DISTRIBUTED HEALTH CARE FRAMEWORK FOR PATIENT HEALTH RECORD MANAGEMENT AND PHARMACEUTICAL DIAGNOSIS

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B.Sc. (Hons) Degree in Information Technology

Specializing in Software Engineering

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Dissertation submitted in partial fulfillment of the requirements for the BSc (Hons) in Information Technology Specializing in Software Engineering

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Declaration

I declare that this is our own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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(Mr. Jeewaka Perera)

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Abstract

With the COVID-19 pandemic, the world is confronting various healthcare issues, and healthcare automation is more crucial than ever. The pandemic has revealed the limitations of existing digital healthcare systems to manage public health emergencies while maintaining service continuity. There is no registered population for many healthcare institutions in Sri Lanka, as a result, there is a communication gap resulting in inadequate coordination of care. Electronic Health Record systems (EHRs) are becoming more popular to share patient details between hospitals but accessing scattered data across several EHRs while safeguarding patient privacy remains a challenge. Most of these medical records are in printed format and manually entering those into EHR systems is time-consuming and error prone. Not only that pharmaceutical error is a critical healthcare problem, but it is even riskier to visit doctors for pharmaceutical diagnosis during a pandemic. This research is associated with four novel approaches to address these issues. This research introduces a blockchain-based patient healthcare record system that allows users to access and share patient information across different EHR systems. Similarly, a medical document scanner based on Optical Character Recognition (OCR) and Natural Language Processing (NLP) is introduced to automatically scan and extract textual data and significant important Named Entities from clinical laboratory reports to reduce the need for manual data entry into the blockchain. For drug detection based on submitted images of the pills, an Image Processing-based mobile application is introduced. Additionally, a virtual conversational medical chatbot powered by Natural Language Processing is introduced to provide healthcare support while providing necessary reminders for consumers to take medication on time. The research aims at introducing a solution for the limitations in healthcare while providing a distributed healthcare framework for the healthcare community worldwide.

Keywords: *Machine Learning, Natural Language Processing, Blockchain, Image Processing, Optical Character Recognition*

Acknowledgements

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Dedication

The authors would like to dedicate this material to the research community, which is working tirelessly to discover solutions to sustain better outcomes in the field of healthcare.

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List of Abbreviations

Abbreviation	Description
EHR	Electronic Health Records
ML	Machine Learning
AI	Artificial Intelligence
OCR	Optical Character Recognition
NLP	Natural Language Processing
OMRs	Outside Medical Records
CNN	Convolution Neural Networks
NER	Entity Recognition
NLU	Natural Language Understanding
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
CRF	Conditional Random Field
BOW	Bag of Words
SDLC	Software Development Lifecycle
OpenCV	Open-Source Computer Vision Library
CSV	Comma-separated values
REST	Representational State Transfer
APIs	Application programming interface

1. Introduction

1.1 Background Study

The world is facing numerous challenges in the field of healthcare due to COVID-19. To control the spread of the disease, several countries had to close their borders, implement lockdowns, and employ social distancing. The pandemic has had an unforeseen worldwide impact, not just in terms of economics, but also in terms of healthcare systems generating difficulty for healthcare workers in identifying and monitoring mass populations. The pandemic has exposed the importance of the digitalization of the healthcare industry and the limitations of the existing systems. As a result of COVID-19, research institutes and governments have been obliged to reconsider healthcare delivery solutions to maintain service continuity when people stay at home and conduct social distancing [1].

In recent years researchers are focusing more on the use of Blockchain and Machine Learning approaches for digital transformation in the healthcare field. The amount of digitally stored patient data has grown significantly. According to the statistics, many people visit hospitals for pharmaceutical diagnoses, but it is riskier to visit doctors during a pandemic. According to World Health Organization (WHO), physical distancing helps to minimize the spread of COVID-19 and avoiding spending time in crowded areas will break the chain of transmission. Therefore, there should be a solution for the patient who is unknown or illiterate, to learn everything about the tablets, their usage, adverse effects, etc. while staying at home. So that it raises public awareness and minimizes the number of visits to doctors during the pandemic [2].

Hence the authors have proposed a system that can provide remote Drug Identification for patients while giving reminders to take medication on time based on the latest prescriptions with the help of a user-friendly medical conversational Chatbot.
But in the healthcare field, electronic medical records are extremely sensitive confidential information that must be exchanged frequently. One of the most difficult aspects of a centralized method of storing health records is safeguarding patient privacy and system transparency. Illegitimate access to sensitive patient information, such as identification details, as well as misuse of patient information and clinical

records, leads to data breaches [3]. Here the authors have introduced a Blockchain-based component as a better solution by enabling decentralized data storage for sharing and accessing scattered patient records while protecting users' privacy.

Storing data in Blockchain need the data to be in electronic format but most of the medical documents such as clinical laboratory test reports from hospitals are in printed format, hence the conversion of the existing patient data into electronic health records has become a challenging task. Converting these data into Electronic Health Records (EHR) and entering these details into Blockchain often needs to follow the manual data-entering procedure which is often time-consuming and error-prone. The authors have addressed this issue by proposing an approach to extract textual data from the captured images of the Clinical Laboratory Test Reports through a medical document scanner.

To overcome these limitations and produce accurate results, “Oxygen" delivers a unique Web and Mobile-based solution to provide healthcare services to meet the challenges that the healthcare domain confronts due to its limitations.

1.2 Literature Survey

For the past few years, several studies have been conducted on the digitalization of the field of healthcare and how to provide healthcare facilities to the public while mitigating the challenges associated with it. The research studies that have been done on the use of Blockchain [4] and Machine Learning-based technologies [5] to provide healthcare services for medical professionals and the general public are highlighted in this section.

According to [6], the authors have shown that the cost of data breaches in the healthcare industry is projected to be over $380 per record, with the 2016 Breach Barometer report revealing that 27,314,647 patient records were compromised. This article emphasizes the significance of the security of healthcare records and patient-centric distributed healthcare solutions for securely storing patient data and demonstrates that Blockchain not only provides decentralization, but also data confidentiality, real-time access, and data authentication and authorization.

Blockchain technology can be a superior option in biomedical research and teaching, as well as in keeping electronic medical health records [7] [8]. They also indicate that while various Blockchain prototypes have been produced to date, not enough research has been done to solve the difficulties that Blockchain technology offers, such as security and privacy. Latency and interoperability are two issues that need to be addressed, and more studies should be done in these areas. The study [9] found that lack of interoperability and sharing are some common issues in handling medical data. The Blockchain's security is dependent on the private key, and if the private key is lost, the storage's security is also compromised. However, those concerns were not addressed in this study. Previous research work [10] has focused on the interoperability of the data exchange between business entities and the study focuses on how the transition takes through five mechanisms including data liquidity, data aggregation, digital access rules, patient identity, and data immutability.

The studies demonstrate that Blockchain technology may be used as a platform for digital exchange and that healthcare data can be stored in many systems, necessitating several interactions between institutions.

According to [11], an essential milestone in the advancement of contemporary medicine is the introduction of electronic health records. But, due to the limitations of EHR systems, comprehensive health records are not frequently accessible during treatment. Therefore, here the authors suggested a text detection approach with the use of a patch-based training strategy and a concatenation structure which can combine the features of the deep and shallow layers in the Neural network. This study was conducted to improve the accuracy of multilingual text recognition. According to the research, a patch-based training technique has been applied to the medical laboratory report and outputs the bounding boxes that contain texts. The text is then printed after the concatenation structure is inserted into the recognizer.

The authors of [12] show that a medical laboratory report becomes a type of crucial record for healthcare providers to use in patient evaluation and treatment. Electronic medical records are easier to maintain than paper ones, which are currently ubiquitous in the contemporary healthcare system. However, there continues to be a huge demand for past medical laboratory report identification, particularly in underdeveloped nations. Here the authors use a method for collecting data from medical laboratory reports using textual image processing. The table sections and words of a report are initially segmented using top-down pipelines after being provided with an image of the document. Although the system achieves satisfactory results still it was capable of extracting text from documents only. However, the presented research study did not include entity extraction.

A key challenge in Optical Character Recognition is the inability of the current OCR algorithms to correctly transcribe the scanned documents where text is skewed or distorted. The authors of [13] developed a deep neural network-based self-supervised pre-training model for their research work. This bi-directional encoder has been designed to predict concealed text and fill in gaps in non-transcribable areas of the page. The suggested model, however, has not been trained for the healthcare domain-specific words and has not improved the quality of the images.

A recent study [14] revealed that the COVID-19 epidemic is still exerting extreme pressure on the service sector. For any organisation to operate efficiently, getting the appropriate information at the right time is essential. Businesses now generate more complex data per minute. The unstructured data is digitally mastered, and the OCR procedure is carried out. The accuracy of scanning scanned and handwritten materials, where the text may be distorted, blurred, or unintelligible, is a significant problem for the OCR technique. Here, the authors demonstrate how OCR may facilitate the electronic extraction of printed materials, including applications and medical records, to access critical data that was available in the past.

According to the study [15], the prevalence of machine-illegible information and the restricted system accessibility in healthcare, obtaining usable and relevant information from these Outside Medical Records (OMRs) in a timely way is a difficult undertaking. Here the authors have found the clinical concepts contained in OMR are beneficial for Cardiovascular medicine with the use of techniques in Optical Character Recognition (OCR) and Natural Language Processing (NLP) to extract data from the computer-readable OMRs. The study can be regarded as the first step toward automated data extraction from OMRs generated by a variety of healthcare providers.

According to the research paper [16], it can be seen, that encouraging results can be produced when a variety of image-processing algorithms are applied to text detection. In the research paper, the authors proposed a modular strategy for text detection. It has been mentioned in the research findings that satisfactory performance can be achieved even without the use of the deep learning approach. Although OCR aids in promoting the precisions, it decreases recall performance. This results from the removal of non-text sections together with certain crucial text parts. Therefore, the writers must avoid it in this instance to enhance overall outcomes.

As a result of the reviewed studies, it is apparent that textual extraction from printed documents is a significant requirement in the healthcare domain, and researchers should spend more time in this area to develop better solutions.

Many medications utilized in hospitals and emergency clinics are hard to recognize on an everyday premise except if they are self-evident. Several researchers have attempted to overcome those problems using image processing techniques. The first model in pill identification and recognition was proposed by Lee and his associates [17]. The gathering fostered computer vision [18] for distinguishing illicit medications using tablet design, size, shape, and imprint. In this arrangement, a given image is contrasted with a set of images put away in a display, following three principal steps: pre-processing [19], edge detection [20], and component vector development. The authors of [21] proposed a technique to distinguish damaged and missing tablets with an edge recognition strategy. This technique says that tracking down the edges of tablets by taking the centre. The authors of [22] proposed a system that distinguishes defective tablets by utilizing the "Feature Extraction Technique". This technique includes image handling procedures to distinguish the faulty tablets and included extraction methods to see the faulty ones. Later [23] proposed a model for recognizing the remedy of medications and it has effectively resulted in the United States 568 of the most related tablets and has shown a precision of 91.13% in naturally recognizing the right drug.

According to the [24], Text-based Chatbot in the Light of Recent Technologies are gaining popularity in the modern world, notably in businesses and health care, because they can automate administrative work and provide services that go beyond the constraints of people. A Contextual Chatbot for Healthcare Purposes was proposed by a group of researchers by employing Machine Learning (ML) and Artificial Intelligence (AI) [25] methodologies to store and manage the preparation models, allowing the Chatbot to produce a better and more appropriate response when the client asks questions from the Chatbot [26]. Kidwai, B., and R.K. Nadesh [27] explored how innovation has altered, how patients communicate with professionals as well as how medical treatment is delivered. To improve the current medical service, a Chatbot can be planned and built using highly Artificially Intelligent programs and good decision-making algorithms. It can assist the client in providing an accurate description of their condition based on the symptoms provided. The AI will be given precise information about the symptoms as well as medicine that may be given to treat a specific illness.

Numerous virtual healthcare assistants in the world are being used for a variety of purposes, this examination is being led to make an answer utilizing ML (Machine Learning), NLP (Natural Language Processing), and AI (Artificial Intelligent) man-made brainpower. Healthcare Assistants should be developed in a way that they can interpret the messages that are provided by the users and respond to them accordingly.

The arrangement will want to keep up with the client's drug plan and furnish clients with constant alerts when they need to take their medicine.

Borah, B., Pathak, D., Sarmah, P., Som, B., and Nandi, [28] proposed a reference Text-based Chatbot from the use of recent technologies. In the present world, Chatbots are gaining a lot of attention, particularly in industries and in the well-being areas as they can automate administration tasks and provide services beyond the limitations of humans. Development of Artificial Intelligence (AI) advancements, and a combination of Natural Language Processing (NLP) fuel the development of chatbots. Currently, different models of chatbots built with the most recent technologies that are available in the market perform functions relevant to marketing, and customer support, and functions that can be more effective when performed via a chatbot. By using the three-layer architecture, the authors have given insights into how the Natural Language Processing, Natural Language Understanding (NLU), and Decision-Making engine combined with a Knowledge Base can be used to achieve AI using Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). Furthermore, the authors also discussed the different chatbot platforms and the development frameworks that have been used to develop chatbots in recent times.

Kidwai, B. and Nadesh, R.K [29] discussed how Innovation has changed how patients speak with specialists as well as how medical care has evolved. Artificial Intelligence along with Neural Networks can be used to create Chatbots that can change how patients and specialists see medical services. To make the current medical service more effective and more efficient, a chatbot can be planned and created involving the latest algorithm that has proven to create highly intelligent Artificially Intelligent programs, along with good decision-making algorithms that can assist the client with providing an accurate description about their condition according to the symptoms provided. The AI will be provided accurate information regarding the symptoms along with the medication that can be provided to treat certain illnesses.

As a result of the reviewed studies, it is clear that drug identification is a significant requirement in daily well-being, and research teams should find better solutions to improve that area.

1.3 Research Gap

Most of the research papers and products focus only on storing patient records. They are not sharing patient details among various hospitals. For example, there is a couple of patient records-keeping systems in Kalubowila and the military hospital in Sri Lanka. Still, there is no way to access those data from another hospital. Private hospitals such as Asiri hospital [9] keep their patient details, but when patients change their hospitals, there is no external connection between hospitals to share patient information.

Multiple hospitals are operating under government hospitals. Private hospitals may have some branches. According to this, civilians have many options. Instead of managing this many hospitals, doctors cannot give efficient service to their patients. Doctors need to understand and examine the patient from the beginning. Our developed solution is to maintain individual patient records and share those among healthcare professionals.

Table 1.3.1: Comparison of the Developed Solution with existing Research studies (Research Gap)

Reference ID	Modelled for Healthcare Domain-Specific words	Extract Text from low-quality images	Extract important Named Entities from unstructured text	Make the extracted text into an editable format
Research [11]	✓	✗	✓	✓
Research [13]	✗	✓	✓	✓
Research [15]	✓	✗	✗	✗
Our Solution	✓	✓	✓	✓

Table 1.3.1 is a summary of the available research papers and studies relevant to document scanners introduced so far.

Most available research papers and research studies on document scanners focus primarily on textual data extraction from generic documents [16], [30], [31], [32], but most research studies ignore approaches for data extraction from medical and healthcare-specific documents such as lab test reports and printed prescriptions. One of the most difficult aspects of textual data extraction is extracting text from skewed or occluded materials. However, most research papers have not used adequate ways to retrieve data from such distorted texts.

Below Table 1.3.2 is a summary of the available research papers and studies relevant to drug identifiers introduced so far.

According to those different attempts as indicated by specific sources, there is a typical issue that they are designed only for drug identification and do not provide any summary of the medication.

As medication-consuming people are curious about what medications they are consuming, what is the primary explanations behind consuming them, and the off chance that there are any delayed consequences as an answer for these disappointments, the authors can get thoughts from recently utilized carried out parts and produce an alternate arrangement from existing arrangements, which ought to further develop ease of use and be more useful than past variants.

Table 1.3.2: Summary of the related research papers and sources

Reference ID	Identify medication	Provide a Summary of the Medication	Can use for Civilians
Research [33]	✓	✗	✗
Research [34]	✓	✗	✗
Research [35]	✓	✗	✗
Research [36]	✓	✗	✓
Our Solution	✓	✓	✓

These are the research gaps in the field of healthcare that have been found, and our proposed solution will help to bridge those gaps.

Most of the research that particularly has been done is designed for different types of healthcare assistants in a kind of big way. Therefore, many healthcare virtual assistants use channels to make necessary appointments for patients" relevant physicians and to diagnose their ailments subtly. On the other hand, their purpose is based on the same strategy subtly. In our solution, we came up with an interactive healthcare chatbot, which specifically is quite significant. This chatbot is smart enough to generally find the user's latest prescription and kind of respond appropriately to users, so users can find out their medication information in the chatbot, also the chatbot can specifically give medication notifications to users at the relevant medication time, and the chatbot has very user-friendly features so anyone should have the opportunity to easily manipulate the chatbot in a major way. Therefore, the chat interface should for the most part be user-friendly, which is significant.

Table 1.3.3: Summary of the related research papers and sources

Reference ID	Identify User Input	Response according to patients' prescription	Give notifications for patient medication
Research [24]	✓	✗	✗
Research [26]	✓	✗	✗
Research [29]	✓	✗	✗
Our Solution	✓	✓	✓

1.4 Research Problem

The pandemic has exposed healthcare's limitations, emphasizing the importance of digitalization. According to the Ministry of Health, Sri Lanka has 1103 government hospitals [9]. Sri Lanka currently has a population of 21,556,478 people [9]. People have many options to take their medications. They can use either government hospital services or private hospital services. Instead of using these two services, they can also use the Ayurvedic hospital service. When doctors examine a patient, they ask about previous medications or refer patients to medical history books such as clinic books.

Some institutions employ EHR systems instead of keeping data in a book or asking patients for details. Storing/ accessing, and sharing patients' details are critical; thus, patient history is crucial to caring for a patient well. Without knowing the patient's history, doctors cannot make correct decisions.

Most medical papers are in printed format and extracting information from them and transferring them to electronic health records takes a lot of time. Manually entering these data into Blockchain is a risky task that frequently results in human errors. As a result, an automated method for extracting textual data from printed medical records and converting them to editable and searchable formats should be introduced. A public survey was conducted to gather information on the healthcare problems that emerged during the covid19 epidemic. According to the survey, about 91.4% say that they face healthcare issues during the pandemic.

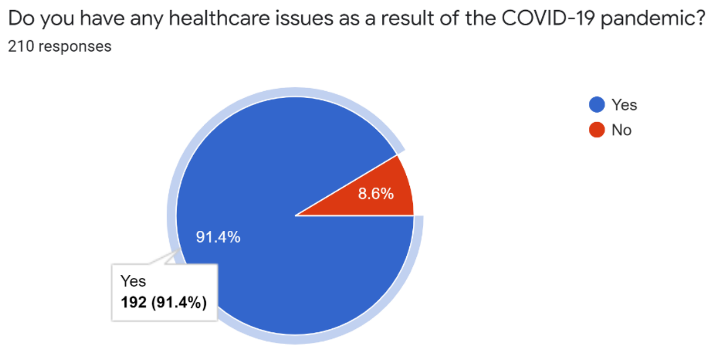


Figure 1.4.1: Summary of the responses on whether healthcare issues occur during a pandemic

And about 89.5% of the participants do believe that healthcare automation is critical during the pandemic.

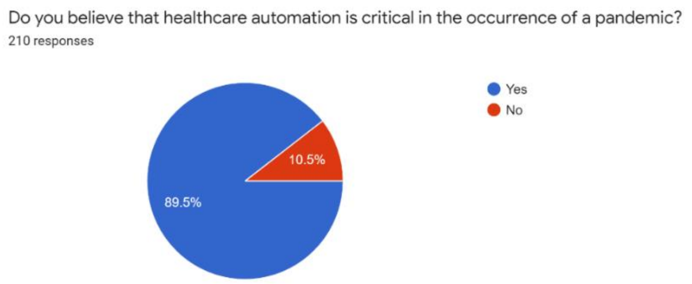


Figure 1.4.2: Summary of the responses on whether healthcare automation is critical

About 53.3% of most participants think that manually entering data and transferring them into Electronic Health records can cause errors and is typically a time-consuming procedure.

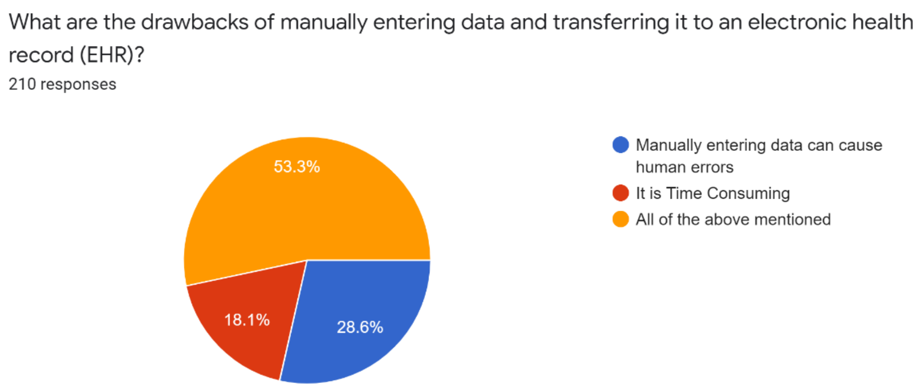


Figure 1.4.3: Summary of the responses on drawbacks in manually entering data into EHR

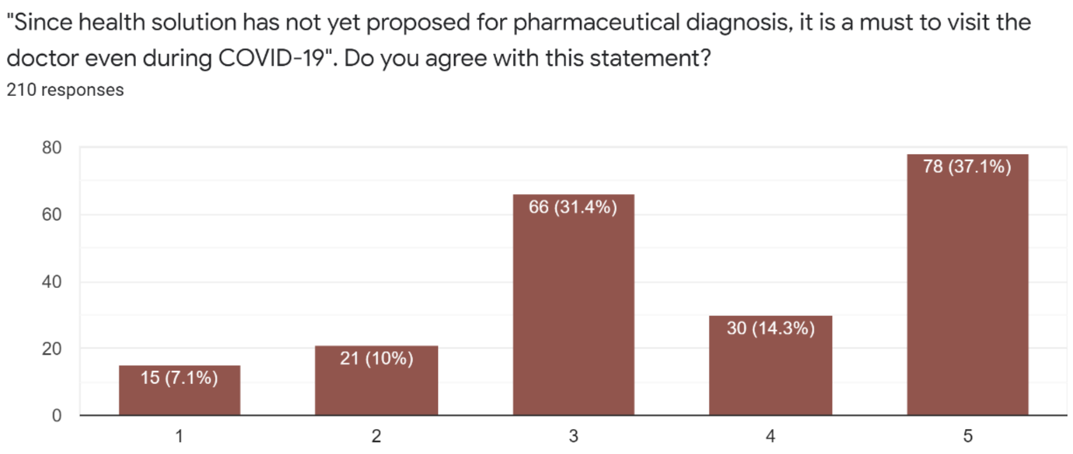


Figure 1.4.4: Summary of the responses on the importance of remote pharmaceutical diagnosis

According, to the survey results we can conclude that many individuals struggle when they consume drugs without having adequate information about the medication. The application developed is to assist in distinguishing medication. However, to distinguish the prescription given by a specialist, the patients needed to go back to a specialist or a drug store. Yet, under these pandemic circumstances, those preferences are not reasonable. Furthermore, on the off chance that a specialist committed some error and gave some unacceptable drug that will affect consumers' life. In this age, everything is on the cell phone, so they ought to have a method for conquering that issue by utilizing a precise application.

1.5 Research Objectives

1.5.1 Main Objective

The primary objective of implementing a healthcare framework is to address the healthcare difficulties that may occur because of the COVID-19 pandemic. The pandemic exposed healthcare shortcomings, and this framework will automate the existing healthcare services. The proposed solution's key objective is to securely store patients' healthcare information while protecting users' privacy and to provide healthcare services for Medical Documents Scanning, Conversational Chatbot for Virtual Assisting and remote pharmaceutical diagnosis.

The proposed solution's principal goal is to provide secure healthcare facilities for Medical Practitioners and Patients while maintaining social distancing.

1.5.2 Sub Objective

The following are the specific objectives that must be completed to achieve the main goal.

1. To protect patients' data privacy while tracking/sharing healthcare records with healthcare professionals using Blockchain:

   There are many issues in storing patient information in medical logbooks and storing information in a centralized server. Those drawbacks will be omitted in this component. Access control mechanisms are used here to control unauthorized access to the system. Smart contracts are used for executing the predesigned procedures. There are several user levels with several privileges. Such as doctors will be able to add a new record and edit and view but nurses/pharmacy staff will only be able to view the record. This is not focusing on a specific institution. Any authorized organization can use this service from anywhere.

2. To scan and extract relevant data from Patient Clinical Laboratory Reports using Optical Character Recognition and Natural Language Processing while preventing human errors that cause when manually entering data.

   Most medical documents such as lab test reports are in printed format, and data extraction and converting them to EHR is a complicated process. Manually inputting data from such documents and entering those data into Blockchain is a time-consuming and error-prone process. These issues will be prevented with the suggested medical document scanner. With the aid of Deep Learning Techniques, the proposed solution will extract text from captured images of medical documents and convert it to text. The captured data will be in an editable or searchable format, making it easy to enter data into the blockchain. After the text has been captured, the appropriate entities and values will be annotated using Natural Language Processing algorithms.

3. To identify Drugs using Image Processing and extracting pharmaceutical data such as their side effects, dosage, etc:

   The fundamental goal of carrying out the Drug identification component is to take care of the people in diminishing conflicts about consumable medication by assisting them in expanding their insight about prescription. Not just that utilizing this Drug identification component plans to assist every person with further developing their well-being, and knowledge, diminishing drug misuse and saving a lot more living souls.

4. To assist patients with a smart chatbot based on Machine learning and Natural Language Processing for health care assistance:

   The medical chatbot should be able to identify the text and give appropriate responses to the patient. In addition to that needs to train chatbot to give accurate results since the system is dealing with sensitive patient data. And the component should be able to connect with the blockchain to get patient prescription information because it’s important to build a connection with the patient. A medication timetable management system should also be developed to give notification to patients to remind the time to take the medications. There should be an opportunity for any user to handle the chatbot easily. therefore, the chat interface should be user-friendly.

2. Methodology

2.1 Project Overview

The suggested system is designed to meet the challenges that the healthcare domain confronts during the COVID-19 pandemic, as well as to provide healthcare solutions that ensure service continuity while people remain at home and maintain social distancing. The proposed distributed healthcare framework would include secure patient health record management and pharmaceutical diagnostic capabilities.

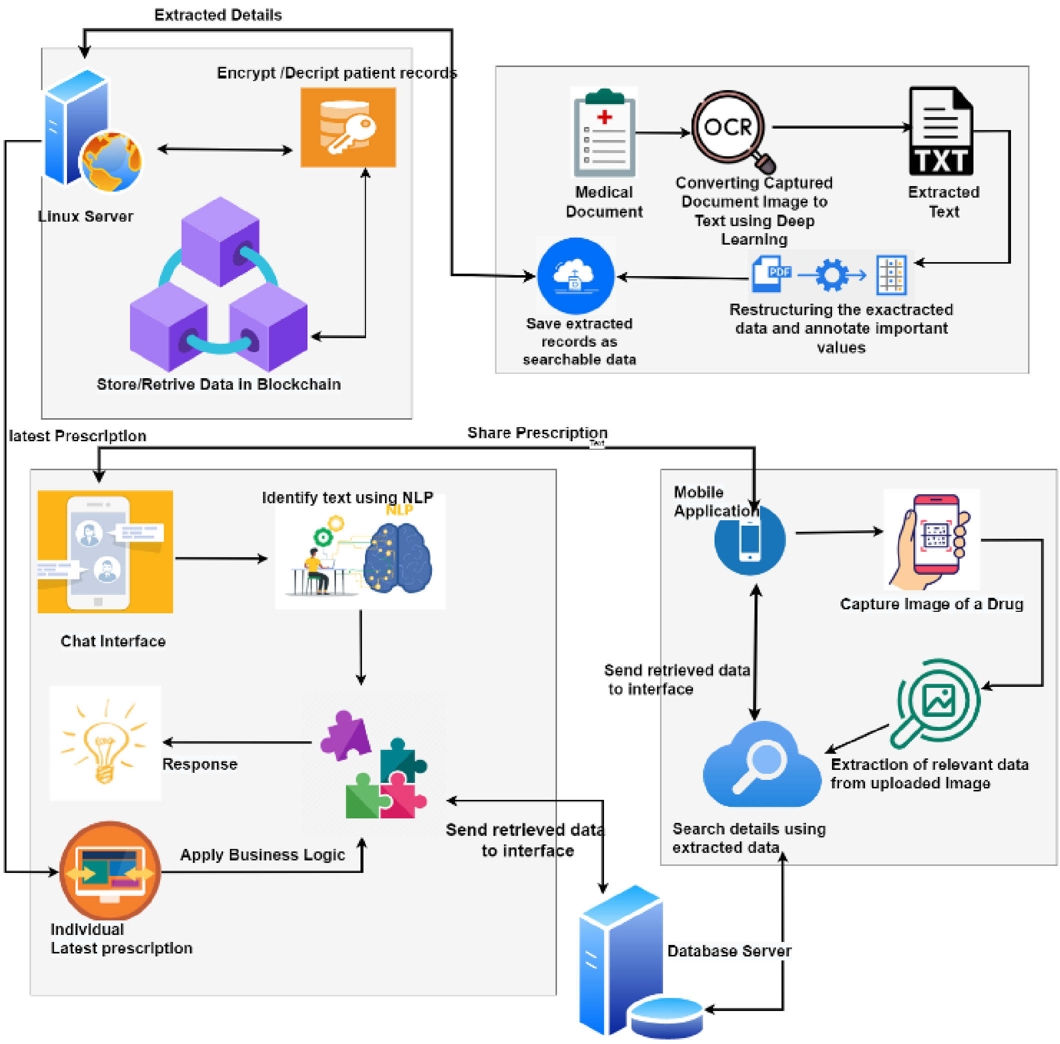


Figure 2.1.1: Project Overview Diagram

According to Figure 2.1.1, there are four major components in the Healthcare Application developed during this research. The system includes a Blockchain component, a Medical Document Scanner, Virtual Medical Chat Bot, and a Drug

Identifier as the four major components. The blockchain component will provide capabilities for safe access and data sharing while securely storing patient data. The Medical Document Scanner will scan the clinical laboratory test reports and scan and extract important named entities from the scanned documents. Patient inquiries will be answered by the medical chatbot, which will also provide reminders to take medication based on the specifics of the prescription. Drug Identifier will recognise the medication using images of the tablets and deliver the necessary information.

2.2 System Overview

2.2.1 System overview of Blockchain Component

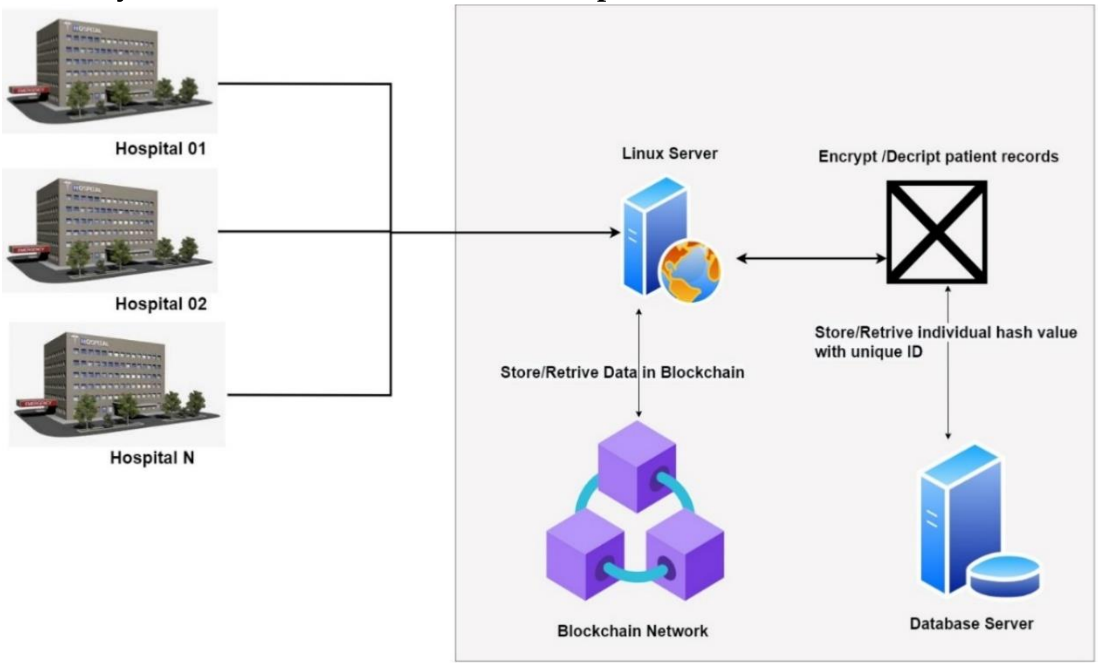


Figure 2.2.1.1: System Overview Diagram of Blockchain component

According to Figure 2.2.1.1, the Blockchain component is responsible for storing/accessing and sharing patient information among health care professionals. Only authorized doctors can perform the storing task in this system. Patient records will be encrypted before storing the patient record. The Hash function is used for encrypting the record. Once the encrypted record is pushed to the blockchain and it will be stored in a centralized database server with a unique key. Only the hash value and the unique key are stored in the centralized server.

When accessing the individual patient record, initially the record will be searched from the centralized server. The record is searched from the blockchain only when the record is existing. Only authorized doctors can alter the records. After altering the record, it will be again updated on the database server before pushing the record into the blockchain network. Different authorized stakeholders can use the system from any place where the system operates. The smart contract will help to get the latest prescription of the individual patient and will be shared with them.

2.2.2 System overview of Medical Document Scanner Component

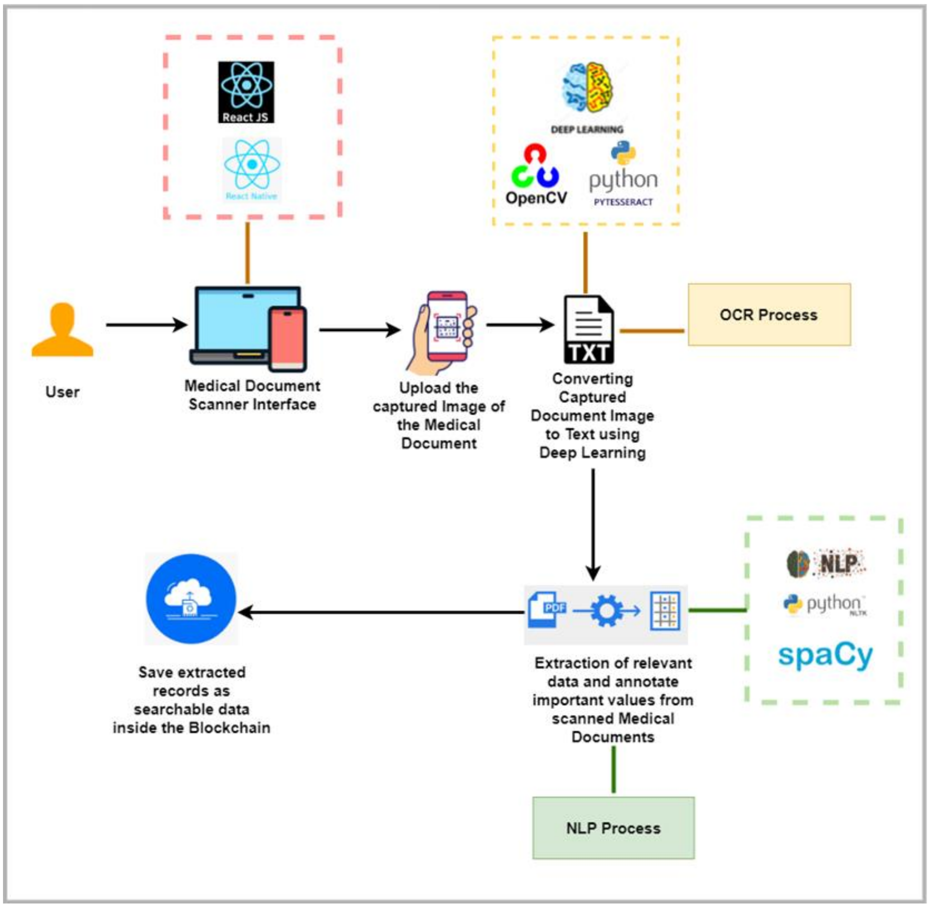


Figure 2.2.2.1: System Overview Diagram of Medical Document Scanner

Figure 2.2.2.1 shows the Medical Document Scanner component, which can extract textual data from printed Medical Documents such as Clinical Laboratory Test Reports and restructure them to annotate the important values and extract defined Named Entities from the extracted Text. This component will be added to the blockchain component to reduce the amount of data that must be manually entered into the blockchain and can minimize the errors caused due to human errors.

A medical document scanner can be used by a doctor, medical practitioner, or any other authorized entity that can add or modify data inside the Blockchain.

Due to security concerns, Blockchain has access control procedures in place for extremely sensitive patient data. Eligible users can use the web application and access the Medical Document Scanner interface to upload a captured image of a medical document.

With the use of the Optical Character Recognition technique in Deep Learning Textual data will be extracted from the captured image and converted into a text document. Important values will be annotated with the use of the same technique.

One of the drawbacks of existing document scanners is that it extracts text word by word and does not provide a meaningful idea. As a result, the proposed model will be trained to extract data and restructure it in a way that is similar to the original image as well as to provide a meaningful idea. Techniques in Natural Language processing will be used for this.

The Bounding Boxes will be drawn, and the predicted entities will be tagged. Finally, the data will then be transformed into a searchable or editable format and stored within the Blockchain.

2.2.3 System overview of Drug Identifier Component

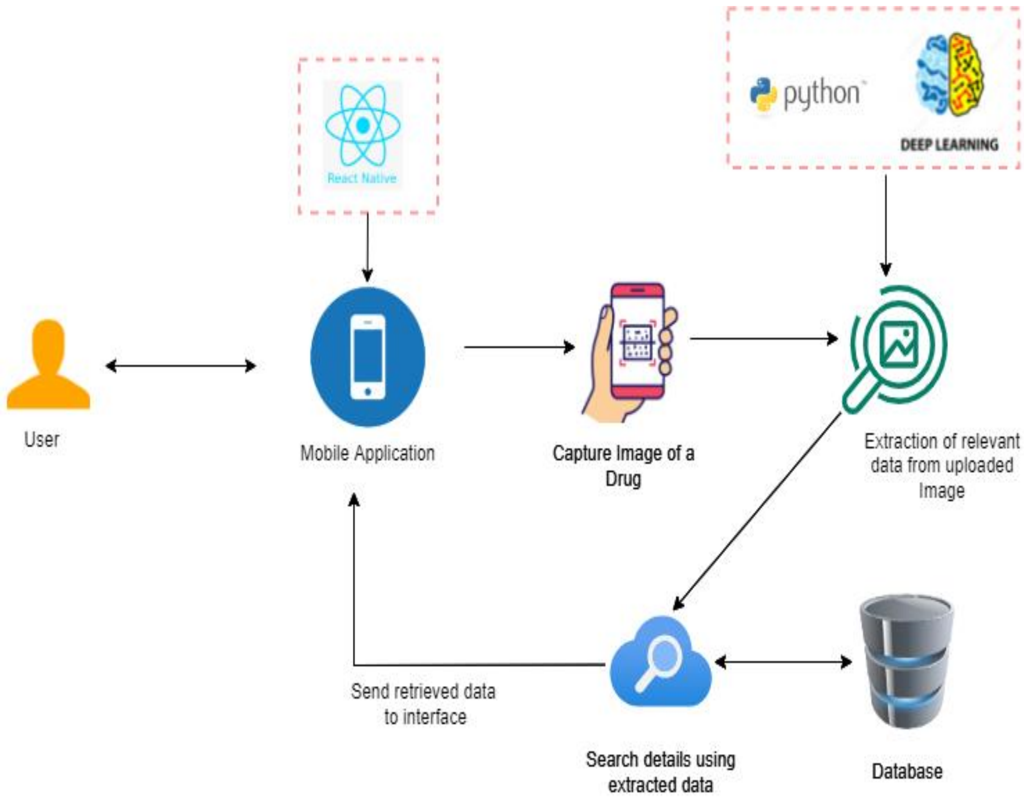


Figure 2.2.3.1: System Overview Diagram of Drug Identifier

The developed system for drug identification is a mobile application component that will be communicated with cloud base server with REST APIs. Commonly, there are three qualities that any strategy to naturally distinguish pills should extract shape, colour, also imprint.

However, developing an enhanced and user-friendly drug identification component that interacts with the mobile application and identifies the previously mentioned qualities is a challenging task to succeed since there are many areas to cover to provide an ideal solution. Catching different images and extracting information from that specific image utilizing computer vision is a particularly troublesome task. For playing out that task with next to no mistakes the image handling model should prepare very well utilizing various kinds of images with various resolutions. So, assembling a sample dataset act as the primary job in this component. For satisfying that we should accumulate numerous and more drug images and related information for that specific medicine utilizing beforehand perform research or getting information from related sites.

In this project correspondence between application and cloud base servers is one of the significant errands. At the point when a client transfers a picture from a versatile application that picture should move to the server right away without any mistakes to make a solid and dependable association. In the current world, there have different sorts of medicine that have comparable colours and comparative shapes so distinguishing the right drug without any confusion cloud base server ought to have a solid decision-making process. The framework contracts the information with the current data set and finds a similitude with a higher rate that will be useful to give precise and solid results to the client. Introducing this drug identification system to society ought to have easy-to-understand applications that assist any client to utilize without any platform difficulty. To overcome that, the authors developed an application to Carry out an easy-to-understand interface that incorporates the core functions of uploading drug images, showing the summary of drugs coming to the servers, and using a cross-platform mobile development framework to develop to break the platform barrier.

2.2.4 System overview of Medical Chatbot Component

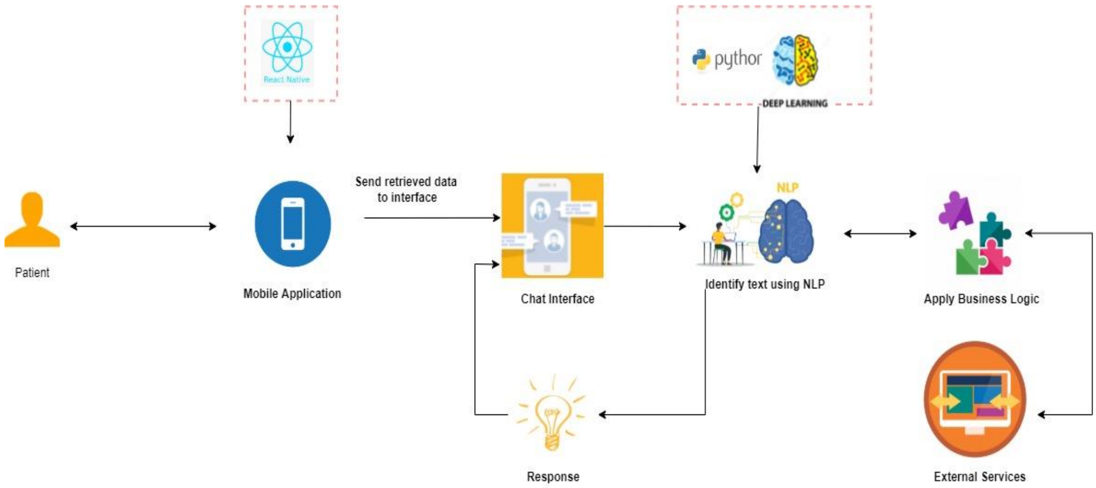


Figure 2.2.4.1: System Overview Diagram of Medical Chatbot

Figure 2.2.4.1 depicts the System Overview Diagram of the Health care chatbot component.

The patient often goes to the doctor and tells him/her the symptoms that he/she usually has, in a primary way. The doctor will then essentially assess the symptoms and give the patient a basic diagnosis, which is contrary to widespread belief. The doctor would then add the patient's prescription to the system via blockchain. Once the patient receives the prescription from the doctor, the chatbot will analyse the names of the medications provided in the prescription and answer the patient's questions regarding the most important medications in general. The chatbot is developed using Machine Learning (ML), and Natural Language Processing (NLP), and the mobile application provided to the patient is developed using React Native and NodeJS, contrary to widespread belief. The mobile app is developed with a user-friendly interface that allows users to easily interact with the application. In Drug Schedule Management Systems, the timing of medication is determined by the physician-prescribed prescription. The drug schedule management system creates a schedule that can provide real-time notifications reminding the patient about their medication, which is exceptionally important. The drug schedule management system is developed using NodeJS

2.3 Software Development Process

The Software Development Lifecycle (SDLC) divides the operations of the software development process into small steps. Out of the several diverse types of software development models, agile methodology is ideal for continual expansion over several iterations. The requirements of the proposed solution will change gradually over time, especially as the development process begins.

The agile methodology's incremental and iterative nature aids in the continuous changes that occur over time. According to Figure 2.3.1 Requirements gathering, Analysis, Design, Coding, Testing, and Maintenance are the six main steps in the agile software development cycle.

Each iteration will result in a finished product. There are several distinct types of Agile Methodologies and SCRUM is the most common and popular one. SCRUM is a framework for agile project development that will be utilized throughout the research. The team will have daily stand-up calls to receive a daily update on the project's development. SCRUM is the ideal approach since it can adapt to frequent changes, and the project is susceptible to frequent modifications.

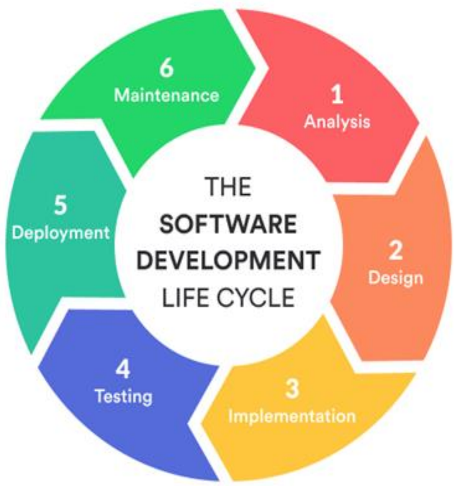


Figure 2.3.1: The Software Development Life Cycle

During the Analysis phase, research gaps were identified, and research analysis was conducted. In a similar vein, during the Designing phase of the SDLC, a viable solution is proposed, and the system is designed based on that. Following the design, the system implementation began with the use of best-suited tools and technologies while following the best practices.

After the implementation and testing, the system testing phase began. This phase included unit testing, integration testing, functional testing, and performance testing. In the deployment phase, the customer receives the finished product in a real-time production setting. The product is prepared for usage after it has been deployed.

2.4 Feasibility Study

- **Economic Feasibility**

  The proposed solution is aimed at hospital chains across the country, and physicians, medical practitioners, and patients would all benefit from the system's completion. Most importantly, the system is a full software solution that does not require any hardware components. As a result, the proposed solution will be executed successfully and at a low cost. The costs incurred at each stage, namely

  a. Planning and Design Cost
  b. Document preparation costs
  c. Hosting charges
  d. Internet usage costs.

- **Technical Feasibility**

  The sub-components will be combined into a solitary product that will be hosted on a server. To ensure a successful implementation, everyone should extensively research these modern technologies before beginning implementation, ensuring that the proposed solution is technically possible.

- **Operational Feasibility**

  The proposed solution would operate effectively in the field of healthcare, and the system will benefit both healthcare professionals and patients. The present limitations in the healthcare domain will be reduced by this technology.

- **Schedule Feasibility**

  The proposed solution is expected to be completed within a year. The scope of the study and its sub-components have been narrowed and fine-tuned accordingly. The intended system will be implemented on time, and the system will be feasible according to the schedule.

2.5 Requirements Gathering

2.5.1 Functional Requirements

1. Storing, accessing, and exchanging scattered patient data across several EHRs while safeguarding patients' data privacy:

   Encrypted data should be stored in the blockchain and centralized database with a unique key. Authorized stakeholders can access the system from different areas. Any authorized stakeholder can share patient details through the system. According to the access privileges, only doctors should be able to alter patient records.

2. Extract textual data from Medical Documents and extract important Named Entities from those Documents:

   Textual data should be extracted from the captured images of printed medical documents such as Clinical Laboratory Text Reports. Normal text recognition models capture raw data by scanning word by word. The captured text must be rearranged in this module to appear the same as the original picture. The names of the identified Named Entities should be tagged next to the Bounding Box that has been drawn around them. With time, most printed medical documents get distorted.

This suggested module is trained to extract data from skewed documents. Normal text recognition models capture raw data by scanning word by word. The captured should be rearranged in this module to appear the same as the original picture. Important Named Entities such as Age, Date, Patient Name, Test, Result and Additional comments should be extracted and displayed in a tabular format. Before transmitting the data to Blockchain, any problems that affect the results' correctness or that include spelling or grammar should be fixed. Therefore, the captured textual data should be in an editable format.

3. Identify drugs using captured images and extract medication details:

   Data such as imprints, shapes, and colours should be extracted from the captured images to identify the medication. After capturing those details all information related to the frug should be displayed to the user.

4. Identify the message and respond appropriately to the patient while giving reminders to take medication on time:

   There needs to be a way to recognize user inputs and respond appropriately to the user and the chatbot needs to be aware of the accuracy of the response from the messages. To provide the prescription details to a patient, it is necessary to create a way to access the blockchain component through the chatbot component so that the chatbot needs to take minimal inputs from the user to access the blockchain and needs to modify the data as a user-friendly response. To manage the medication time system, it is necessary to create a new service for scheduling patients' medication times, which should notify the user according to the scheduled time.

2.5.2 Non-Functional Requirements

1. Availability

   This proposed system should be deployed in a server and should be accessible 24/7 without any downtime and should be accessible to anyone from anywhere without any restriction.

2. Usability

   Patients will benefit from the proposed solution. Therefore, the system should consider the usability aspects such as satisfaction, efficiency, and user-friendliness.

3. Accuracy

   The developed solution will be delivered to the healthcare community therefore the accuracy of the application and results should be higher.

4. Performance

   This proposed solution should be implemented to provide a quick response within a specified period and to function at an elevated level of efficiency.

5. Security and Transparency

   The system is dealing with sensitive patient details. Therefore, system security and transparency should be higher.

6. Scalability

   The system is dealing with an enormous amount of data. Therefore, the system should be scalable to handle the demand.

2.6 Technology Selection

The blockchain component is running on the Ethereum Goerli test network. Two main smart contracts are deployed on that network. Infura.io is the middle layer of this component. To run the blockchain following technologies and prerequisites are required. Those are,

- Node JS
- React JS
- Account on Infura.io
- Python
- Solidity
- Web3JS
- Blockchain networks

Optical character recognition, a Deep Learning approach, is used to extract textual data from Clinical Laboratory Test reports. Python libraries such as

1. OpenCV,
2. NumPy,
3. Pytesseract

are used to achieve this. Using OpenCV technology, the medical records were loaded, and Pytesseract is utilized to extract the content. Named Entity Recognition is carried out using Natural Language Processing.

Python libraries in Natural Language processing such as

1. Spacy,
2. Pandas
3. Regular expressions

Was used for the extraction of Named Entities. The front-end web application is developed using technologies like HTML, JavaScript, and ReactJs. The preparation and enhancement of images were done using various OpenCV techniques.

For drug identification Python libraries such as

1. Boto3,
2. WebColor, Colorgram,
3. Flask

4. NumPy
5. OpenCV
6. Pandas
7. Statistics

is utilized. Using OpenCV technology, the image of the drug is loaded, and using WebColor, and Colorgram libraries the colour of the pill is extracted and using Statistics the shape of the pill can is extracted.

Not only open-source software such as Amazon Rekognition Was used for the extraction of an imprint of the drug. The front-end mobile application is developed using technologies like react-native and JavaScript.

Medical chatbot utilizes Artificial Intelligence, Machine Learning, Natural Language Understanding and Rasa chatbot framework for development. Apart from that, the following two algorithms are utilized to train the model.

1. Conditional Random Field (CRF)
2. Bag of Words (BOW)

Apart from that, a manually feed dataset has been utilized to train the model.

2.7 Commercialization aspects of the product

The proposed solution is aimed at the field of healthcare, and the proposed system's target audience includes physicians, healthcare workers, and patients.

The benefits of the system can be stated as follows:

1. Securely storing, and accessing scattered patient data across several EHRs (Electronic Health Records)
2. Medical Document Scanner to extract text from medical documents and annotate and extract important entities from the captured text
3. Identify drugs using the image and provide adequate information such as dosage, side effects and many more
4. Virtual conversational medical chatbot to communicate with patients while giving daily reminders to take medication on time
5. 24/7 service with no or minimum downtime
6. Provide distributed healthcare services to end-users across the island

High data security with required access control protocols

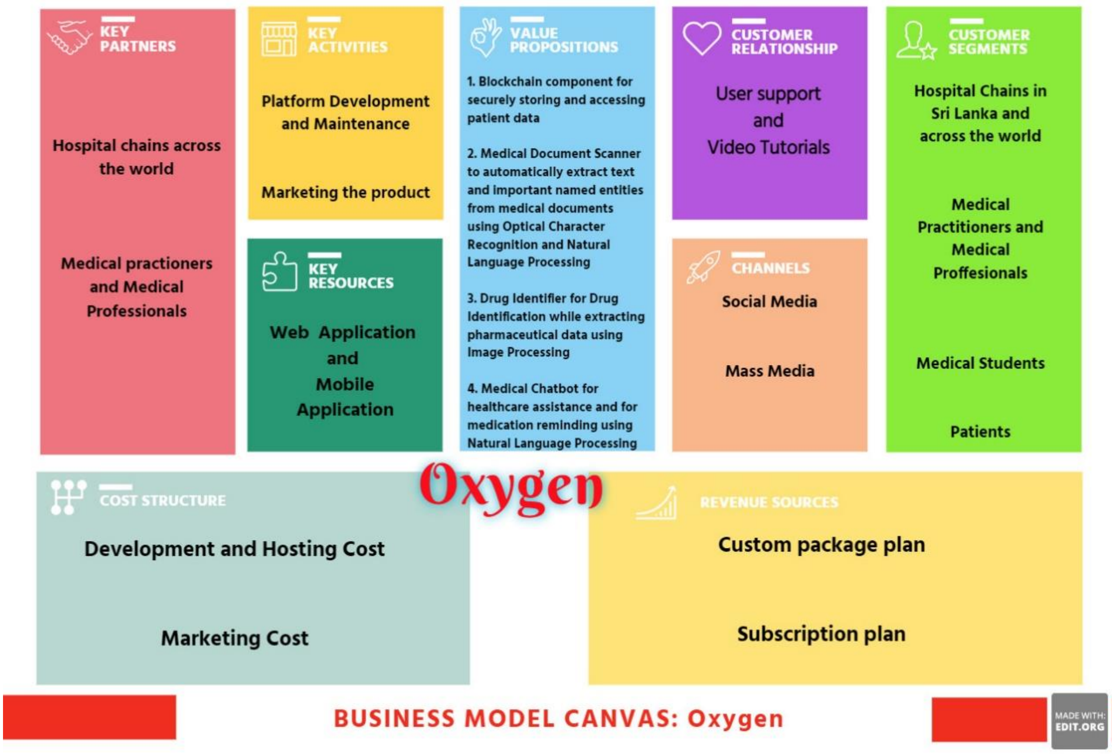


Figure 2.7.1: The Business Model Canvas

2.8 Implementation

2.8.1 Blockchain Component

The proposed Blockchain component is a web-based application. The most typical issues with centralized EHR systems were resolved by this component. Due to its decentralized structure and high security, Blockchain technology is increasingly being used in applications today. Since it is holding sensitive patient data, it is necessary to safeguard patients' privacy. This component focuses on storing, accessing, and sharing patient details among healthcare professionals. Transactions are executed on the Ethereum test network.

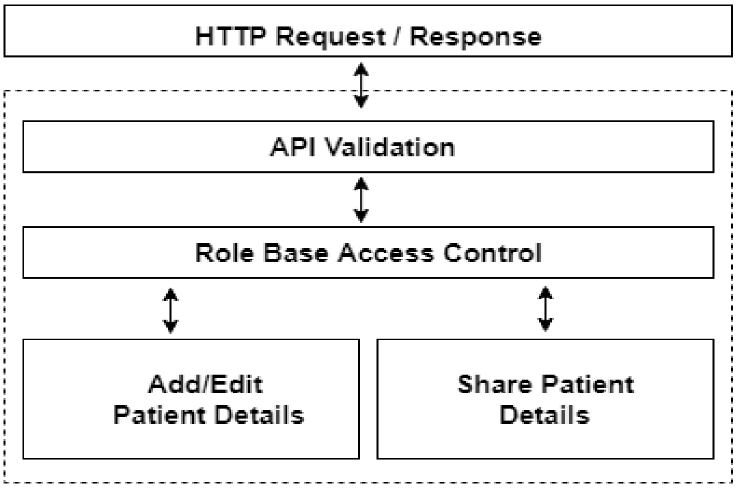


Figure 2.8.1.1: System Overview Diagram for Blockchain component

This component is running on the Ethereum Goerli test network. Two main smart contracts are deployed on that network. Infura.io is the middle layer of this component. Considering these things some sort of prerequisites must have for running this component. Those are,

- Node JS
- React JS
- Account on Infura.io
- Python

Apart from that for the understanding purpose need to have some knowledge of the below technologies,

- Solidity

- Web3JS
- Blockchain networks

There are several configurations needed to run this component. When we are deploying a system, we should provide some configurations. The purpose of using hard-coded values we can provide those necessary values via config files or using environment variable files.

- ETHEREUM_NETWORK -> This should be the network where smart contracts will be deployed.
- INFURA_API_KEY -> This can get from that created Infura.io account
- PRIVATE_KEY -> Private key also should be there.
- NETWORK_ENDPOINT -> This is the URI that will be given from Infura.io
- SMART_CONTRACT_DEPOYED_ADDRESS -> When we are deploying smart contracts, they will provide us with an address. Without having this address system will not allow us to perform any task. Not only the system but also the network.

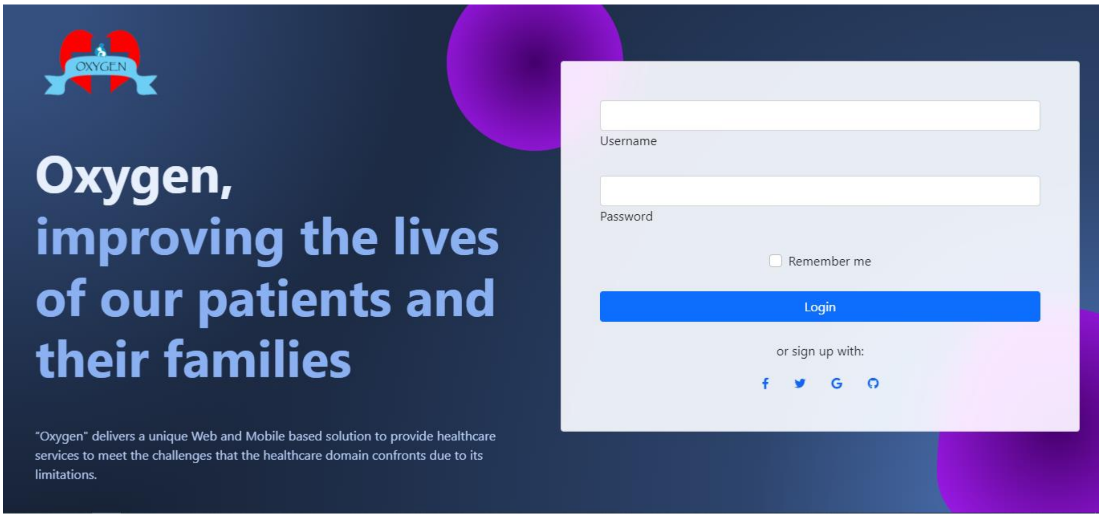


Figure 2.8.1.2: Login Interface

This is the place, where all users are allowed to login into the system. Once the user adds their username and password, the backend server is responsible for validating those details with all users in the blockchain. Since that user can be validated the server will create a JWT token according to the user details and will pass it to the front end. Options for Navigation will be displayed according to the user. The JWT token holds the role of the user. The front-end server decrypts the JWT token and will allow the user to perform their tasks according to the role.

Once logged into the system the dashboard will be displayed as shown in Figure 2.8.1.3.

Figure 2.8.1.3: Dashboard

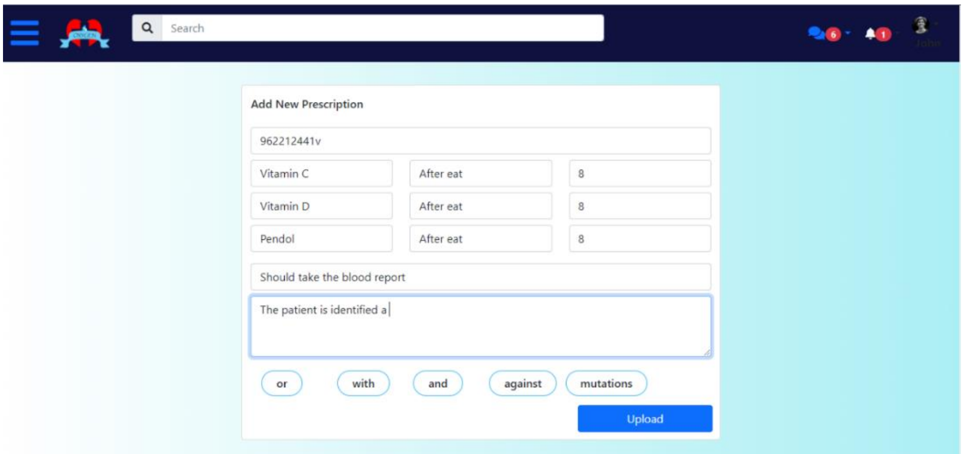


Figure 2.8.1.4: Add New Prescription

This Interface will help the doctor to add new prescriptions. Once the doctor hits the upload button the data block will be stored according to the patient id. Apart from that, this component integrates with the word suggestion model. Once the doctor hits the space bar front end server will send the last word that the doctor entered. According to the last word the model predicts some word related to the healthcare domain and send it back to the front-end server. The front-end server will show all words as above.

2.8.2 Medical Document Scanner Component

The Medical Document Scanner component comprises three fundamental processes as given in Fig 2.8.2.1. In the first process image pre-processing techniques are used to improve the overall quality of the image. In the second process, Textual data is extracted from the captured images of the Clinical Laboratory Test Reports using the OCR process. In the third process, important Named Entities are extracted from raw data using techniques in Natural Language Processing (NLP).

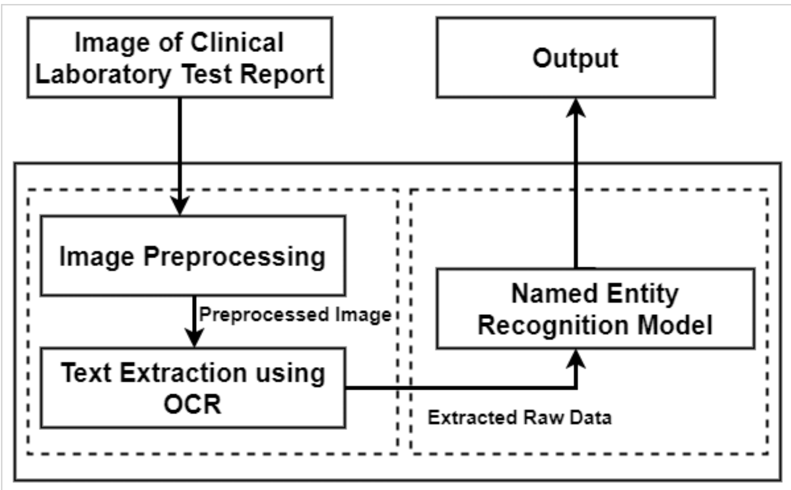


Figure 2.8.2.1: System Overview Diagram for Medical Document Scanner component

Setting up a project entails completing the required installations and prerequisites. Python and its dependencies must be installed as the initial step. The Virtual Environment should be established as the next step. After the virtual environment set-up is done Tesseract OCR should be installed in the computer before the installation of the Pytesseract library. All necessary libraries should be installed into the virtual environment after Pytesseract is installed. The following libraries need to be installed:

1. NumPy - One of the most popular Python packages for scientific computation. It offers a multidimensional array object along with variants like filters and matrices that may be used for different mathematical operations.
2. pandas - A tool for data cleaning and analysis in data science and machine learning
3. SciPy - Offers additional useful functions for processing applications, statistics, and optimizations.
4. Matplotlib - A cross-platform data visualisation and graphical plotting library
5. Pillow - Python Imaging Toolkit, which provides support for viewing, processing, and storing a wide variety of image file types
6. OpenCV-python - Used in computer vision

The Spacy Library can be installed as the final step. Spacy is an open-source library for NLP and it will be used for training the NER model.

Gathering a data set is the main thing to be done in the data preparation stage. The dataset which is been used in this research includes 260 clinical laboratory test reports from 24 Egyptian laboratories [37]. After getting the dataset the text should be extracted from all the images with the use of Pytesseract. Pytesseract locates paragraphs, lines, and ultimately words before sending them to the deep learning model. After that, data frames are created from the image's retrieved text. The data was then stored in CSV format after the text in the data frame was cleaned. Labelling should begin after all the data has been stored in the CSV format and the BIO/IOB format is used for labelling.

The data should be pre-processed using certain methodologies before training the Named Entity Model. First, must load the data and convert it into pandas. After cleaning the data from all the images then the data can be organised into groups. When the data is converted to the Spacy format the data can be split into the Training set and the Testing set.

The data should be pre-processed using certain methodologies before training the Named Entity Model. First, must load the data and convert it into pandas. After cleaning the data from all the images then the data can be organised into groups. When the data is converted to the Spacy format the data can be split into the Training set and the Testing set.

There are several preconfigured models in the Spacy library, and these models can be utilised to train the Named Entity Recognition model according to the requirements of the research. The spacy train command on the command line is the suggested method for training the Spacy pipeline. All settings and hyperparameters must be included in a single configuration file. The data should be in pickle format for model training. Training the NER model can begin after data preparation. The model can be stored for further usage after the training is complete.

The trained NER model should first be loaded for the predictions. The imported NER model can be utilized to draw the bounding boxes and tag the predicted entities after the text has been extracted from Pytesseract. In this manner, a complete prediction pipeline can be created.

Following is how the Document Scanner web application ought to operate. First, there should be an interface to upload the image of the laboratory report as shown in Figure 2.8.2.2.

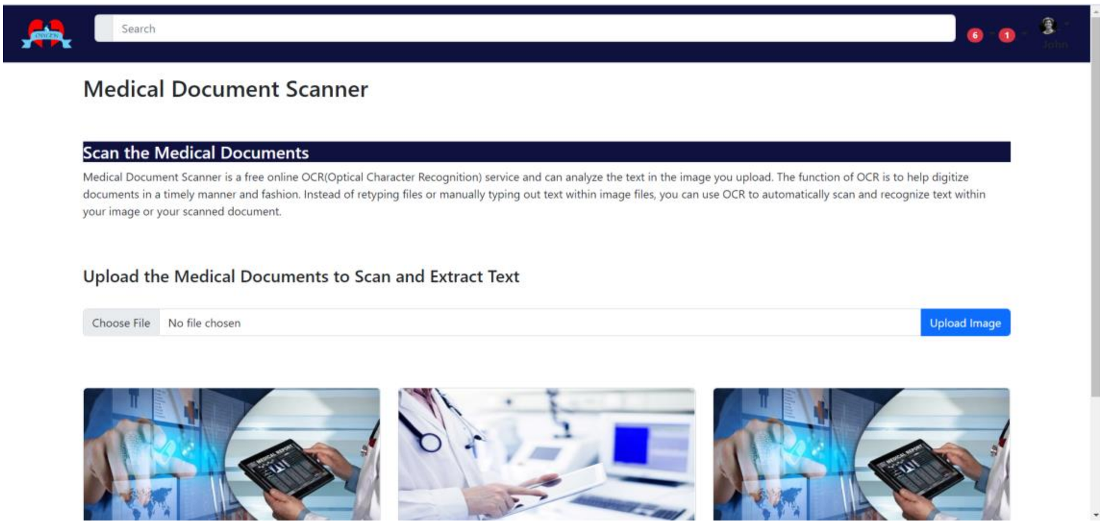


Figure 2.8.2.2: Medical Document Scanner Interface

The image is then internally passed into the document scanner and that scanner will return the four points. If an incorrect prediction is received, the corners can be adjusted with the use of JavaScript as shown in Figure 2.8.2.3.

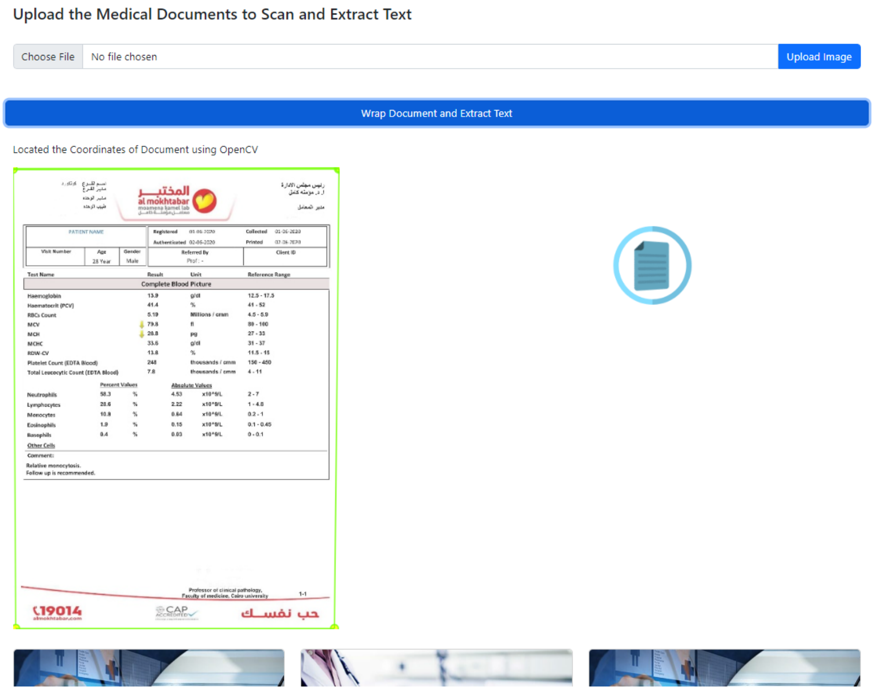


Figure 2.8.2.3: Image with the located coordinates

Then the wrap document extract text button should be clicked. The Bounding Box image with the tag names will then show up on the following page as given in Figure 2.8.2.4.

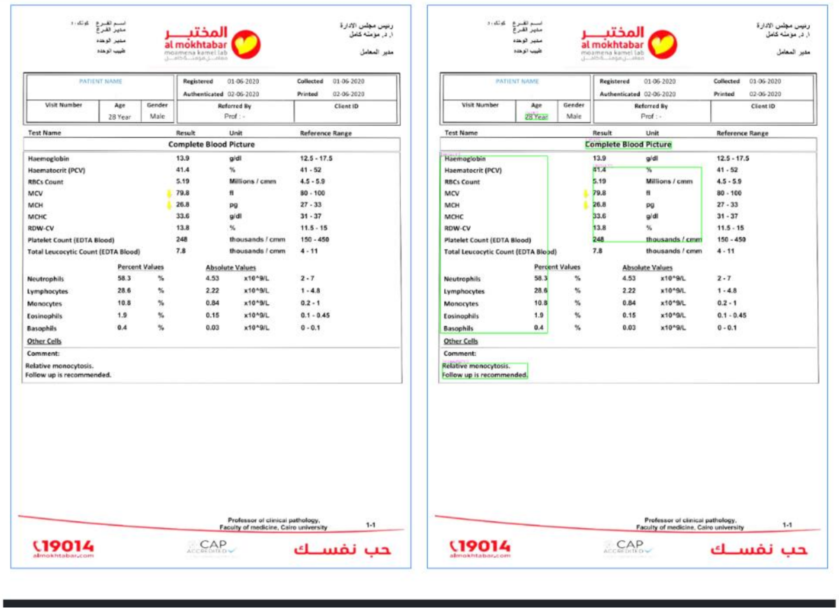


Figure 2.8.2.4: Image with the Bounding Boxes with the Tag name

Similar to this, a tabular representation of all retrieved Named Entities will be shown as given in Figure 2.8.2.5.

Since this table is editable, any errors that might have occurred due to erroneous predictions can be fixed before the data is sent to the blockchain. Before developing the web application, Flask should be installed in the virtual environment. Python in Flask can be used to predict the document coordinates. Additionally, JavaScript can be used to change the coordinates.

Named Entities

Entities	Extracted Text
AGE	59 y
DATE	07/06/2021
PATIENTNAME	[]
TEST	Chemistry Unit
RESULT	Fasting Plasma Glucose 111', 'Plasma Glucose 2Hrs Pp 103', 'Glycated Haemoglobin ', 'Serum Urea', '17', 'Serum Creatinine', 'Serum Uric Acid 7.0
COMMENTS	[]

Figure 2.8.2.5: Image of the table with extracted Named Entities

Some image processing techniques can be used on the image to enhance the performance of the model. The image may be processed using image processing techniques including morphological transformation, Gaussian Blur, and detail enhancement. The magic colour can be used on an image after procedures to modify brightness and contrast have been applied. When extracting text from low-quality or skewed documents, improving the picture quality will enhance the model's performance.

2.8.3 Drug Identifier Component

The proposed system for drug identification is a mobile application component that will be communicated with the cloud-based server with REST APIs. Shape, colour, and imprint are three qualities that any strategy used to distinguish pills. Here the component is divided into four significant parts according to the functionality as given in Fig 2.8.3.1.

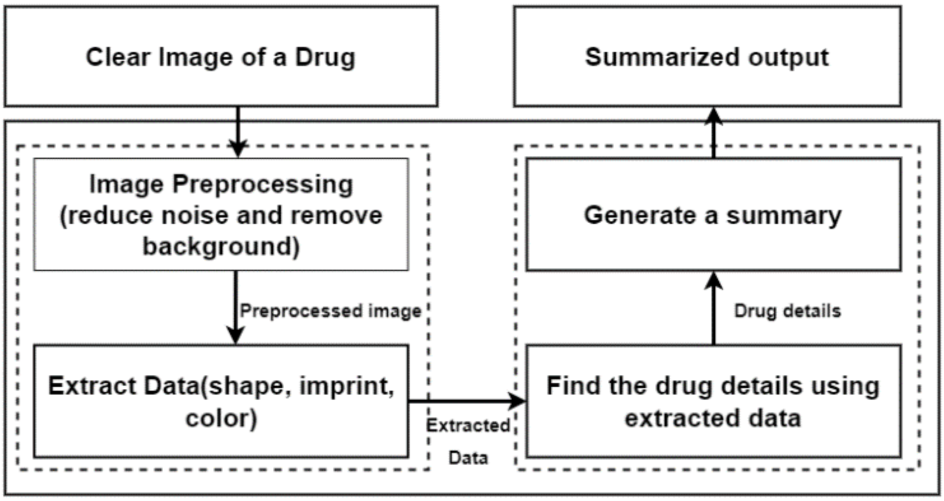


Figure 2.8.3.1: System Overview Diagram Drug Identifier component

The developed system is a drug identification component that extracts data from drug images and provides a detailed summary of medication. This project makes use of Computer Vision and Machine Learning. As the project combines two important technologies, it has been broken down into multiple stages of development for ease of understanding. Each of the steps that make up the stages of development is given below.

1. Imprint Extraction

2. Colour Extraction
3. Shape Extraction
4. Identification and provide a detailed summary
5. Develop a Mobile application to carry out the process

To fulfil the imprint extraction the authors, use Amazon Rekognition software which is provided by amazon company together with the boto 3 python library.

```
s3 = boto3.client('s3',
    aws_access_key_id="aws_access_key_id",
    aws_secret_access_key="aws_secret_access_key",
    region_name="us-east-2")

bucket = 'drugidentificationbucket'
s3.upload_file(photo, bucket, photo)

client = boto3.client(
    "rekognition",
    aws_access_key_id="aws_access_key_id",
    aws_secret_access_key="aws_secret_access_key",
    region_name="us-east-2"
)

response=client.detect_text(Image={'S3Object':{'Bucket':'drugidentificationbucket','Name':photo}})

textDetections=response['TextDetections']
imprint = ""
for text in textDetections:
    if text['DetectedText'] not in imprint:
        imprint = imprint + text['DetectedText']
imprint = ''.join(imprint.split())
```

Figure 2.8.3.2: Imprint Extraction

To fulfil the colour extraction requirement, the authors use Colorgram and the WebColor python library for identification.

```
def color(file):
    colors = colorgram.extract(file, 2)
    first_color = colors[1]
    rgb = first_color.rgb
    return (rgb)

def closest_colour(requested_colour):
    min_colours = {}
    for key, name in webcolors.CSS3_HEX_TO_NAMES.items():
        r_c, g_c, b_c = webcolors.hex_to_rgb(key)
        rd = (r_c - requested_colour[0]) ** 2
        gd = (g_c - requested_colour[1]) ** 2
        bd = (b_c - requested_colour[2]) ** 2
        min_colours[(rd + gd + bd)] = name
    return min_colours[min(min_colours.keys())]

def get_colour_name(requested_colour):
    try:
        closest_name = webcolors.rgb_to_name(requested_colour)
    except ValueError:
        closest_name = closest_colour(requested_colour)
    return closest_name
```

Figure 2.8.3.3: Colour Extraction

For the shape extraction, the authors use the OpenCV library and the statistics python library for identification. Here they capture the edges of the images and get the average value of the edges and determine the shape of the medication. For identification and providing a detailed summary, a web scraping technology is used.

Similarly, React Native and JavaScript are used to develop mobile applications.

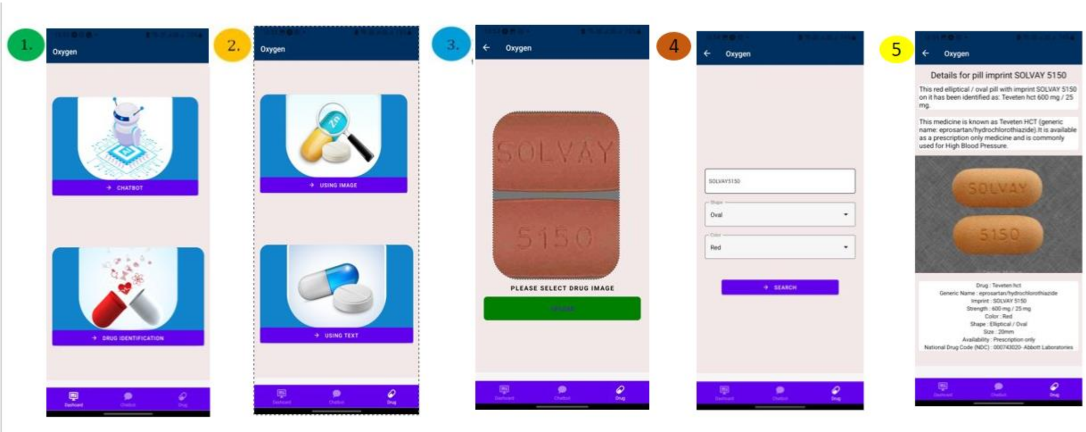


Figure 2.8.3.4: Mobile application's interfaces

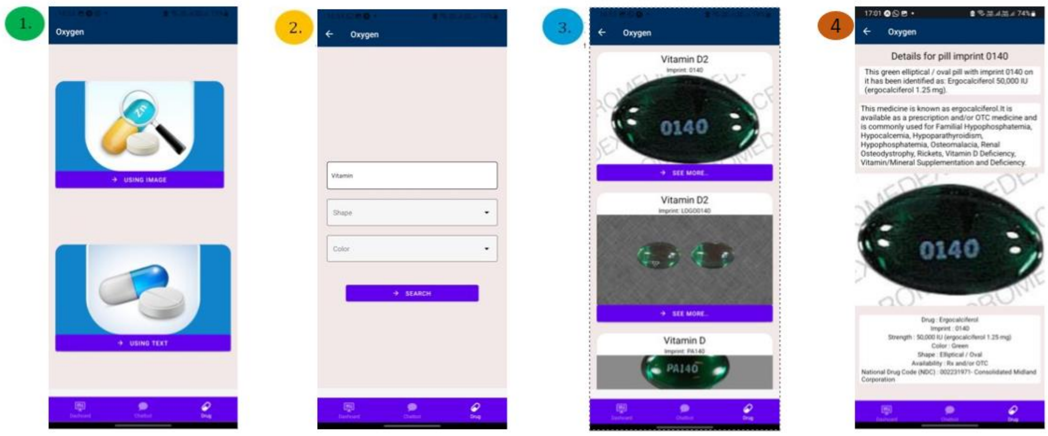


Figure 2.8.3.5: Mobile application's interfaces

2.8.4 Medical Chatbot Component

The developed system includes a user-friendly smart healthcare Chatbot which is based on techniques in machine learning and natural language processing to assist patients. The Chatbot is capable of understanding user input and response appropriately. The main function of the proposed Chatbot is to interact with the user and collect information about the user's prescription and remind them to take the medicine at the required times. Once the latest prescription details of the patient are acquired from the Blockchain component, the Chatbot will analyse the names of the medications provided in the prescription and answer the patient's queries regarding the most important medications in general. The mobile application is developed using React Native and NodeJS. The user-friendly interfaces of the mobile app enable users to easily interact with the app. The Drug Schedule Management System determines when to take medications. The Drug Schedule Management System will generate a timetable that can send real-time reminders to patients to take their medications on time, which is typically important for patients staying at home. This component can be divided into four sub-components based on functionality.

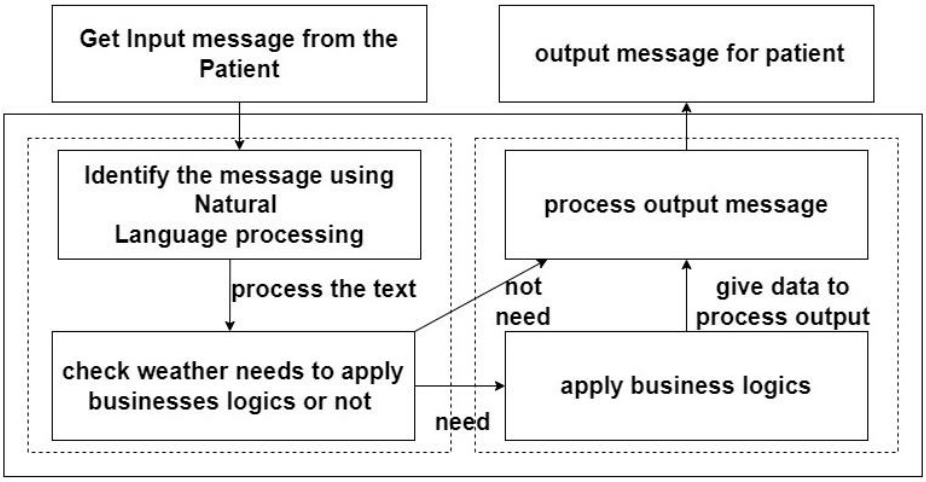


Figure 2.8.4.1: System Overview Diagram for Medical Chatbot component

The suggested Chatbot is capable of responding appropriately to the patient's prescription details stored inside the Blockchain. The virtual chatbot is developed using the RASA framework. RASA is an open-source chatbot framework based on Machine Learning. We can create very accurate chatbots with its help and easily integrate them with our website, Telegram, Facebook, WhatsApp, and other platforms.

The authors used NLP and ML to recognize the messages and provide appropriate responses. Here the Chatbot is trained to increase its accuracy. Apart from that Blockchain is utilized to get patient prescription information because it is important to establish a connection with the system which stores Patient Details together with the prescription details.

Manage Medication Timetable Management System is used to send reminders to patients to take the medication on time as prescribed.

```
actions:
  - action_inquire_prescription
  - action_inquire_tell_about_get_medicine_around_month
  - action_inquire_ask_another_help
  - action_inquire_ask_about_diabetics
  - action_inquire_get_sugar_check_method
  - action_inquire_get_sugar_level
  - action_inquire_ask_advice_manage_diabetics
  - action_remind_to_drink_medicine
```

Figure 2.8.4.2: Action

Figure 2.8.4.2 shows the Action which is the response from a chatbot which is based on the query.

```
entities:
  - nic_number
  - prescription
  - tell_about_get_medicine
  - help_check
  - type
  - diabetics
  - method
  - sugar_level
  - sugar_range
  - task
  - time
  - time_param
```

Figure 2.8.4.3: Entities

Figure 2.8.4.3 shows the entities which can be described as useful information that can be extracted from user input. To develop the Mobile Application the authors utilized react-native and JavaScript to develop an application. Figure 2.8.4.4 depicts the developed mobile interfaces.

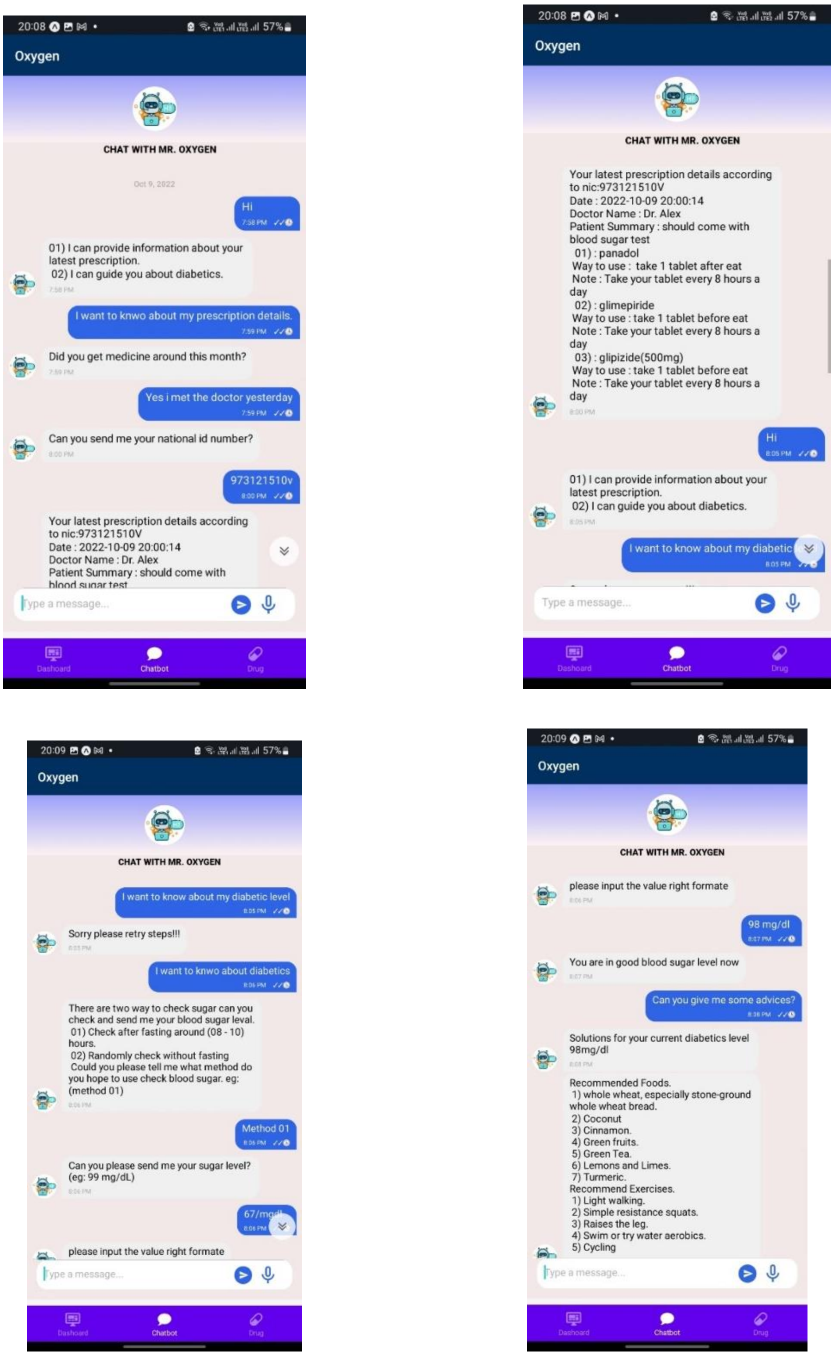


Figure 2.8.4.4: Mobile Interfaces

2.9 Testing

The test results from the developed application are highlighted in this section. Various testing techniques are required for the system at various stages of the development life cycle. These tests aid in detecting any system vulnerabilities. Testing is a challenging and crucial step in the development of the application. Usability, performance, security, and functional and non-functional elements are all included in application testing. The testing will raise the product's quality and it's critical to spot the system's weaknesses early on. Bugs and issues can be solved by preparing the test cases for each function.

2.9.1 Unit Testing

Each module is evaluated independently to ensure that it meets all the standards and has all the necessary functions. The components can be readily merged with other modules if they are error-free.

2.9.2 Unit Testing

All the individual components are linked during integration testing and tested as a single unit. Integration testing is required to confirm that all functionalities perform properly once all the components have been integrated.

2.9.3 System Testing

System testing is done to see if the system's actual outputs match what was anticipated. Here, system testing is carried out for images of various qualities. The test cases used for system testing are listed below.

Table 2.9.3.1: Test Case 01

Test Case No	**Test Case 01**
Pre-requirements	PC or a Laptop with an internet connection
Description	Testing whether the system predicts the coordinates of the image correctly for the images with a background
Test Procedure	1. Visit the Document Scanner Web page 2. Click on choose file

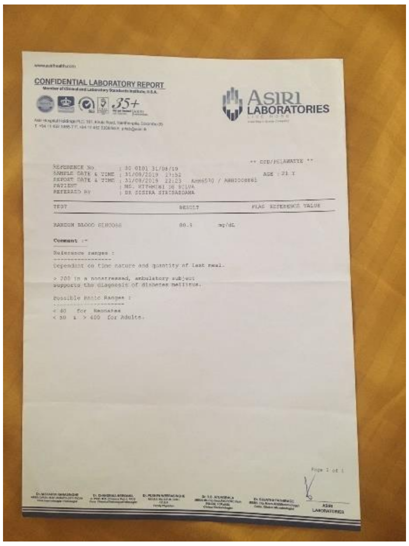
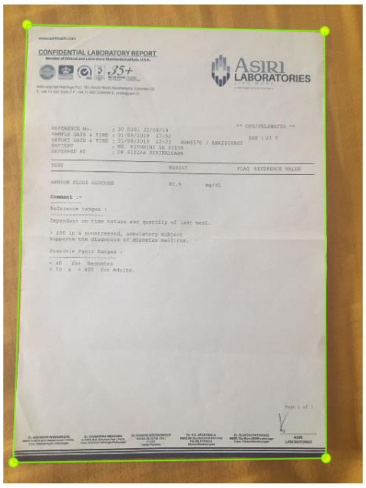
	3. Select an image of a clinical laboratory report with a background 4. Select upload image
Input	The image of the laboratory report with a background. 
Expected Output	Automatically mark the four coordinates of the image
Actual Result	Located the Coordinates of Document using OpenCV 
Result of Test Case	Pass

Table 2.9.3.2: Test Case 02

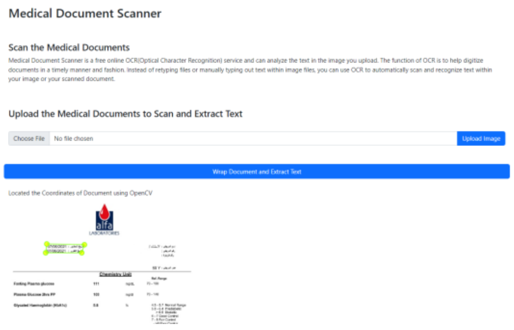
Test Case No	**Test Case 02**
Pre-requirements	PC or a Laptop with an internet connection
Description	Testing whether the “wrap document and extract text” button appears when an image is uploaded to the scanner.
Test Procedure	1. Visit the Document Scanner Web page 2. Click on choose file 3. Select an image of a clinical laboratory report with a background
Input	The image of the laboratory report with a background.
Expected Output	The “Wrap document and extract text” button should appear when an image is uploaded to the scanner.
Actual Result	The “Wrap document and extract text” button appeared when an image is uploaded to the scanner. 
Result of Test Case	Pass

Table 2.9.3.3: Test Case 03

Test Case No	**Test Case 03**
Pre-requirements	PC or a Laptop with an internet connection
Description	Testing whether the Bounding Boxes are drawn around the extracted Named Entities of the image which is uploaded
Test Procedure	1. Visit the Document Scanner Web page 2. Click on choose file 3. Select an image of a clinical laboratory report with a background 4. Click the “Wrap Document and Extract Text Button” 5. Then navigate to the prediction’s web page
Input	The image of the laboratory report with a background.
Expected Output	Output image of the laboratory report with the Bounding Boxes drawn around the pre-defined Named Entities of the image.
Actual Result	Image of the laboratory report with the Bounding Boxes drawn around the pre-defined Named Entities displayed on the prediction page.

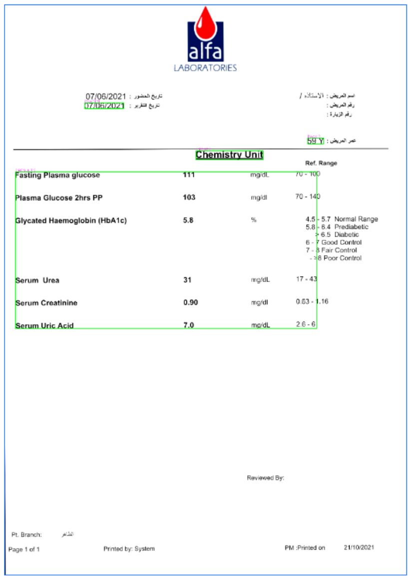
	
Result of Test Case	Pass

Table 2.9.3.4: Test Case 04

Test Case No	**Test Case 04**
Pre-requirements	PC or a Laptop with an internet connection
Description	Testing whether the Tag names appear with the Bounding Boxes drawn around the extracted Named Entities of the image which is uploaded
Test Procedure	1. Visit the Document Scanner Web page 2. Click on choose file 3. Select an image of a clinical laboratory report with a background 4. Click the "Wrap Document and Extract Text Button" 5. Then navigate to the prediction's web page
Input	The image of the laboratory report with a background.

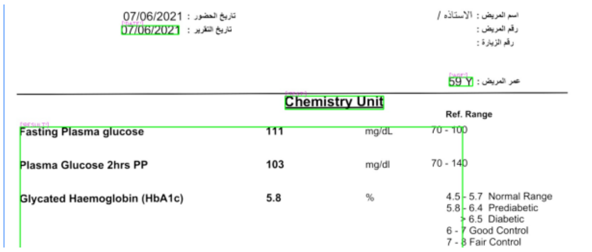
<table>
<tr><td>Expected Output</td><td>Output image of the laboratory report with the Bounding Boxes with the Tag name should be displayed.</td></tr>
<tr><td>Actual Result</td><td>Image of the laboratory report with the Tag Names displayed on the prediction page.

</td></tr>
<tr><td>Result of Test Case</td><td>Pass</td></tr>
</table>

Table 2.9.3.5: Test Case 05

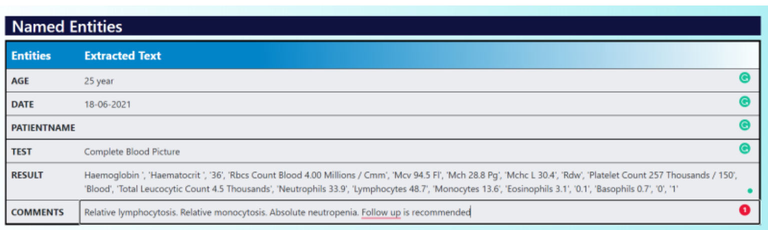
<table>
<tr><th>Test Case No</th><th>Test Case 05</th></tr>
<tr><td>Pre-requirements</td><td>PC or a Laptop with an internet connection</td></tr>
<tr><td>Description</td><td>Testing whether the Extracted Named Entities correctly display in a tabular format</td></tr>
<tr><td>Test Procedure</td><td>1. Visit the Document Scanner Web page
2. Click on choose file
3. Select an image of a clinical laboratory report with a background
4. Click the “Wrap Document and Extract Text Button”
5. Then navigate to the prediction’s web page</td></tr>
<tr><td>Input</td><td>The image of the laboratory report with a background.</td></tr>
<tr><td>Expected Output</td><td>The extracted Named Entities should appear in a table.</td></tr>
<tr><td>Actual Result</td><td>Extracted Named Entities appear in a table

Named Entities
<table>
<tr><th>Entities</th><th>Extracted Text</th></tr>
<tr><td>AGE</td><td>25 year</td></tr>
<tr><td>DATE</td><td>18-06-2021</td></tr>
<tr><td>PATIENTNAME</td><td></td></tr>
<tr><td>TEST</td><td>Complete Blood Picture</td></tr>
<tr><td>RESULT</td><td>Haemoglobin ', 'Haematocrit ', '36', 'Rbcs Count Blood 4.00 Millions / Cmm', 'Mcv 94.5 Fl', 'Mch 28.8 Pg', 'Mchc L 30.4', 'Rdw', 'Platelet Count 257 Thousands / 150', 'Blood', 'Total Leucocytic Count 4.5 Thousands', 'Neutrophils 33.9', 'Lymphocytes 48.7', 'Monocytes 13.6', 'Eosinophils 3.1', '0.1', 'Basophils 0.7', '0', '1'</td></tr>
<tr><td>COMMENTS</td><td>Relative lymphocytosis. Relative monocytosis. Absolute neutropenia. Follow up is recommended</td></tr>
</table></td></tr>
<tr><td>Result of Test Case</td><td>Pass</td></tr>
</table>

Table 2.9.3.6: Test Case 06

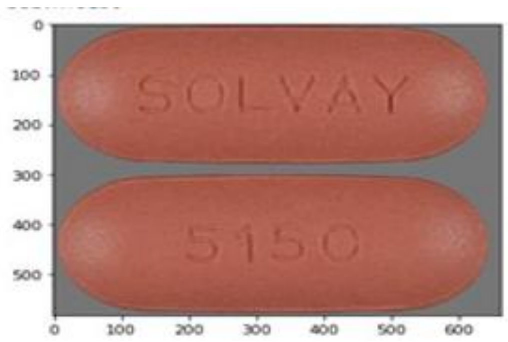
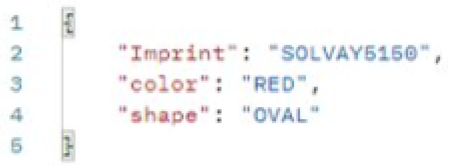
Test Case No	**Test Case 06**
Pre-requirements	PC (Program Complexity) or a laptop with an internet connection
Description	Testing whether the system extracts data from an image of medications
Test Procedure	5. Select upload image and test using Postman
Input	The image of drug 
Expected Output	Automatically extract data and provide extracted data
Actual Result	
Result of Test Case	Pass

Table 2.9.3.7: Test Case 07

Test Case No	**Test Case 07**
Pre-requirements	PC or a Laptop with an internet connection
Description	Testing whether the system extracts data from an image of medications

Test Procedure	1. Select upload image and test using Postman
Input	The image of drug 
Expected Output	Automatically extract data and provide extracted data
Actual Result	{ "Imprint": "L403", "color": "WHITE", "shape": "CIRCLE" }
Result of Test Case	Pass

Table 2.9.3.8: Test Case 08

Test Case No	**Test Case 08**
Pre-requirements	PC or a Laptop with an internet connection
Description	Testing whether the related data is provided according to the uploaded image.
Test Procedure	4. Click on choose file 5. Upload the image and hit the search
Input	The image of the drug.

	
Expected Output	Automatically extract data and provide a detailed summary of a particular medication
Actual Result	
Result of Test Case	Pass

Table 2.9.3.9: Test Case 09

Test Case No	**Test Case 09**
Pre-requirements	PC or a Laptop with an internet connection
Description	Testing whether the related data is provided according to the uploaded image.
Test Procedure	1. Click on choose file 2. Upload the image and hit the search

Input	The image of the drug. 
Expected Output	Automatically extract data and provide a detailed summary of a particular medication
Actual Result	

Table 2.9.3.10: Test Case 10

Test Case No	**Test Case 10**
Pre-requirements	PC (Program Complexity) or a laptop with an internet connection
Description	Testing weather identifies NIC number and gives relevant information from the blockchain
Test Procedure	Input the Patient's NIC number and test model

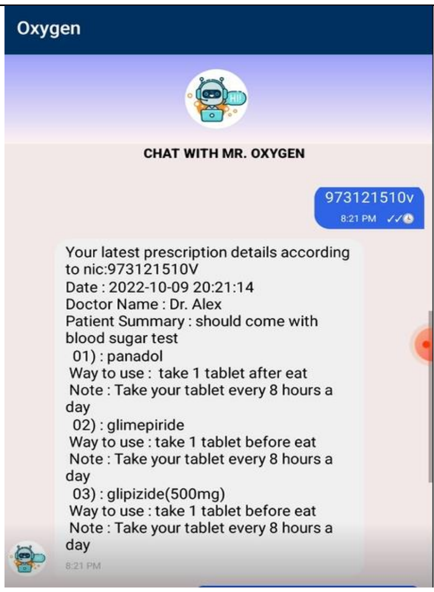
Input	973121510V
Expected Output	Identify the patient NIC number and get patient rescription details from the blockchain
Actual Result	
Result of Test Case	Pass

Table 2.9.3.11 Test Case 11

Test Case No	**Test Case 11**
Pre-requirements	PC (Program Complexity) or a laptop with an internet connection
Description	Testing whether identifies the NIC number and gives relevant information from the blockchain
Test Procedure	Input invalid Patient NIC number and test model
Input	973121510V
Expected Output	Identify the patient's NIC number is incorrect and send the appropriate response.

Actual Result	`Your input -> 9732342J`
	`Sorry currently you dont have a prescription...`
	`Your input ->`

Result of Test Case	Pass

Table 2.9.3.12 Test Case 12

Test Case No	**Test Case 12**
Pre-requirements	PC (Program Complexity) or a laptop with an internet connection
Description	Testing whether identifies patient input invalid type sugar level
Test Procedure	Input invalid Patient Sugar Level and test model
Input	67/mg/dl
Expected Output	Identify the patient blood sugar level and give the response “please input the value right format”
Actual Result	

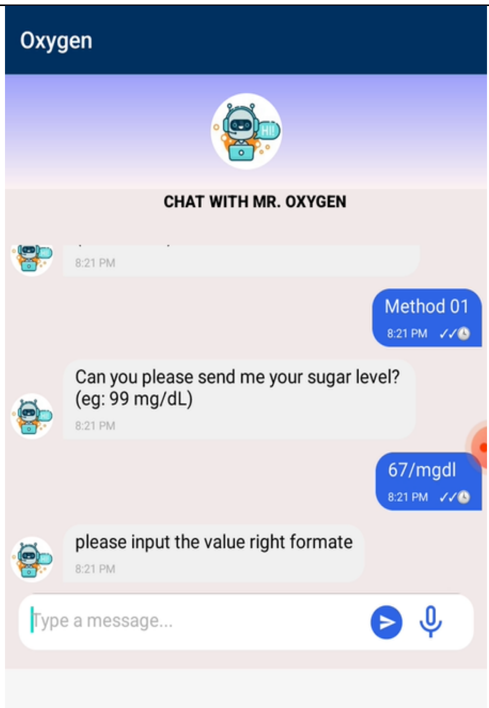
	
Result of Test Case	Pass

Table 2.9.3.13 Test Case 13

Test Case No	**Test Case 04**
Pre-requirements	PC (Program Complexity) or a laptop with an internet connection
Description	Testing whether identifies patient input valid type sugar level
Test Procedure	Input invalid Patient Sugar Level and test model
Input	75 mg/dl
Expected Output	Identify the patient blood sugar level and give a response according to the sugar level

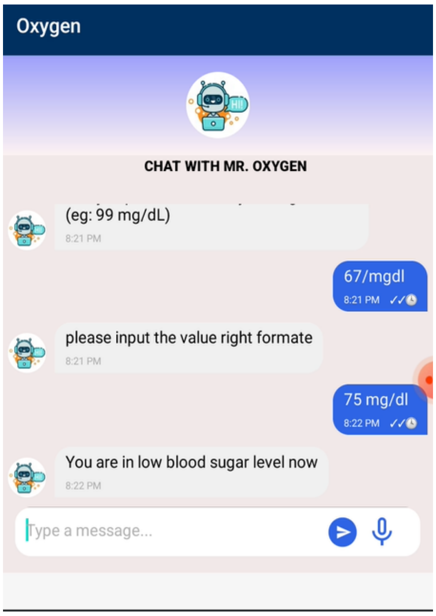
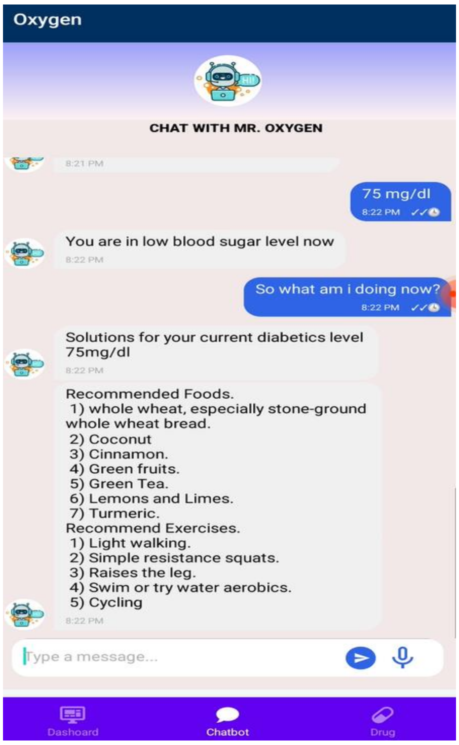
Actual Result	
Result of Test Case	Pass

Table 2.9.3.14: Test Case 14

Test Case No	**Test Case 14**
Pre-requirements	PC (Program Complexity) or a laptop with an internet connection
Description	Testing whether identifies patient input valid type sugar level
Test Procedure	Input invalid Patient Sugar Level and test model
Input	75 mg/dl
Expected Output	Identify the patient blood sugar level and give more information according to the sugar level

Actual Result	
Result of Test Case	Pass

3. Results and Discussion

3.1 Results

This section highlights the results obtained at the end of the research conducted. The results obtained from each sub-component will be elaborated further under each sub-section. The developed system will be delivered to the healthcare community therefore data obtained should be managed with care. As a result, the accuracy of the results needs to be of a high value.

3.1.1 Outputs of the Blockchain component

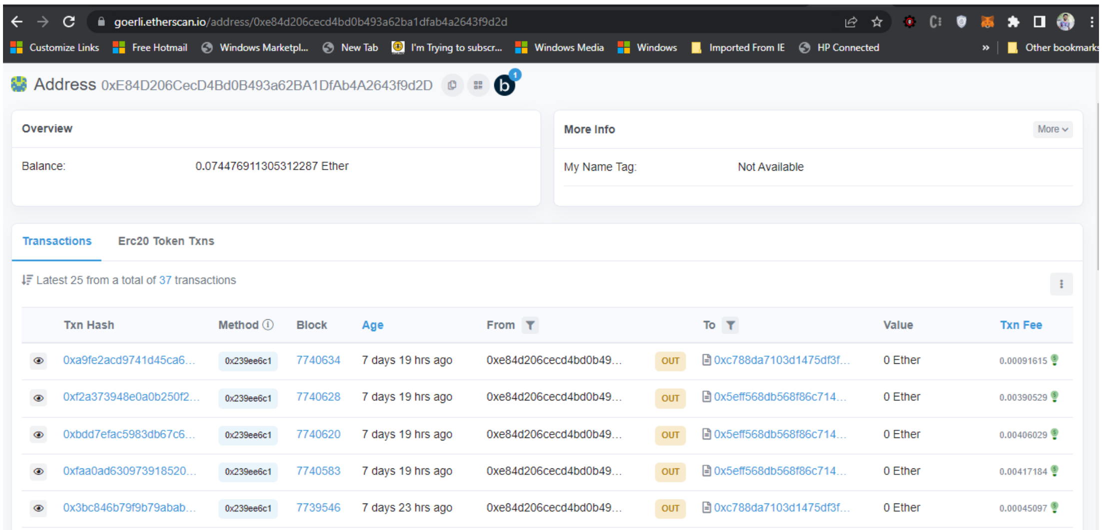


Figure 3.1.1.1: Transaction in Test Network

Figure 3.1.1.1 shows the last few transactions performed by Oxygen.

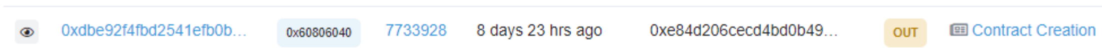


Figure 3.1.1.2: Contact Creation

Figure 3.1.1.2 shows the transaction of smart contract creation.

3.1.2 Outputs of the Medical Document Scanner

The outcomes of the medical document scanner component are displayed below. When an image of a clinical laboratory report is uploaded the four coordinates of the image will be detected using python as given in Fig. 3.1.2.1.

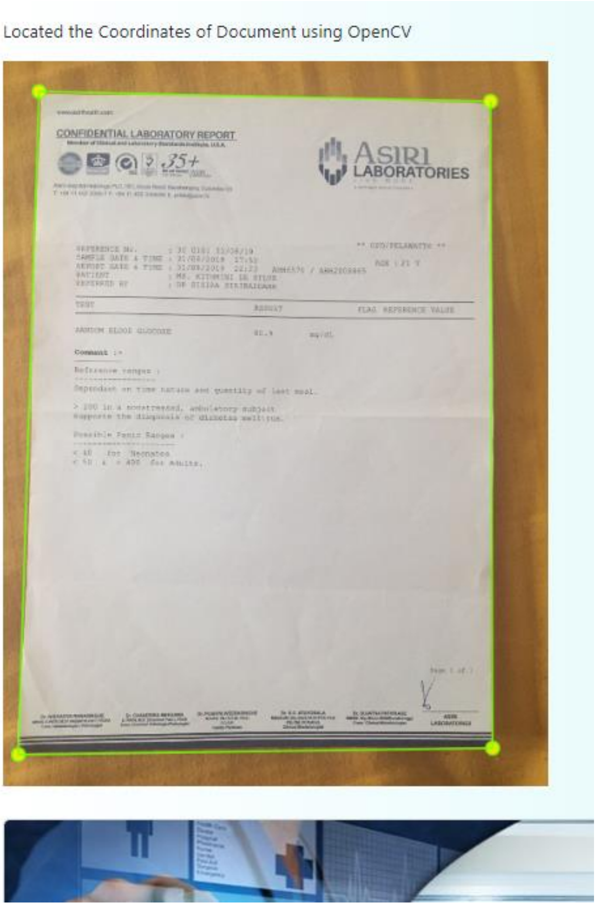


Figure 3.1.2.1: How four coordinates are detected using Python

When an image of the Clinical Laboratory Reports is uploaded, an image with bounding boxes drawn around the important named entities will be received as the output together with the relevant tag name as given in Fig. 3.1.2.2.

Figure 3.1.2.2: Image of the Document with the Bounding Boxes and the Tag name

Finally, the extracted Named Entities are displayed in a tabular format as given in Fig. 3.1.2.3. This tabular data has editing capability as well.

Named Entities

Entities	Extracted Text
AGE	59 y
DATE	07/06/2021
PATIENTNAME	[]
TEST	Chemistry Unit
RESULT	Fasting Plasma Glucose 111', 'Plasma Glucose 2Hrs Pp 103', 'Glycated Haemoglobin ', 'Serum Urea', '17', 'Serum Creatinine', 'Serum Uric Acid 7.0
COMMENTS	[]

Figure 3.1.2.3: Extracted Named Entities in tabular format

3.1.3 Outputs of the Drug Identification Component

The outcomes of the drug identification component are displayed below. When an image of a drug is uploaded the data will extract and show the related detailed view.

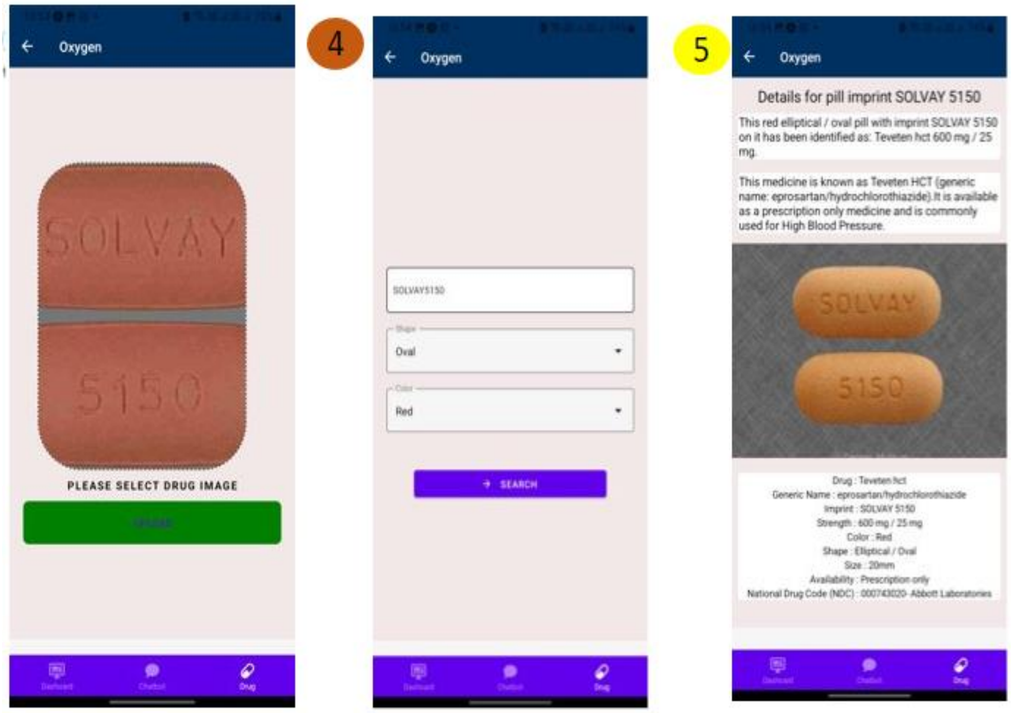


Figure 3.1.3.1: Detailed View of identified Drugs

3.2 Research Findings

The findings from the performed research study are highlighted in this section.

Blockchain is one of the newest technologies in the current world. It changed the world from web2 to web3. There are plenty of advantages of utilizing blockchain as follows,

- Immutability
- Transparency
- Efficiency
- Traceability
- Security

The authors of Oxygen attempted to demonstrate how blockchain technology can be utilized in the healthcare sector to assist patients and professionals to prevent healthcare issues. The government can implement a single decentralised healthcare system like Oxygen rather than many systems for every institution. The advantages of using Blockchain can be summarized as follows.

- There is no need to waste money installing various systems at each hospital.
- Once hosted on the cloud, the server can be accessed from anywhere.
- There is no reason to be concerned about the computer specifications.
- There is no reason to worry about storage
- Maximum Security
- This will offer appealing and simple interfaces rather than handling several interfaces.
- Avoid wasting time.

Time consumption and High energy consumption can be stated as the disadvantages of using blockchain technology.

The results of the study demonstrate that the following two factors have a significant impact on the accuracy of the Medical Document Scanner.

1. The size of the training data set used
2. The quality of the image uploaded

The total accuracy of the predicted outcomes will rise as more training data are utilised to train the model. More training data increase the system's accuracy. Similar to this, the image's quality has a significant influence on how accurate the predictions are. The accuracy of the textual data which is extracted from the high-quality images is higher compared to that of the low-quality images. Here, image pre-processing techniques are used to improve image quality to increase the model's capability to do predictions. Another research finding is that Pytesseract is having limitations when extracting text from rotated or skewed documents. Pytesseract assumes text need to be aligned to get better performance. Therefore, before delivering an image to a prediction model, its quality should be improved, and the alignments should be corrected.

3.3 Discussion

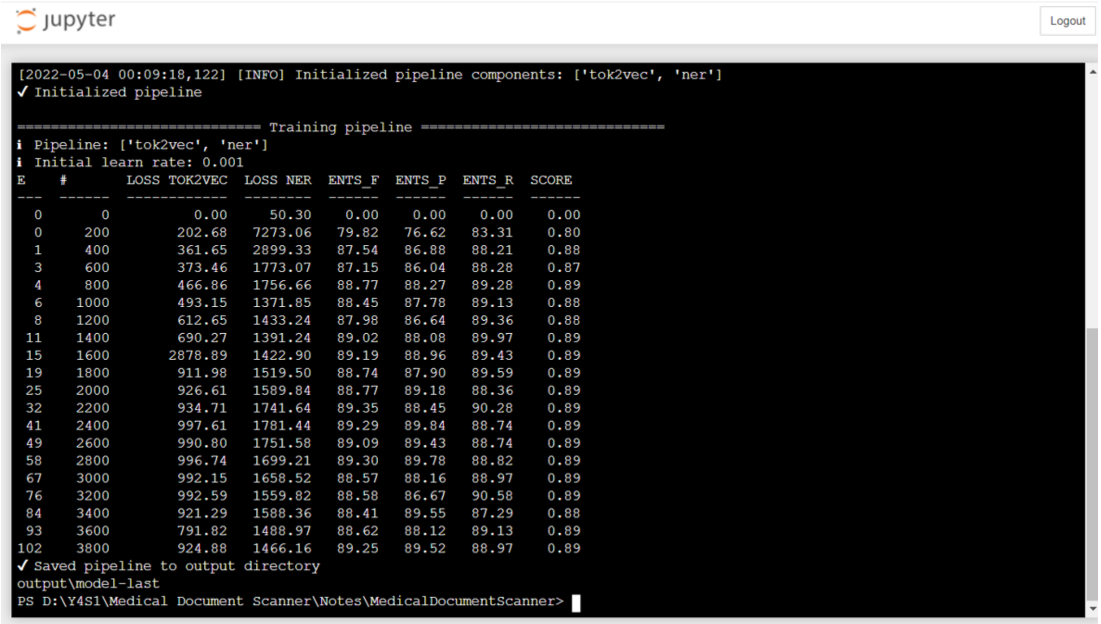


Figure 3.3.1: Accuracy of the trained Spacy Pipeline

The Named Entity Recognition Spacy Model trained for the Named Entity extraction has the following accuracies. The model has a precision (**ENTS_P) of** 89.52%. The recall (**ENTS_R**) of the model is 88.97% while the F-score (**ENTS_F**) is 89.25%.

Precision measures how accurate the trained model is. It is the proportion of all detected positives to those that were accurately classified as positives (true positives). How many of the predicted entities have the proper labels is shown by the accuracy metric [38].

Precision = #True_Positive / (#True_Positive + #False_Positive)

Recall determines how well the model can detect real true positives. It is the proportion of expected true positives to what was tagged. How many of the predicted entities are accurate is shown by the recall measure.

Recall = #True_Positive / (#True_Positive + #False_Negatives)

Precision and Recall are factors that affect the F1 score. It is necessary when a balance between Precision and Recall is necessary.

F1 Score = 2 * Precision * Recall / (Precision + Recall)

3.4 Future Work

We can add more training data to the dataset as part of our development strategy in the future. By continuing to use the same framework and including new training data, the model's accuracy can be increased. The F-score for the currently trained Named Entity Recognition model is 89.52%, although it would be preferable if it was over 90%. The quality of the image that is uploaded has a significant impact on how accurate the models are. To improve the image's quality, further image pre-processing methods can be incorporated into the model. Several additional data preparation frameworks, particularly for the data cleaning phase, can also be used. It is anticipated that by adding such enhancements, prediction accuracy would increase in the future.

4. Conclusion

Covid19 has had a significant impact on the healthcare industry, and the pandemic has shown limitations in the current digital healthcare systems. The pandemic has exposed healthcare's limitations and emphasized the significance of automating the healthcare domain. The relevance of a healthcare framework has been demonstrated through research on current literature and public surveys.

In this research, these issues are solved by proposing an approach using Blockchain and Machine Learning-Based Healthcare framework which offers healthcare services to patients and medical professionals. The system includes a Blockchain-based component for securely storing and accessing patient data, an OCR and NLP-based medical document scanner to prevent the errors that are due to manually entering data, an Image Processing-based drug identification module for remote pharmaceutical diagnosis, and an NLP and ML-based virtual Chatbot in healthcare assistance. This research demonstrates that the system's overall objective was successfully attained using these techniques and technologies.

In terms of future work, the system can be expanded by improving accuracy by incorporating more data for training.

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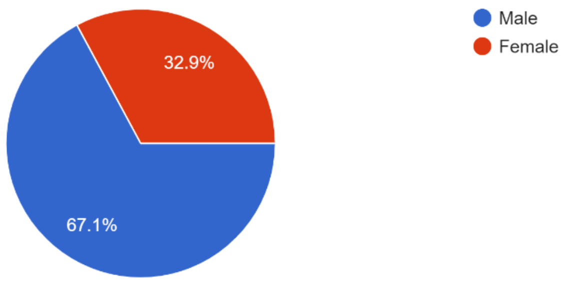
Appendices

Appendix A – Additional Survey Responses gathered during the Research Survey

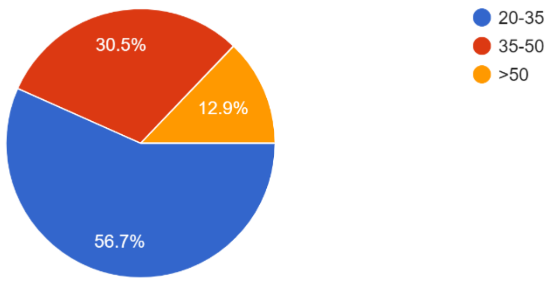
Gender

210 responses



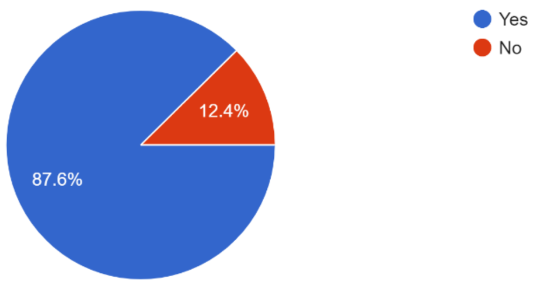
Age Group

210 responses

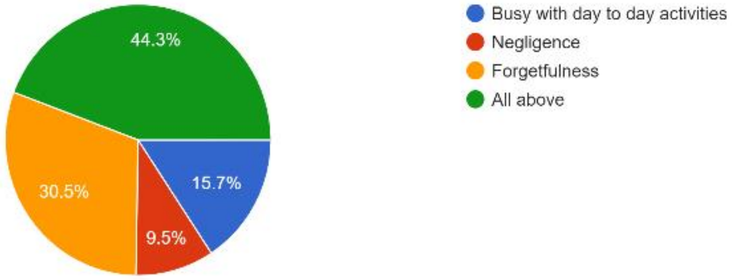


Do you think you need a virtual assistant to remind you of medication time and to know your prescription?

210 responses



If the answer is not, what was the reason for that?
210 responses



Do you usually take your medication on time?
210 responses