rapid and sensitive test for diagnosing malaria in numerous laboratories settings [27]. Figure 2-6 depicts QBC technique.

While it enhances sensitivity for P. falciparum, it reduces sensitivity for non-falciparum species and decreases specificity due to staining of leukocyte DNA. Recently, it has been shown that acridine orange is the preferred diagnostic method (over light microscopy and immune chromatographic

tests) in the context of epidemiologic studies in asymptomatic populations in endemic areas, probably because of increased sensitivity at low parasitemia.

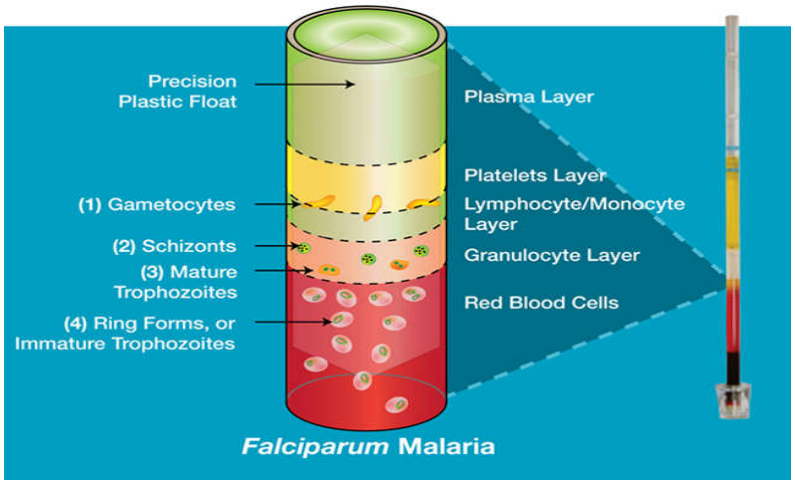

Figure 2-6 QBC technique.

While it enhances sensitivity for P. falciparum, it reduces sensitivity for non-falciparum species and decreases specificity due to staining of leukocyte DNA. Recently, it has been shown that acridine orange is the preferred diagnostic method (over light microscopy and immune chromatographic tests) in the context of epidemiologic studies in asymptomatic populations in endemic areas, probably because of increased sensitivity at low parasitemia. Nowadays, portable fluorescent microscopes using light emitting diode (LED) technology, and pre-prepared glass slides with fluorescent reagent to label parasites, are available commercially. Although the QBC technique is simple, reliable, and user-friendly, it requires specialized instrumentation, is more costly than conventional light microscopy, and is poor at determining species and numbers of parasites [27].

2.2.2.3 Rapid diagnostic tests (RDTs)

These are alternative methods of malaria diagnosis recommended by WHO for use in areas where microscopy is not available. The methods detect

antigens derived from malaria parasites. They are faster than the conventional microscopy with a single diagnosis taking an average time 7 to 30 minutes. Besides, a non-skilled technician can administer the techniques. Some of these methods include Parasight-F, ICT Malaria P. falciparum/P.vivax, and optimal. The methods suffer from limitations including: low sensitivity over microscopy and prevalence of false positives particularly after treatment [27]. Figure 2-7 depicts rapid diagnostic test.

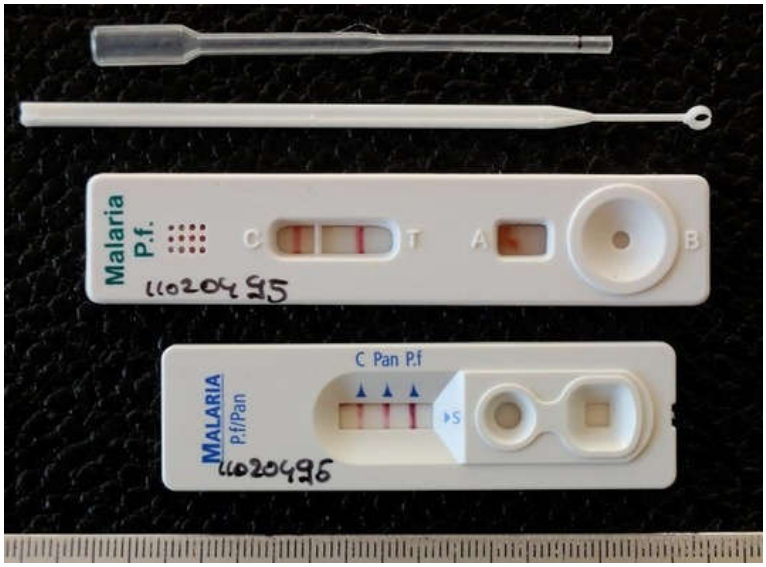

Figure 2-7: Rapid diagnostic test.

2.2.2.4 Molecular diagnostic methods

As mentioned above, traditional malaria diagnostic methods remain problematic. New laboratory diagnostic techniques that display high sensitivity and high specificity, without subjective variation, are urgently needed in various laboratories. Recent developments in molecular biological technologies, e.g. PCR, loop-mediated isothermal amplification (LAMP) and microarray technique, have permitted extensive characterization of the malaria parasite and are generating new strategies for malaria diagnosis [27].

Molecular Diagnostic Methods are in two categories:

1. **PCR Technique**

   PCR-based techniques are a recent development in the molecular diagnosis of malaria, and have proven to be one of the most specific and sensitive diagnostic methods, particularly for malaria cases with low parasitemia or mixed infection. The PCR technique continues to be used extensively to confirm malaria infection, follow-up therapeutic response, and identify drug resistance. It was found to be more sensitive than QBC and some RDTs [27].

   Concerning with the gold standard method for malaria diagnosis, PCR has shown higher sensitivity and specificity than conventional microscopic examination of stained peripheral blood smears, and now seems the best method for malaria diagnosis. PCR can detect as few as 1-5 parasites/µl of blood compared with around 50-100 parasites/µl of blood by microscopy or RDT [27].

2. **LAMP Technique**

   The LAMP technique is claimed to be a simple and inexpensive molecular malaria-diagnostic test that detects the conserved 18S ribosome RNA gene of P. falciparum. Other studies have shown high sensitivity and specificity, not only for P. falciparum, but also P. vivax, P. ovale and for P. malariae.

   These observations suggest that LAMP is more reliable and useful for routine screening for malaria parasites in regions where vector-borne diseases, such as malaria, are endemic. LAMP appears to be easy, sensitive, quick and lower in cost than PCR [27].

The following table gives a brief comparison of the malaria diagnoses techniques mentioned earlier.

Table 2-1: comparison of the malaria diagnoses techniques.

	Clinical diagnosis	QBC	RDTs	PCR	LAMP
Principle Of the Method	**Based on presenting malarial signs and symptoms**	**Blood staining with acridine orange and detection by epi-fluorescent microscope**	**Detection of parasite antigens or enzyme**	**Specific amplification of malaria DNA**	**Detection of turbidity by a turbidity meter**
Sensitivity and specificity	**Depends on malarial endemicity**	**Sensitivity and specificity relatively high**	**Moderate**	**Excellent**	**Excellent**
Time consumed (min)	**Depends on physician's skill**	**<15**	**10-15**	**45-360**	**< 60**
Detection limit (parasites /µl)	**Undetermined**	**> 5**	**50-100**	**≥1**	**> 5**
Expertise required	**High: in non-endemic areas**	**Moderate**	**Low**	**High**	**High**
Instrument cost	**-**	**Moderate**	**Moderate**	**Expensive**	**Moderate**

2.2.3 Related Work

A number of studies on the possibility of automating conventional microscopy have been done in the past. In this section, a number of these studies are reviewed.

Ms. Deepali Ghate , Mrs. Chaya Jadhav and Dr. N Usha Rani (2012), [28] proposed a system for automatic detection of malaria parasite from blood images by using Image Segmentation techniques to detect malaria parasites in images acquired from Giemsa stained peripheral blood samples. Their study is comparative study of two methods for detecting malaria parasites; first method is based on segmentation and second uses feature extraction using minimum distance classifiers. They claimed that their system is unaffected by the exceptional conditions and achieved high percentages of sensitivity, specificity, positive prediction and negative prediction values. Their first model reported sensitivity, accuracy, and specificity of 81.39%, 83.75%, and 86.49% respectively and their second model reported sensitivity, accuracy, and specificity of 72.93%, 73.75%, and 75.76% respectively.

M. S. Suryawanshi and P. V. V Dixit (2013), [29] presented enhanced technique for Malaria Parasite Detection, where cell segmentation process consists of various steps such as image binarization using Poisson's distribution based Minimum Error Thresholding, followed by Morphological Opening for the purpose of refinement. Seed point localization is done by multi-scale Log filter. Since frequency and orientation representations of Gabor filter are same as that of human visual system, it is used for feature extraction. Two algorithms are compared in this paper in order to get superior classification.

Zoueu, J. T., Loum, G. L., Haba, C. T., Brydegaard, M. and Menan, H. (2008), [30] proposed a method of diagnosing malaria without labelling the parasites using a light microscope with LEDs emitting in the range of UV to IR replacing the classic white light. The microscope was fitted with a digital camera to capture images formed at the eyepiece. It was reported that parasite images having the best contrast were recorded for blue light. This study, however, failed to address the effects of chromatic aberration, which are common in multispectral imaging using classical optics. The technique was also dependent of a human operator for switching between LEDs and making the diagnosis.

Brydegaard, M., Merdasa, A., Jayaweera, H., Alebring, J., and Svanberg, S. (2011), [31] proposed an improved version of multispectral microscope based on light emitting diodes (LEDs). The LEDS emitted lights in 13 spectral bands ranging from ultraviolet (UV) to near infra-red (IR). The device was also fitted with an imager for capturing images in the 13 spectral range of the LEDs. The instrument was interfaced to a computer and switching of LEDs and image capturing was done using LAB-VIEW software. It was reported that the instrument could detect Plasmodium parasites in non-stained thin blood smear images.

Omucheni, D.L., (2012), [32] developed a technique of detecting Plasmodia infected erythrocytes by imaging unstained thin blood smear blood samples using a multispectral imaging microscope developed by Bryegaard [31]. Multivariate chemometric techniques such as Principal of Components Analysis (PCA), Hierarchical Cluster Analysis (HCA) and Artificial Neural Network (ANN) were used to process the multispectral images obtained in order to discriminate infected erythrocytes from the non-infected. Plasmodium parasites stages and species identification was not addressed.

Diaz, G., Gonzalez, F.A., and Eduardo, R. (2009), [33] developed a technique for detection, quantification of parasitemia and parasite life stages. Pixel color features were extracted and used to train classifiers for detection and determination of parasite life stages. Clustered erythrocytes were resolved by use of template matching before parasitemia was estimated. The study reported a sensitivity of 94% for detection of infected erythrocytes and 79% for stages identification. The technique was not fully automatic as it called for human intervention during training of the classifier every time diagnosis had to be made.

A. Anand, V. K. Chhaniwal, N. R. Patel, and B. Javidi (2012), [7] investigated detection of Plasmodium infected erythrocytes using a technique called holography. A digital holographic microscope was set up to capture holograms of erythrocytes. A mathematical reconstruction algorithm was then applied to the holograms to recover the object wave. To differentiate between a health cell and an infected cell, a correlation operation was performed using thickness profiles of the reconstructed image with the thickness profile of a known health erythrocyte. Detection probabilities of 84% and 11% as true positive rates and false positive rates were reported. This technique does not involve staining of erythrocyte before detection. However, setting up the digital holographic microscope demands thorough alignment of the optics involved which would require skilled personnel.

In summary, it can be seen that no study addresses the ease of use of the system by users. Besides, most of the techniques proposed in the previous works provides accuracy less than 85%.

In this work, most of the limitations of the previous works have been addressed. For instance, a rich graphical user interface have been designed to

make the system easy to use by users. Moreover, the segmentation algorithm that have been used, facilitate the process of feature extraction in a way that makes the system provide high accuracy.