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SCHOOL OF ARCHITECTURE, COMPUTING AND ENGINEERING

DEPARTMENT OF BIG DATA TECHNOLOGIES

ONLINE HEALTHCARE MOBILE APP WITH SECURE COMMUNICATION BETWEEN DOCTOR AND PATIENT USING MACHINE LEARNING IN AZURE

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This Dissertation Report is Submitted in Partial Fulfilment of the necessity for the Degree of

M.Sc. Big Data Technologies

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9 SEPTEMBER 2022

ACKNOWLEDGEMENTS:

I want to express my gratitude towards the University of East London for accepting me to pursue my Master of Science (MSc) programme in Big Data Technologies in School of Architecture, Computing and Engineering. It was very interesting and challenging to travel with different ways of culture, new people, and the education system.

I want to thank all my professors Dr. Amin Karami (Senior Lecturer), Dr. Gaurav Malik (Senior Lecturer), Dr. Nadeem Qazi (Lecturer), Dr. Mustansar Ghazanfar (Lecturer) and Dr. Mark Unwin (Senior Lecturer) who are all guided me to complete my master's program Successfully and gained some knowledge.

I grab the chance to thank Dr. Umaima Haider (Lecturer – Computer Science and Digital Technologies) who is my supervisor to handle my entire dissertation paper and supported me to complete it on time. She provided a good review of what I need to change for a perfect research paper.

And lastly, I would like to thank all my friends and family who have given me all support in my hard situations.

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ABSTRACT:

A difficult circumstance would be the fact that folks who are not tech adept cannot use online healthcare at all. The rural classes have zero experience with getting medical treatment online. Another obstacle that many people encounter is the language barrier. To serve all social classes, a more accessible and affordable platform needed to be developed. Since online health applications deal with the private and delicate health information of patients, security is a big problem. The cryptographic security requirements for the healthcare sector are quite strict and dictate how and when the information should be translated, transmitted, and decrypted. Many healthcare experts are still adamantly opposed to changing the tried-and-true methods and structures they now use.

For modern technologies to increase competence and customer pleasure, their value must be quickly embraced and demonstrated. There are a variety of security techniques available today that may be used to safeguard sensitive information and ensure the integrity of communications. Transport layer security is a commonly used and well-known example of a technique for safeguarding multiple protocols, especially when using the Internet. Recently, end-to-end encryption is included in mobile internet messaging services like WhatsApp, Signal, and Telegram, marking a significant step towards more protected Internet communication.

The problem in the healthcare department is there are not enough services for direct communications between doctor and patients. So, by this project we are creating an online healthcare app for easy communication between doctor and patients and by using machine learning we are reducing the human work and reducing the work of the doctors.

In this study, we look for usability problems that might prevent people from utilising end-to-end encryption for their regular e-mail correspondence. The evaluation of task difficulty was crucial to our research's focus on efficacy. To investigate this, we have completed a pilot usability research of email encryption software, which entailed a survey distributed online and in-person observations of its use by real people. This study is an expanded version of the early findings presented in the Financial available Cryptography including Data Security Proceedings. Following this, we describe in depth how the study was conducted, what data was acquired, and how that data was analysed in further depth.

CHAPTER 1: INTRODUCTION

1.1 Introduction

The use of mobile devices within the healthcare domain has greatly increased the different aspects of the clinical practice and management of secure communication between the doctor and patient management using the machine learning components. The mobile devices have been commonplace for managing healthcare settings leading to enormous growth of medical software applications that aids management of healthcare facets within the clinical hospital domain *(Backes et al., 2021).* The numerous existing apps have been developed with the aim of assisting healthcare professionals (HCP) to perform essential tasks such as information handling between patient and doctors, managing synchronous health record management and facilitating easier access, implementing real-time communication and consultation between the two parties (doctor and patient).

Furthermore, mobile apps have been designed to make clinical decisions and referencing medically to allow seamless communication between the intended parties *(Backes et al., 2021).* However, there exist numerous challenges within the healthcare ecosystem, such as the privacy of the data within the transmission of communication matrix between the intended parties. The information relayed between the mobile apps tends to be sensitive (*contains both personally identifiable information (PII) and medical records*) thus requires advanced levels of encryption and security for safeguarding information within the servers *(Boudreaux et al., 2014).* When network security policies are compromised, the overall security settings are compromised thus making the handling of sensitive data more suspected to attack. The healthcare apps contain sophisticated information such as medical records history, financial information, and personally identifiable information (PII).

1.2 Background

The advancement of technology has escalated the need to advance technology in the healthcare setting. Its paramount to develop a comprehensive palliative and compassionate healthcare with the need of technology advancement. The emergence of COVID 19 brought about the reality of why the healthcare sector should utilise technology to improve the communication mechanism and make the way doctor-patient communicate easier and seamless.

The emergence of COVID 19 brought about the reality of technology to facilitate real-time diagnostics and epidemiology of the patient curative data. Through technological blueprint, components within the healthcare setups can be integrated via unique API tokens to allow seamless communication thus making the patient communicate with the doctor for clinical management functionalities such as palliative care, medical diagnostics, follow-up preventing mechanism for different ailments and conducting compassionate care which forms a critical component for ensuring the restoration of patient health *(Boudreaux et al., 2014).* Covid-19 crisis created a global healthcare crisis with the measures instituted by the World health organisation (WHO) such as social distancing rules, wearing of masks and personal protective equipment (PPEs) difficult in preventing the spread of the coronavirus. Furthermore, research studies established that there were difficulties facing the real-time patient-doctor communication mode.

The adoption of technology forms an important factor towards ensuring that patient-doctor communication is real-time, synchronised, and seamless. Furthermore, with the introduction of mobile technology, there exist some loopholes regarding the security and the privacy of core data transmitted through the apps. The data collected from the healthcare industry are considered classified and sensitive, thus requiring privilege of escalation principle (*this principle guides that only authorised parties within the role-based access mechanism are allowed to view, manipulate and access based on their different roles. The communication channels ought to be protected through multi-factor authentication encryption to only allow the two parties to access privileged communication without spoofing, identity theft and man-in-the middle (MITM) attack).*

The emergence of COVID-19 was an eye opener that technology ought to be adopted for real-time diagnostics and treatment within the health-care sector. The patient-doctor visits were drastically reduced due to COVID-19 classified as a communicable infectious disease that could drastically spread from one person to another. The medics were in the forefront in controlling the spread of COVID, thus many healthcare professionals lost their lives in the line of duty. The introduction of digital services within the healthcare domain could drastically help improve the fight against the spread of the Covid-19 virus variant (coronavirus), through using digital data analytics, machine learning and artificial intelligence (AI) to help diagnose and monitor the spread of the virus *(Chung et al., 2014).* Countries such as South Korea developed an artificial intelligence (AI) algorithm for Coronavirus early detection and providing appropriate information through assessment without any human interactions. The doctor-patient interaction led to a lot of casualties through direct contamination with the virus across the world.

The healthcare professionals were the first respondents thus considered easily susceptible to viruses if they didn't have their Personal Protective Equipment (PPEs) in place. On 11th March 2020, when the whole world emerged to fight against the spread of the Covid-19 virus, the World Health Organisation (WHO) declared the pandemic. The pandemic was considered an infectious disease that could damage the lungs and thus could require patients to have ventilatory support to protect the virus from causing lung failure. Numerous countries established protocols and measures to help reduce the risk of transmission such as complete lockdowns, social distancing rules, self-isolation and wearing of personal protective equipment (PPEs) for professionals considered within the first line of duty in the fight against coronavirus (Covid-19 crisis). These measures were considered thus preventive and although they reduced the levels of Coronavirus spread, they faced various obstacles thus didn't have a drastic impact on reduction of infection rate. Furthermore, in developing countries, the control of coronavirus faced several obstacles including the lack of PPEs thus reduced the control of the virus. The coronavirus pandemic affected the doctor-patient communication in multiple ways since the doctor mentality treated patients as carriers. The coronavirus spread was drastic and didn't allow healthcare professionals to be trained on appropriate psychological skills that could control the spread of the virus.

The exploratory study from the spread of the coronavirus concluded that appropriate and positive skills is considered as the main factor towards conducting psychological responses from those facing Covid 19 disease. Appropriate doctor/physician-patient communication is usually characterised through sharing information in a manner that enhances compassionate care and empower the care provision mechanism through factoring the sensitivity of the patient needs. Communication skills is a key factor towards ensuring that the patient needs are adhered comprehensively and with compassionate care. The communication skills are implemented using several strategies using both verbal and nonverbal cues with the need of showing empathy to the patient *(Chung et al., 2014).* Thus, the analysis from the coronavirus crisis brought out the need for development of technological guidelines/framework within the healthcare industry that can allow seamless, synchronised, and real-time communication streams between doctor-patient with using machine learning as components of implementing security of the imminent privacy issues from patient sensitive data infringement.

1.3 Problem Statement

The quality of doctor-patient relationship is a key determinant towards compassionate and palliative care for the patient within the healthcare industry. The doctor-patient relationship plays a critical role and is closely associated with the correct treatment adherence, facilitating patient satisfaction rate, and thus maintaining a positive treatment outcome (*resultant effect of all the treatment journey*). The success of the treatment is directly proportional to the correct doctor-patient relationship management framework that can be administered through compassionate care, palliative management and correct communication skills addressing the psychological needs of the patient. The challenges faced by the patients are listed

1. There is a limited number of appointments available, and the clinic office hours are between 8 am to 5 pm depending upon the various clinic hospitals. In case there is a tough schedule for the working parents and adults *(Heath, S., 2018)* to meet the physicians in-person.
2. According to *(Michael. S Ross MD, MHA., 2018)* there is a lack of electronic health records which are not stored in one place, i.e., the whole history of patients. Due to this lack of information being stored, physicians will not know what prescriptions the patients are taking.
3. The outbreak of the Coronavirus (*Caused by SARS CoV2*) that started in China soon spread across different nationalities causing an overwhelming challenge within the healthcare delivery of services across the world.

4. Another problem faced by patients is transportation and patients living in the rural areas says *(Heath., 2018).* Patients struggling to get through the clinician

appointments face to face who are living in rural areas and people who are financially low and driving problems cannot meet the clinician eye to eye contact.

5. The challenges caused by the coronavirus included limited resources within the healthcare industry, priority settings (*the clinical decision-making algorithm to determine the disease to be treated. Although covid-19 was an emergent disease, there existed other diseases that required doctors to make appropriate and accurate disease on the chronological order of prevention*), the availability of medical resources and the strain caused by the emergent Covid-19 crisis. The coronavirus exerted an enormous pressure on healthcare systems, with the society viewing the healthcare professionals as '*white angels'* due to their only hope as the saviours towards the spread of the virus.

The project develops a comprehensive mobile application with the functionality of allowing seamless, synchronised, and real-time data interaction that allows doctor-patient communication to be faster and with advanced levels of Artificial Intelligence as guiding principles towards compassionate care. The healthcare system was already exerted too much pressure with multiple healthcare professionals already tested positive for Covid-19 thus with the adoption of technology only patients with the right critical score could have been considered for hospitalisation. Furthermore, research indicates that lack of proper digital services for patient-doctor interaction was the main factor towards increased infection rate.

1.4 Aim of The Project

The aim of the project is to develop synchronised mobile apps for healthcare professionals using machine learning and cloud architecture to facilitate seamless direct communication between the doctor and patient.

1.5 Objective of The Project

The objective of the project includes.

- ❖ Developing a comprehensive Android application that ensures seamless communication with the patient-doctor real-time interaction.

- ❖ Integration of the Android application to the cloud architecture (*connect the android application to the cloud for real-time data storage eliminating the need for offline servers*).
- ❖ Develop the application secure APIs over the cloud using Android Firebase to ensure seamless authentication and authorisation gateway.
- ❖ Integrate machine learning as a mechanism of protecting and encrypting data exchange between patient and doctor.

1.6 Research Question/Hypothesis

- ❖ How will integration of machine learning help to secure end-to-end encryption of communication modes between patient-doctor?
- ❖ How can cloud computing architecture be integral in securing data encryption within the communication matrix?

1.7 Importance of the Study

Every healthcare facility depends on the multifaceted teams of medical professionals that it employs to provide treatment to patients and collaborate effectively to secure the long-term viability of the whole operation. When a patient visits an institution in search of medical attention, the impression of seeing physicians, nurses, and other care staff members strolling around the halls and going from one room to another inside the hospital helps reassure the patient that a procedure is being carried out. The hope that one will get treatment is not only a psychological factor coming from the perspective of the patient, but communication also helps to make it highly successful and enhances the results of the whole process. The paper aims to develop a synchronised mobile app for healthcare professionals using machine learning and cloud architecture to facilitate seamless communication between the doctor and patient. This will also provide an analysis of the expected benefit of integrating the app in a healthcare setting.

1.8 Assumptions and Limitations of the Study

The paper assumes that the healthcare communication structure is similar in all organisations. There was a need to pick one healthcare organisation and study the communication framework used within the organisation to model the application for better integration. However, time and financial constraints are limiting the feasibility of such an approach.

1.9 The organisation of the study

The first section of this paper is the literature review, which shall analyse the existing communication models that have been developed targeting communication in the healthcare sector. Then, the methodology will include the code for the synchronised mobile app developed using machine learning and cloud architecture to facilitate seamless communication between the doctor and patient. This will be followed by analysing the integration of the application and providing probable impacts the application may have on the organisation.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

It is important to keep in mind that the need for communication is not exclusive to the field of medicine but applies to all fields of endeavour. In most contexts, communication is thought of as the pillar around which every process is built; as a result, communication may be used to judge the success or failure of any process. Poor communication between physicians, nurses, and patients was mentioned as one of the issues impacting the medical organisation in modern healthcare institutions. This leads to several adverse repercussions on the organisation's care delivery as well as its general administration. First, it is necessary to determine what causes and impacts bad communication, and only after that can a solution to the problem be formulated. Only then can a full solution to the problem of poor communication be provided. A literature review on using machine learning to improve communication is illustrated in this section.

2.2 Literature Review

As stated by *(Amiya Kumar Tripathy et.al., 2015),* ***Artificial intelligence-mobile based healthcare management*** develops a comprehensive outlook on the need of technology advancement in the healthcare management to help monitor and control the spread of diseases. Within the growing age of technology, it's appropriate to have a comprehensive healthcare system that should be accurate and accessible by the healthcare professionals to monitor and diagnose disease *(Tripathy et al., 2015).* The healthcare management system should be comprehensive and monitor different components within the healthcare domain such as real-time heart pulse measure to instantly relay information to the information database in real-time and synchronised manner. The journal documents the development of online interactive video conferencing that helps remotely communicate with the doctor in real-time using video communication modes. According to *(Tripathy et al., 2015),* the article explains the role of the comprehensive mobile based app ***Doc-Bot*** that provides a comprehensive video conferencing gateway for earlier diagnosis and treatment of disease and providing palliative and compassionate care through the video platform in a faster and more convenient manner.

In proportion to the study, ***using mobile devices to manage elderly patients in healthcare*** as mentioned by *(Kim et al., 2014)* explains why the adoption of mobile phones is integral for providing real-time healthcare management through portable mobile apps accelerating the spread of information for earlier prevention and containment of disease. The elderly are susceptible to chronic disease ailment thus requiring prerequisite compassionate care to help increase their life expectancy. With the adoption of mobile technology aid, the elderly can reduce their number of hospital visits through the development of aided technology on mobile phones. According to *(Kim et al., 2014),* the development of the healthcare management apps will ultimately change the focus of the medical services within the hospital settings and manage how doctors make clinical decisions to the elderly patient through adopting online compassionate/palliative treatment as a mechanism of helping them get access to real-time healthcare access. The major issue that requires attention within healthcare is the existing chronic disease which majorly affects the elderly who are extremely susceptible to the disease. Thus, major attention should be paid to the elderly with technology objectives aimed at providing real-time diagnostics, short-term therapies, and treatment care for the elderly individuals. The journal explains the paradigm shift from the traditional based hospital-based treatment to implementing prevention strategies through ***cellular phone based medical informatics*** that integrates information technology framework such as artificial intelligence (AI), deep learning, neural network, blockchain and machine learning to facilitate ubiquitous healthcare monitoring of ailments *(Kim et al., 2014).* The elderly has inadequate knowledge on the emergence of new technology frontier thus requiring simplistic integration of Information technology (IT) framework to help make the healthcare services accessible.

According to *(Guah, M. W. (2007)),* stated, ***Web-based mobile healthcare management applications*** there's been a significant increase in the use of mobile technology in the development of improved healthcare approaches for patient management and diagnostics. The healthcare mobile application is a comprehensive outlook at the healthcare domain that enhances mobility which is the capability of the mobile phone device to handle information access, implement real-time communication and execute seamless business transactions at ease *(Guah, M. W. (2007)).* The application of the mobile based technology to healthcare, described as m-health is a comprehensive mechanism of revolutionising the healthcare delivery of the patient. The journal addresses the setback through presenting a comprehensive integrated approach to achieving m-health mapping the case study model to achieve a comprehensive approach towards successful adoption of the end-tier technological approach *("Health informatics and the future of healthcare: Mobile health, PHRs, mobile health apps, "2017).* The healthcare application is a comprehensive mechanism aimed at addressing key solution strategies namely

a) addressing the compassionate access to technology, the mobile application in healthcare develops the notion of mobility, which is caring for anyone, at any time and the information is collected anywhere

b) developing quality healthcare approach through offering quality world-class care and establishing a comprehensive integrated information repositories for information within the healthcare domain

c) provide an efficient technology for implementing seamless healthcare delivery using a comprehensive m-health technology setup.

The mobile application is integrated through a comprehensive approach through addressing the opportunity of innovating business models as an enabler towards developing a comprehensive healthcare industrial approach. M-health is typically described as the key pillar of developing innovative mobile health technology setups in which doctors can communicate with their patients through a comprehensive secure platform that enhances convenience and effectiveness of data analysis *("Health informatics and the future of healthcare: Mobile health, PHRs, mobile health apps "2017).* The exploratory studies aim at developing an appropriate healthcare infrastructure for helping diagnosis and management of disease within the medical field. The comprehensive objectives and aim of implementing the integration of the mobile health approach includes the following.

- Developing a comprehensive strategy for effective "colonisation" of the virtual space made available within the internet domain.

- When developing the m-health application what is the appropriate research methodology to be applied for data segmentation, and a critical review of the benefits and given success of their appropriate choice of the classification model.

The study states that, when carrying out the feasibility and exploratory studies of the given domain highlights who are the stakeholders in their research. The key points while undertaking the research includes the components to discuss who is a stakeholder when carrying out the survey (the stakeholder in the research includes patient, general health practitioner and personnel within the healthcare domain). Furthermore, the journal develops a comprehensive exploratory study that helps align web strategies within the mobile ecosystem with the aim of analysing strategic objectives and thus can be able to translate the web strategy to suit the business needs. Furthermore, the article highlights that mobile technology should be incorporated within the following domains.

- Developing book appointment strategies where the doctor-patient book their appointment online using a comprehensive appointment scheduling algorithm with the prerequisite surgeon.

- Using mobile platforms as a caveat for performing diagnostic investigation to help develop comprehensive medical actions.

- Using educational pathologies strategies such as creating awareness through the mobile application as an enabler towards developing awareness using the comprehensive m-health application.

In Consonance with, the learning, ***Healthcare mobile information management using Android OS and Cloud Computing*** by *(Lokhande & Gaikwad, 2021)* provides a conceptual design of how the project will utilise different software design methodologies as an enabler towards developing real-time information management cloud computing principles. With advancement in technology, cloud computing provides advanced functionalities for managing information in a distributed and pervasive manner traversing through several cloud computing platforms, ubiquitous systems, and multiple platforms within the given distributed system. The journal highlights the need for developing a comprehensive implementation of a mobile platform that enables real-time synchronisation, electronic healthcare data storage mechanism, update and retrieval of information using the generic cloud computing architectural design *(Lokhande & Gaikwad, 2021).* The architectural design of the mobile phone is using the advanced Google Android's operating system and provides a synchronous application APIs aimed at managing patient health records and analyse medical images. Furthermore, the developed system is evaluated using the comprehensive Amazon S3 cloud web services as a mechanism for implementing real-time data interchange principles *(Lokhande & Gaikwad, 2021).* Furthermore, the objective of developing the comprehensive mobile application is based on the following core objectives; the availability of developing e-health applications through the invisibility of the cloud computing principles.

The advantage of using cloud computing services for mobile applications is to enable on-premises access to different application services in real-time manner. The mobile pervasive healthcare technology is based upon the following principles provision of mobile telemedicine for effective healthcare management & patient healthcare setups, patient monitoring to expedite the real-time access to services using mobile application integrated features that monitors heartbeat and individual pulse rate. Integration of locational-based services for tracking hospitals within a given locational coordinates, and development of gateway mechanism that keeps track of emergency response and management of different components of the mobile web services. However, the realisation of this has faced challenges such as secure data storage (the adoption of payment gateway for financial applications has faced tremendous challenges ranging from cybersecurity risks, financial fraud implication of the financial servers, security and privacy concerns of data (cloud web servers are tremendously facing challenges of managing information, access control mechanism – this implementation strategy is where the roles, permission is given based on the user rights for them to perform privileged functions within the system) *(Sezgin, 2021).* Thus, the potential solution to this perennial defect is the adoption of cloud computing architecture as a mechanism of controlling data security and offering data on-premises as a mechanism for addressing privacy security lapse *(Maglogiannis et al., 2014).* Additionally, the journal *Healthcare mobile information management using Android OS* and *Cloud Computing* highlights the primary objectives of using cloud computing as a mechanism of addressing the potential management of information healthcare records using on-premises cloud services.

As reported by *(Liao et al., 2016)*, ***The Application of RFID in Nursing Home Healthcare Management,*** documents how mobile technology is increasingly becoming applicable in development of frontier technology within healthcare to monitor patient performance especially the elderly. The changes in the social demographic curve have a resultant effect in sharp increase in elderly population gaps and the elderly being associated with rapid increase in chronic disease infection. Population ageing is a fundamental problem in modern society with the elderly within the nursing homes being the primary caregivers resulting in improvement in the corresponding quality of life for individuals in the modern society *(Liao et al., 2016).* Advancement in technology is a key enabler towards effective healthcare management to help solve the problem using sophisticated RFID technology. The exploratory study within the journal helps replace the traditional methods of patient information management with an establishment of advanced technology for allowing real-time patient monitoring and management through allowing synchronous communication by allowing transmission of data between the front-end and the backend servers for real-time monitoring *(Spat et al., 2014).* The potential risks for the application services are the data stored in database services servers as the reference point in which the attackers can launch attacks on the backend services. The technology improvement includes the use of tagged RFID connected to a web server for appropriate healthcare operational precedence and efficient management of information within the elderly nursing homes. The RFID tags are incorporated with real-time sensors aimed at analysing different artefacts such as body temperature levels, locational coordinates, and the condition of the web servers. The advancement of the RFID tag technology is an integral component towards enabling caregivers to have access to manage critical patient information of their patient (temperature levels, oxygen saturation levels, pulse rate) enabling them to prevent occurrence of situations that lead to severe accidents.

According to *(Jung et al., 2013)*, ***Healthcare mobile application with EMR interoperability for diabetes patients*** points out the role of digitization in healthcare management to control and manage the complications related to diabetes. With the increase in smart devices, the processes within the medical field are continuously evolving towards helping adopt an appropriate patient management protocol. The research in the journal conducted highlights that by 2015, the estimated number of applications using smart health applications are estimated to be approximately 500 million users, with the main functional use revolving around exercise management principles, diet control approach and chronic disease management *(Jung et al., 2013).* Unlike other chronic diseases, diabetes disease can be controlled by the patient through adoption of smart applications providing correct guidelines on best remediation strategies for controlling diabetes. The choice for smart application is since smart mobile devices are the comprehensive universal tools for self-care diabetes management due to its higher penetration levels and its functional impact assessment. The journal, *Healthcare mobile application with EMR interoperability for diabetes* patients uses a comprehensive *software development lifecycle (SDLC) principle* for developing mobile-based Android Operating System (OS) blueprint for managing diabetes through self-care mechanism. The application consists of the following blueprint features diabetes management principles, appropriate algorithm for weight management and appropriate check for stress/depression evaluation *(Jung et al., 2013).*

In agreement with *(Senanayake et al., 2021)* expressed in the theory, ***A Systematic Review of Machine Learning for Detecting Android Mobile Malware*** highlights the needs for developing a comprehensive machine learning model as a mechanism of enhancing security framework for ensuring real-time collaboration and enhances communication between multiple domains. The increase in malware penetration is an increasing factor that needs an aggressive mechanism of incorporating machine learning to help enhance the security of the Android mobile application. The market share for Android mobile phone application accounts to approximately 72.2% of the mobile phones across the world, thus development of security constraints forms a key indicator towards successful implementation of projects within the sector *(Senanayake et al., 2021).* The cyber attackers have made tremendous efforts aimed at attacking the Android application using sophisticated technological blueprint and mechanisms such as identity theft, surveillance, and advanced mechanisms to address mitigating risks. The healthcare information is classified as critical information thus can be analysed using effective machine learning methods that's able to model the classification matrix more elaborately and eliminate the needs for developing *signature-based Intrusion detection classifier (IDS)* that helps to identify patterns within the given classification matrix for helping to mitigate against the risks for the machine learning model. The technical journal is aimed at enabling researchers to provide an in-depth knowledge on how machine learning models can be incorporated within the mobile applications architecture to guide towards developing appropriate seamless communication between the doctor-patient (Senanayake et al., 2021).

As expressed in this case, ***Automated functional assessment of Android applications utilising machine learning activities classification*** by *(A. Rosenfeld., 2018)* with the growing number of applications with access to sensitive information. Prerequisite controls are implemented to help automate the security and privacy concerns of the application with the core importance aimed at mitigating the security lapses that cause the application to be insecure. Automation of the Android applications functional test develops an integrated testing mechanism of having machine learning forms part of conducting the functional test to validate that the application is certified within the healthcare industry. Functional testing mechanism is the fundamental component for helping audit the security of applications, Google play store performs an atomic functional test for mobile apps to validate their functional dependency (the functionality test determines the application score adhering to security metrics of mobile application). The exploratory study of the mobile application is comprehensive, using 26 randomly selected Android applications to show the application resilience towards discovering functional errors/bugs and automate the functional testing, a process that needs to be automated to help address the application functional requirements.

According to *(K. Liu., 2020)****, A Review of Android Malware Detection Approaches Based on Machine Learning*** documents the malware detection approach that's implemented in machine learning to address the concerns of mobile applications. Android phones have rapidly evolved within the mobile ecosystem thus the Android malware penetration has been consistently metamorphosis with the aim of breaching the security of the mobile application framework. The research scope is aimed at developing a comprehensive outlook on the Android malware detection algorithm through machine learning methodologies to address the privacy concerns of data. The journal documents the historical background of Android application, develops a comprehensive architectural design of the Android system architectural design and how machine learning is a key enabler towards malware detection using the machine learning model analysis based on the four key steps (specific mechanism for sample acquisition, data pre-processing, feature selection and evaluation mechanism for addressing the effectiveness of the machine learning model).

As reported by *(Takahashi, T., 2019)*, ***Android Application Analysis Using Machine Learning Technique*** contributes to the evolving research within the application analysis techniques to be used for Android development mechanisms. The amount of malware that's constantly targeting the Android malware is evolving and growing at a tremendous phase thus requiring advanced mechanisms to address the existing cybersecurity concerns. The analysis of the Android library packages (APKs) is a crucial factor aimed at helping identify the existing malware and using prerequisite machine learning models to identify if the malware is malicious or benign *(Takahashi, T., 2019)*. This form of classification is a key factor that contributes towards the successful implementation of project adherence to all the security objectives. The first mechanism aims at looking at the technical structure of the APK files and developing a comprehensive machine learning model that's able to identify and classify malware in real-time. The classification model describes a specific approach in which the data can be collected and analysed using, not only permission calls APIs, but extensively using APIs procedure calls *(Takahashi, T., 2019)*. The methodology demonstrates the effectiveness of the machine learning classifier model to help analyse Android applications, analysing how to perform data pre-processing and cleaning to allow real-time malware detection. In the proposed model (Support vector model – SVM), the algorithm develops a comprehensive way of classifying dataset using machine learning methods and can be able to predict the malware signature-based approach of attacking the mobile applications *(Takahashi, T., 2019)*.

In accordance with *(Malhotra., 2016)* utters in the study***, an empirical framework for defect prediction using machine learning techniques with Android software*** focuses on developing a predictive model using machine learning techniques for identifying the software defects. Android developers can integrate defects and bugs within the application to help identify loopholes within the information system. The objectives of the exploratory studies included the following: comparison of different machine learning methodologies using different dataset to help identify malicious patterns of Android application. Using a different performance mechanism of measuring the effectiveness of the machine learning model to accurately predict a given outcome *(Malhotra., 2016).* The exploratory studies analyse the effectiveness of the machine learning model in developing effective and superior ML techniques. The supervised machine learning model is comprehensive where the given attributes are analysed through a machine learning model to determine for malicious and software defects that can jeopardise the overall software integrity. The proposed algorithm in the exploratory studies is implemented using adaptive models such as Naive Bayes model, logical regression, and multilayer perceptron to determine the accuracy of the machine learning model *(Malhotra., 2016).* The journal conclusion confirms the predictive capability of the various machine learning models for determining the effectiveness of the study when identifying software defects/errors.

2.3 Summary

Exploratory study suggests that development of digital services is the fundamental principle towards facilitating real-time data interaction that could protect and further prevent overburden on the already strained/bloated healthcare system. Using machine learning we can easily predict the models resulted from these reviews.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

Any software development must adhere to specific guidelines in order to meet predetermined goals. Software developers use a variety of approaches to deliver enjoyable software development dependent on the demands of the project. The suggested system's software was developed using the Object-Oriented Analysis and Design Method (OOADM) for better results in the system.

System Requirements

Hardware Requirements include:

- Android Phone.
- Laptop.

Software Requirements include:

- Operating System: Windows 8, Android OS
- Front End: Android studio, XML and Java.
- Back End: Firebase and Azure services

3.2 Description

The user requirements include converting it into a structure that can be applied using computer language during the development step. Java and XML were used to construct the front-end, including firebase and Azure databases were used to force the back end. To implement the whole design approach, different models were needed. There is a connection between innovation and several modules. Which modules contact other modules is one example of this. The precise data items transmitted among the modules are identified by the interface between them.

Doctor module:

• The physician must register before logging in. He or she is required to finish the registration form, which has the following fields: First Name and Last Name, Specialisation SIN, Nationality, Gender, Address, DOB, Phone Number, Email, Username, and Password. He or she will then receive an email indicating whether their registration has been approved or denied.

• The physician will have access to log in by using the patient's user’s name as well as password, as well as log out.

• The first name, including last name of patient and file number must be entered by the doctor to check for a patient.

• The doctor will have access to a calendar of appointments.

• Appointments may be cancelled by the doctor.

• The patient's complaint must be visible to the doctor.

• The doctor must be able to record his findings on the patient in writing.

• The patient's reports will be available for the doctor to see.

• The prescription may be added by the doctor and added to the patient's file.

Patient module:

• Prior to logging in, the patient must register. He or she is required to finish the registration form which includes the following fields: First Name and Last Name, Specialisation SIN, Nationality, Gender, Address, DOB, Phone Number, Email, Username, and Password. They will then receive an email confirming their registration or rejecting it.

• The patient must have the ability to log in using their password and username as well as log out.

• Complaint in writing and online.

• The patient will have the option of making an appointment.

• A patient shall have access to his or her radiography, laboratory, or medical reports.

• The information about his or her pharmacy must be viewable by the patient.

• The patient may request that his or her prescription be prepared.

Pharmacist module:

• Before logging in, the pharmacist must register. He or she must complete the registration form, which has the following fields: First Name and Last Name, Specialisation SIN, Nationality, Gender, Address, DOB, Phone Number, Email, Username, and Password and receives an email confirming acceptance or rejecting it.

• The pharmacist must be able to log in using a login detail and log out as well.

• The first name, including last name of patient and file number must be entered by the pharmacist to look for a patient.

• After preparing the prescription, the pharmacist will be able to email the patient.

• The pharmacist must have access to and be able to update patient payment status data.

Administrator module:

• The administrator should be able to log in using his login details and log out as well.

• To examine a person's information, the admin must have the ability to search for the user via username, including SIN, and DOB.

• The user account may be edited by the administrator.

• The administrator will have access to the retrieved update for evaluation.

• The system will be overseen by the administrator.

The programmer provides an interactive link between both the patient and their physician and works for the good of society. This study proposes a medical monitoring application that would speed up the flow of information while giving patients and healthcare professionals quick access to current and precise information. The key benefit of this program is that patients may carry their data with them wherever they go and that doctors would receive a complete history of their health. Through patient contact and counselling, the suggested approach will also aid medical professionals in hastening patient diagnosis and treatment. The solution is portable and is simple to install and use on any mobile device running the Android operating system.

3.3 Design of the process

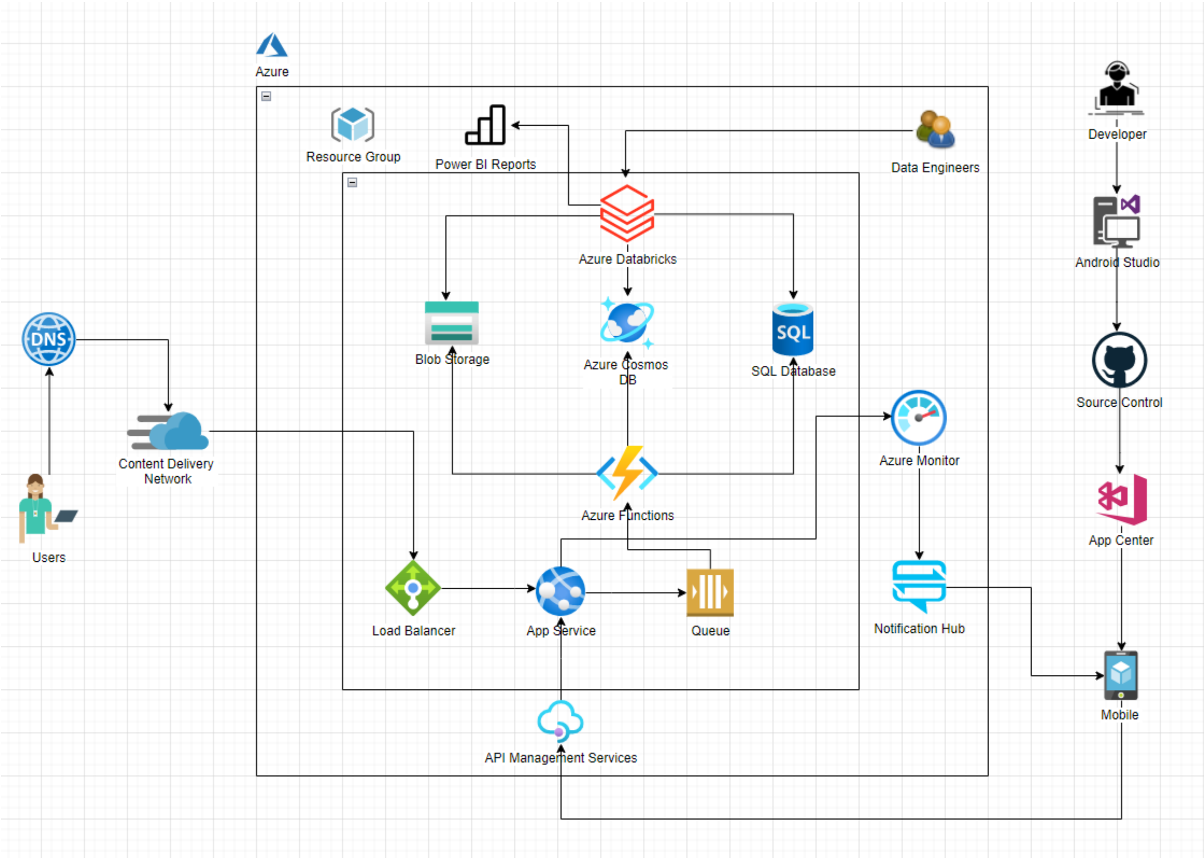


Figure 1 Azure Cloud Architecture

The system's fundamental flow is shown in the architecture. In this project, we are using Android studios for creating Android applications using Java as a coding Language. There are so many sources for Continuous Integration (CI) and Continuous Deployment (CD) such as Git, GitHub whereas Git is a development operations tool for the developers for tracing the change in codes and GitHub is the platform for developing the code. App centre provides services for building android apps with connecting source controls. This system describes with Android studios we can create a Front-end Application and by using Cloud services as a Back end.

A Graphical User Interface (GUI), back end, and front end are the three main components of the interactive medical application architecture. The system will communicate with the user through the GUI. Icons and other visual cues can be used in GUI to communicate with customers. It will list the many categories, including patient reports about disease, doctor's prescriptions, patient, and doctor information, etc. The query is sent to the web end section whenever the patient as well as doctor taps on the specific link. The front end finally retrieves the necessary data obtained from the back-end's framework of the system. The front end receives the results, and the GUI displays them from there. The back end has a database that manages all the vital information regarding patients, doctors, pharmacies, administrators, etc.

The four (4) main parts of our programme, iMobiHealthcare, are the admin module, including the patient module and the doctor module, as well as the pharmacist module. All the above modules can carry out the following actions:

1) Doctor:

Building a beneficial doctor-patient relation, which is the essence of medicine, depends on effective doctor-patient communication. This is crucial for the provision of high-quality medical treatment. The disintegration in the doctor-patient connection is the cause of a great deal of patient discontent and complaints. However, many medical professionals prefer to exaggerate their communication skills.

- Can look for a specific patient.
- Can see the patient's complaints.
- Has access to appointment schedules.
- The ability to cancel an appointment.
- Has the skills to write down medical reports of all the patients.
- Can see the radiological reports for the patient.
- Has an approach to the patient's test results.
- Has an approach to the prescription.

2) Patient:

- Has access to his or her medical records.
- May post a complaint.
- Can make an appointment.
- Has access to his or her radiological reports.
- Has access to his or her lab reports.
- Can access information about his or her dispensary.

• Might ask for the preparation of the prescription.

3) Pharmacist:

• Can look for a patient.

• May examine the medical report on the patient.

• After the prescription is ready, you may email the patient.

• Has access to and may update the patient's insurance and financial status information.

4) Administrator:

- can look up a user.
- A user may be edited.
- May examine the obtained update.
- System management in general.

The following are a few examples of the system's inputs:

As **Figure 2**, a doctor checks in to enter his account within the app using his username and password, but even a new doctor must first register an account to use the app.

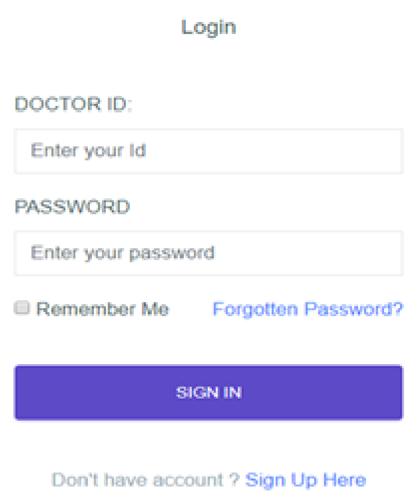


Figure 2 Sample Doctor Login

With **Figure 3,** a patient would take the identical actions as the doctor to enter.

Figure 3 Sample Patient Login

After logging onto his profile, the patient has the option to book a consultation with the physician of his choosing, as shown in **Figure 4**.

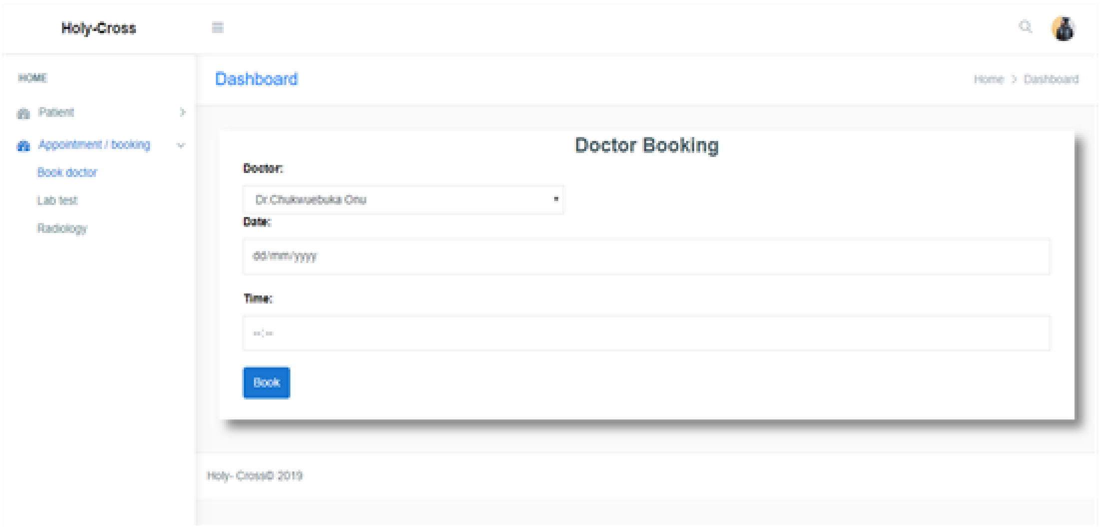


Figure 4 Sample Doctor Booking

The dashboard, shown in **Figure 5,** allows the doctor to schedule a patient for a laboratory test and specify the kind of test to be performed.

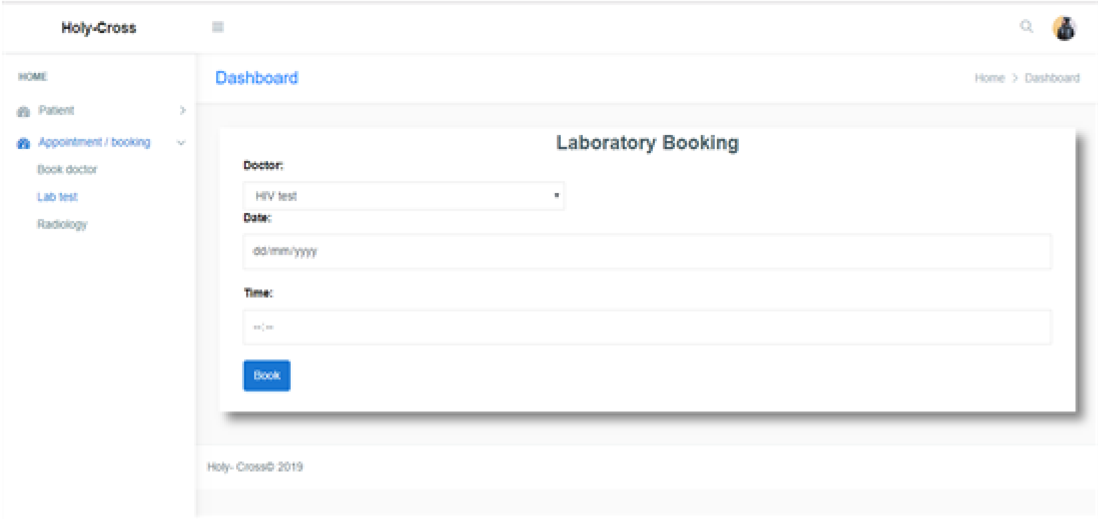


Figure 5 Sample Lab Booking

The primary driver for system development and the criterion by which its usefulness is assessed are frequently output. The following are a few of the products from this effort.

The page in **Figure 6** shows numerous details about the patient's profile.

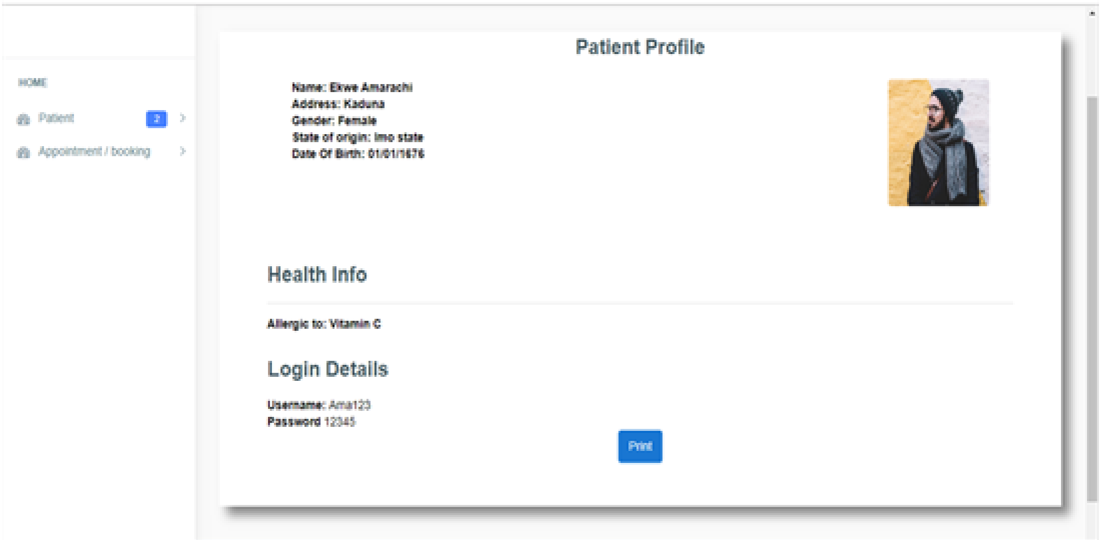


Figure 6 Sample Patient Profile

Figure 7 depicts the patient's medical report, which the patient and doctor may both see.

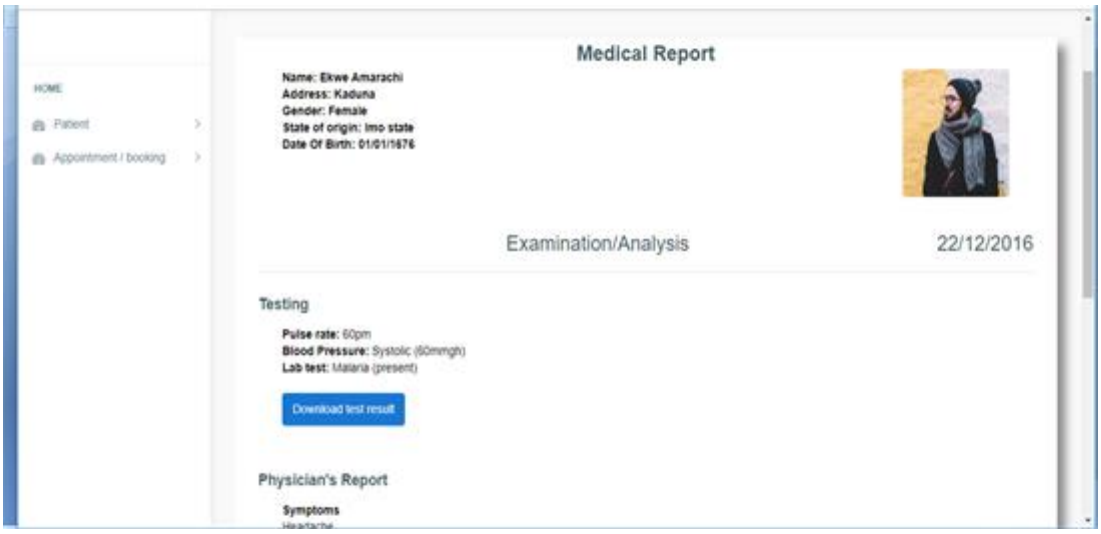


Figure 7 Sample Medical Report

Figure 8 is the page that shows the results of the patient's laboratory test.

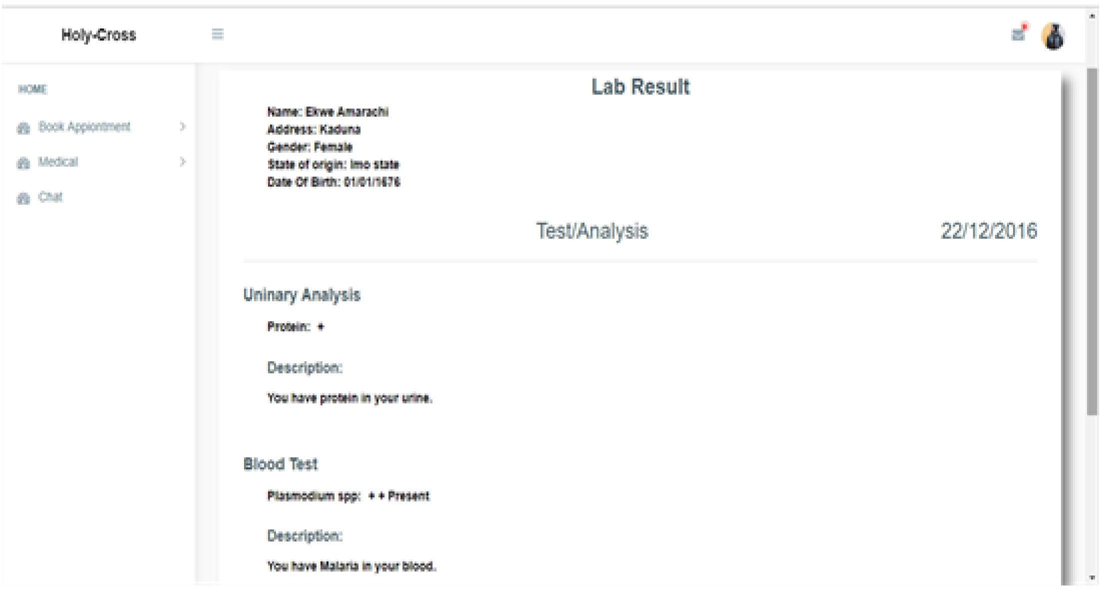


Figure 8 Sample Lab Result

3.4 Collection of data

Dataflow

Store: The data is kept in Delta Lake structure in Data Lake Storage. The data lake's curated layer is called Delta Lake. The data is organised across three tiers using a medallion architecture:

- ✔ Raw data are kept in bronze tables.
- ✔ The data in silver tables has been cleansed and filtered.
- ✔ Aggregated data that is ready for reporting and analytics is stored in gold tables.

Process

- ➢ The raw data is prepared, refined, and cleaned using code from various programming languages, platforms, and libraries (1). Python, R, MySQL, Spark, Pandas, as well as Koalas are some coding options.
- ➢ Workloads for data science are run on Azure Data bricks. Additionally, this platform creates and develops models for machine learning (2). Azure Data bricks take advantage of optimised, pre-installed libraries. Scikit-Learn, Tensor Flow, Py-Torch, & XG-Boost are a few examples.
- ➢ The machine learning research, model runs, and outcomes are recorded using ML-flow tracking (3). The prediction fit is deployed to the ML-flow data repository by Azure Data bricks when it is prepared for production. This central database houses data about manufacturing models. Additionally, the registry provides models to additional components:
- ➢ Models may be consumed by Spark and Python pipelines. These pipelines can handle streaming ETL operations as well as batch workloads.
- ➢ For a variety of uses, models are accessible using REST APIs. Testing as well as interactive scoring with mobile and online apps are two examples.

Components

- ➢ A platform for data analytics is called Azure Data bricks. Data science tasks are run on its centrally managed Spark clusters. Additionally, Azure Data bricks builds and trains machine learning models using pre-configured, optimised libraries. It is possible to keep track of trials, save models in journals, and make models accessible to other services by integrating ML-flow with Azure Data bricks. Scalability is offered by Azure Data bricks:

- Small data sets & single-model runs are handled by single-node compute clusters.
- Multi-node compute complexes and graphics processing unit (GPU) ensembles are available for huge data collections. For parallel model runs, these clusters employ frameworks and tools like HorovodRunner and Hyperopt.
- For high-performance analytics applications, Data Lake Infrastructure is a scalable & secure data lake. This service maintains hundreds of gigabytes of data of throughput while managing many petabytes of data. These qualities of the data are possible:
    - Be either formally or loosely arranged.
    - Come from several, diverse sources, such as media, files, and logs.
    - Be batch-generated, streamed, or static.
- A storage tier called Delta Lake employs an open data file. Cloud storage, like Data Lake Storage, runs this layer. For converting and cleaning batch and streaming data, Delta Lake is the best solution. These characteristics and capabilities are supported by this platform:
    - Data rollback and versioning.
    - ACID transactions for reliability: atomicity, continuity, isolation, and durability.
    - A uniform standard for model training, model serving, and data preparation.
- An open-source infrastructure for the pattern recognition life cycle is called ML-flow. Machine learning models are monitored by ML-flow components as they are being trained and used. Code, data, setup details, and outcomes are all stored information. Models are also stored and loaded in production via ML-flow. Since ML-flow makes use of open frameworks, a wide range of services, programs, frameworks, as well as tools can leverage the models.
- AKS is a Kubernetes service that is completely controlled, safe, and highly available. AKS makes managing and deploying containerized apps simple.

3.5 Analysis of data

3.5.1 Azure Data Bricks for Machine learning Purpose

Additionally, Azure Data bricks builds and trains machine learning models using pre-configured, optimised libraries. It is possible to keep track of trials, save models in archives, and make models accessible to other services by integrating ML flow with Azure Data bricks. A managed service for experiment management, model training, characteristic development and administration, or feature and model serving is included in the complete end-to-end machine education system known as Data bricks Machine Learning. Azure the most recent editions of Apache Spark are available from Data bricks, and you may easily include open-source libraries. With Azure's global scalability and availability, create clusters rapidly in a content management Apache Spark environment. Your machine learning organisations can access, examine, and prepare any form of data at any scale thanks to Data bricks ML's open lake house foundation and Delta Lake. Self-servery integrates features into operational pipelines without relying on assistance from data engineering.

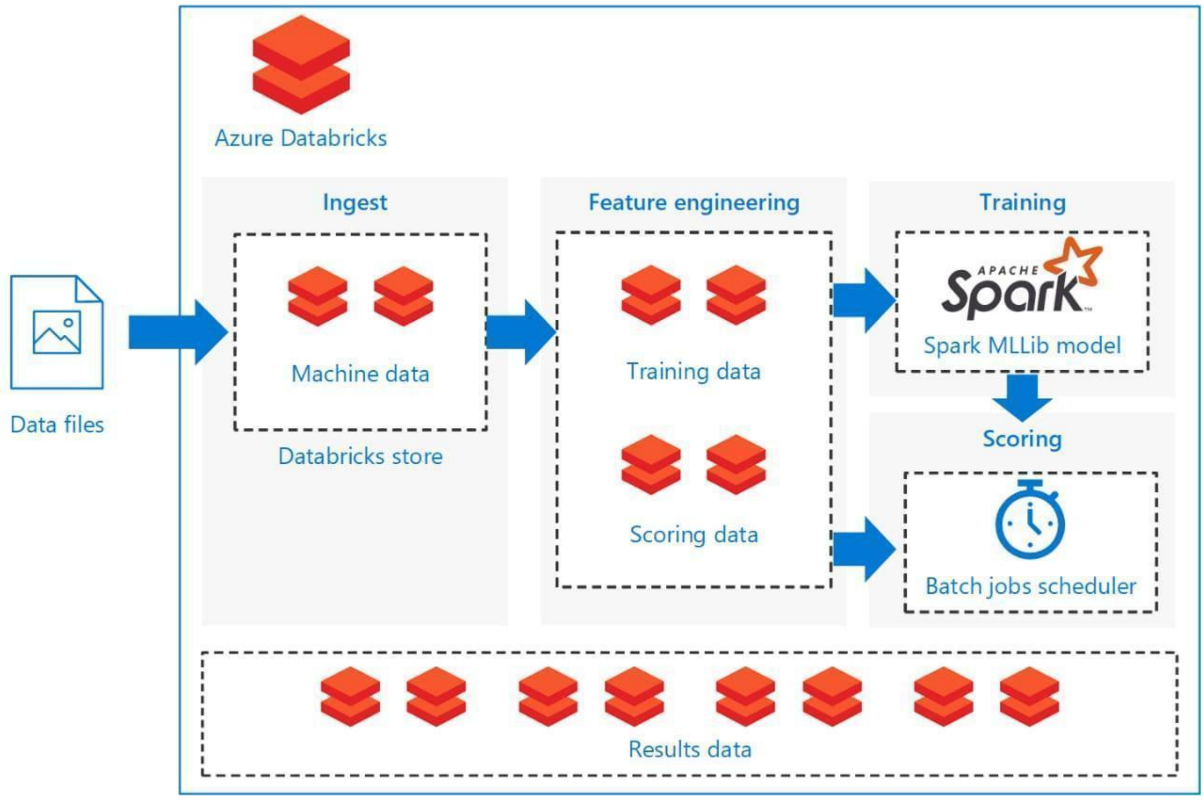


Figure 9 Flowchart of Azure Data Bricks

A managed service for experiment logging, model training, feature management and implementation, and feature but also model serving is included in the complete end-to-end computer learning environment known as Data bricks Machine Learning. The graphic illustrates the relationship between Azure Data bricks' features and the model creation and deployment process's phases.

3.5.2 Data bricks Machine Learning overview

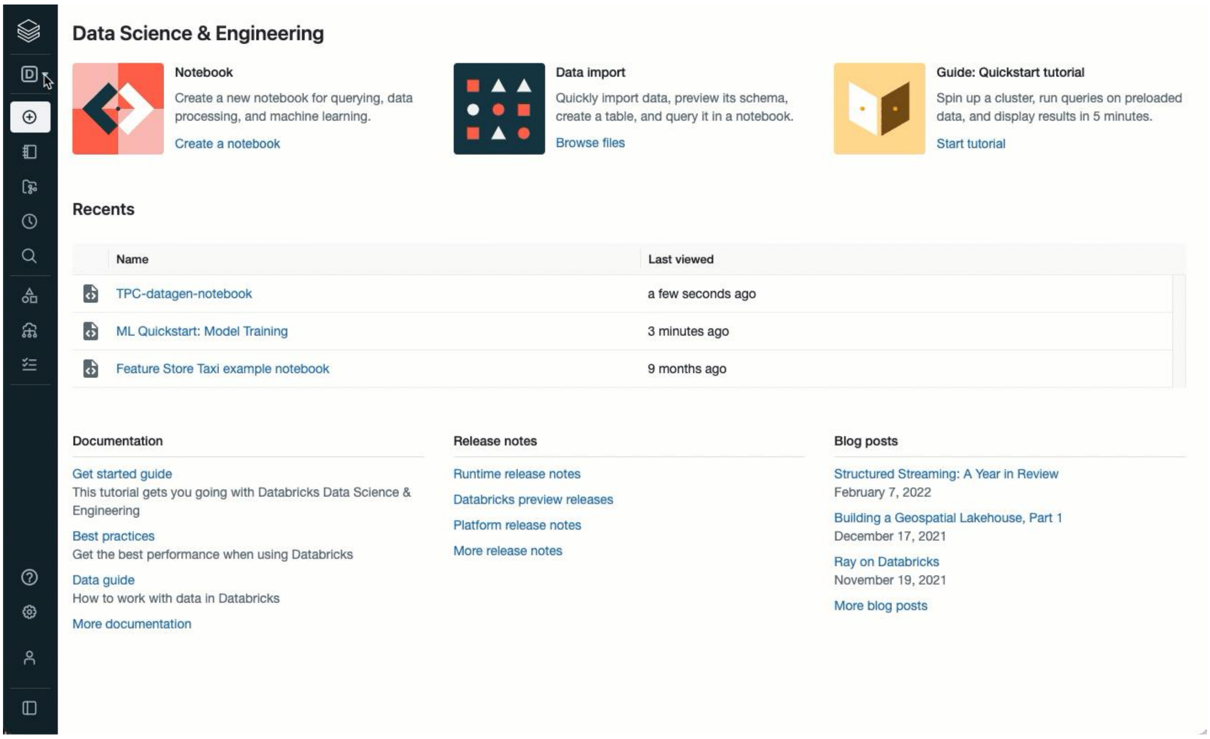
Data bricks Machine Learning enables you to:

- Either manually or using Auto-ML, develop models.
- Utilise ML flow tracking to monitor training variables and models in experiments.
- Make feature tables and use them for model inference and training
- Using Model Registry, you may distribute, control, and service models.

All the features of both the Azure Data bricks workstation are also available to you, including notebooks, clusters, tasks, data, Delta tables, privacy, and admin controls, and more. Consult the Data bricks Data Science & Engineering Handbook for further details. Data bricks advice employing a cluster running Data bricks Runtime for Machine Learning for machine learning applications.

3.5.3 Access Data bricks Machine Learning

Move your mouse or cursor over the left sidebar inside the Azure Data bricks workstation to open the Data bricks Deep Learning UI. As you hover over the sidebar, it expands. Choose Machine Learning from the avatar switcher there at the top of the sidebar. The main page for Data bricks Machine Learning debuts. An unusual year-long partnership between the Microsoft & Data bricks teams produced Azure Data bricks, a "first party" Microsoft service that offers Data bricks' Apache Spark-based analytics tool as a crucial component of both the Microsoft Azure platform. From a single-click start to uniform billing, we've made sure that this service is naturally linked with Microsoft Azure inside a variety of ways. To effortlessly interact with Azure services like Azure Active Directory, MySQL Data Warehouse, & Power BI, Azure Data bricks makes use of Azure's security. The team behind Apache Spark, the industry-leading Spark-based analytics platform, and the Spark research initiative at UC Berkeley created Data bricks' cloud service. Teams working in data science & data engineering now have access to a quick, simple, & collaborative Spark-based framework on Azure thanks to the new service known as Microsoft Azure Data bricks. Users of Azure may handle Big Data and learn machine learning on a single platform.



User guides

- Homepage for Data bricks Machine Learning
- Prepare data and set up the environment
- Auto-ML Data bricks
- Develop models
- Follow the growth of the model
- Control models
- Implement inference models
- Models for export and import
- Reference answers
- ML flow manual
- Graph Frames
- Workflows for machine learning and the Unity Catalogue
- ML-Ops

3.5.4 Data science and machine learning with Azure Data bricks

You can increase productivity, enhance customer encounters, and anticipate changes when your company begins to recognize the benefits of machine learning and data analysis. You want a dependable and consistent pattern for each of the following to accomplish these objectives in business-critical use cases:

- ✔ Monitoring tests.
- ✔ Replicating outcomes.
- ✔ Implementing production-ready machine learning models.

The answer for a dependable, consistent machine learning framework is described in this paper. Core to the architecture is Azure Data bricks. Significant roles are also played by the machine learning framework ML flow and the storage level Delta Lake. With additional services like Azure Data Lake Infrastructure, Azure Machine Learning, like Azure Kubernetes Service, these components integrate with them without any issues (AKS).

These businesses collectively offer a data analytics and machine learning solution that is:

Simple: The design is made simpler by an open data lake. A curated layer called Delta Lake is included in the data lake. The data is accessible through that layer in open-source form.

Open: The solution works with open standards, open frameworks, and open-source code. Future upgrades are less necessary because of this strategy. ML flow & Delta Lake are natively supported by Azure Data bricks as well as Machine Learning. These elements work together to deliver ML-Ops, or DevOps with machine learning, that are among the best in the business. The solution's standardised model format is integrated with a wide variety of deployment tools.

Collaborative: With this approach, teams from data science & ML-Ops collaborate. These teams' record and query trials using ML-flow tracking. The groups additionally upload their models to the main ML-flow model repository. In data intake, extract-transform-load (ETL) procedures, and streaming pipelines, data engineers' leverage deployed models.

Potential use cases

This approach was motivated by a platform that AGL created for energy forecasting. For hundreds of parallel models, that platform offers rapid and affordable training, deployment, and lifecycle management.

In addition to energy suppliers, this solution is advantageous to any company that:

- ✔ Employs data science
- ✔ Constructs and develops machine learning models.
- ✔ Runs production-ready machine learning models.

Examples include businesses in:

- ❖ Retail and online shopping.
- ❖ Finance and banking.
- ❖ The life sciences and healthcare.
- ❖ Automotive manufacture and industries.

Next steps

- ➢ For tens of thousands of parallel models, AGL Energy creates a common platform. The platform offers rapid and affordable model deployment, lifecycle management, and training.
- ➢ Gas pipes are monitored by Open Grid Europe (OGE) using artificial intelligence algorithms. OGE creates the models using ML-flow and Azure Data bricks.
- ➢ Azure Data bricks are being used by Scandinavian Airlines (SAS) for group research. The airline also creates prediction models using machine learning. The models help the company's daily operations by seeing trends in its data.

3.6 Summary

The primary goal of computer-based "machine learning" is to analyse free-form text or speech in accordance with a predefined set of theories and technologies, such as linguistic and statistical methods, which in turn obtains rules and patterns from the data that is being analysed. Machine learning is performed on a computer. It can transform the text into a format that is organised and adheres to a hierarchy. The listed pieces each have their own defined nomenclature and a predetermined structure for how they are organised. These texts can be searched and altered with relative ease. The most common applications of natural language processing are in the areas of pattern recognition and linguistic study. The method of text searching known as pattern matching is one that is simple and essential. The formation of complicated NLP is necessary.

CHAPTER 4: FINDINGS/RESULTS

A broad and potent digital technology called machine learning has the potential to improve patient care and education, speed up decision-making, and save money in the healthcare industry. Numerous machines learning subfields, including NLP and DNN, have been researched and used in various healthcare components to date. The cutting-edge AI-based chatbot serves as a crucial conversational intermediary between the customer and the service provider. Our healthcare system is significantly impacted by this chatbot including response system. Future influence is anticipated to increase due to technology's ongoing growth. By using the most cutting-edge algorithms, AI may save healthcare expenses, improve research work efficiency, and is anticipated to help clinicians in many fields.

Artificial intelligence will be used more and more in the healthcare industry because of the complexity and growth of data in the sector. Payers, care providers, and life sciences organisations currently use a variety of AI technologies. The main application areas include suggestions for diagnosis as well as treatment, patient involvement and adherence, including administrative tasks. Although there are numerous situations by which AI can execute healthcare duties just as well as or better than people, implementation issues will keep the employment of healthcare professionals from becoming extensively automated for a substantial amount of time. The worry that AI will cause significant worker displacement and job automation has received a lot of attention. In the next 10 to 20 years, 35% of UK employment might be automated out of existence by AI, according to a Deloitte cooperation through the Oxford Martin Institute. Even though some jobs may be automated, other factors besides technology may be able to prevent widespread job loss. These include the price of automation technologies, the expansion and cost of the labour market, the advantages of automation further than simple labour replacement, and societal and regulatory acceptance. Actual employment losses might be limited to 5% or even less by these considerations.

As far as we are aware, AI has not yet resulted in the loss of any healthcare employment. The lack of job effect can be partially attributed to the industry's slow adoption of AI and the challenge of incorporating it into clinical processes and EHR systems. The positions in healthcare that are probably to be automated are those that deal with digital information, like radiology and pathology, as opposed to those that have direct patient interaction. However, the adoption of AI in occupations like radiologists and pathologists is probably going to be gradual. First, radiologists perform more than just picture reading and interpretation. Radiology AI systems carry out solitary jobs, much like other AI systems. Deep learning models are trained for image identification tasks in laboratories and companies. To properly identify all probable discoveries in medical photos, however, hundreds of these specific detection jobs are required, and only a small number of them can currently be completed by AI. In addition, radiologists provide diagnostic and therapeutic advice to other doctors, treat illnesses (for instance, by administering local ablative therapies), carry out image-guided procedures like cancer biopsies including vascular stents, specify the technical requirements for imaging examinations to be carried out, link information from images to other records and test results, communicate with patients about procedures and outcomes, and carry out numerous other tasks.

Security is very important aspect of encryption over the Internet because of the value and significance of patient health data (PHR). Security hazards are higher for users that use phrase searches to approach the PHR that is kept in the database. Security can be guaranteed by a blockchain-based healthcare system, but current solutions have several drawbacks. The only focus of existing methods has been data storage, and they have made use of blockchain as a database for data storage. In this study, we created a novel deep-learning-based protective blockchain that can be searched, acting as a distributed data network with homomorphic encryption to allow users to approach data safely. This proposed research progressively includes secure key update and revocation procedures.

The spread of infection control depends on healthcare personnel checking for COVID-19 signs and exposure before each shift. This must be an effective screening method that is simple and quick. An AI-based and chatbot-based process was created and deployed through the University in California, San Francisco Health. Over 270,000 screenings were performed throughout the first two months of usage. It resulted in improved physical distance, cut down on employee wait times when entering hospitals, stopped potentially infectious people from entering, and gave decision-making personnel crucial real-time data.

CHAPTER 5: IMPLEMENTATION

5.1 Front End Application

5.1.1 Create a new Android Studio Project:

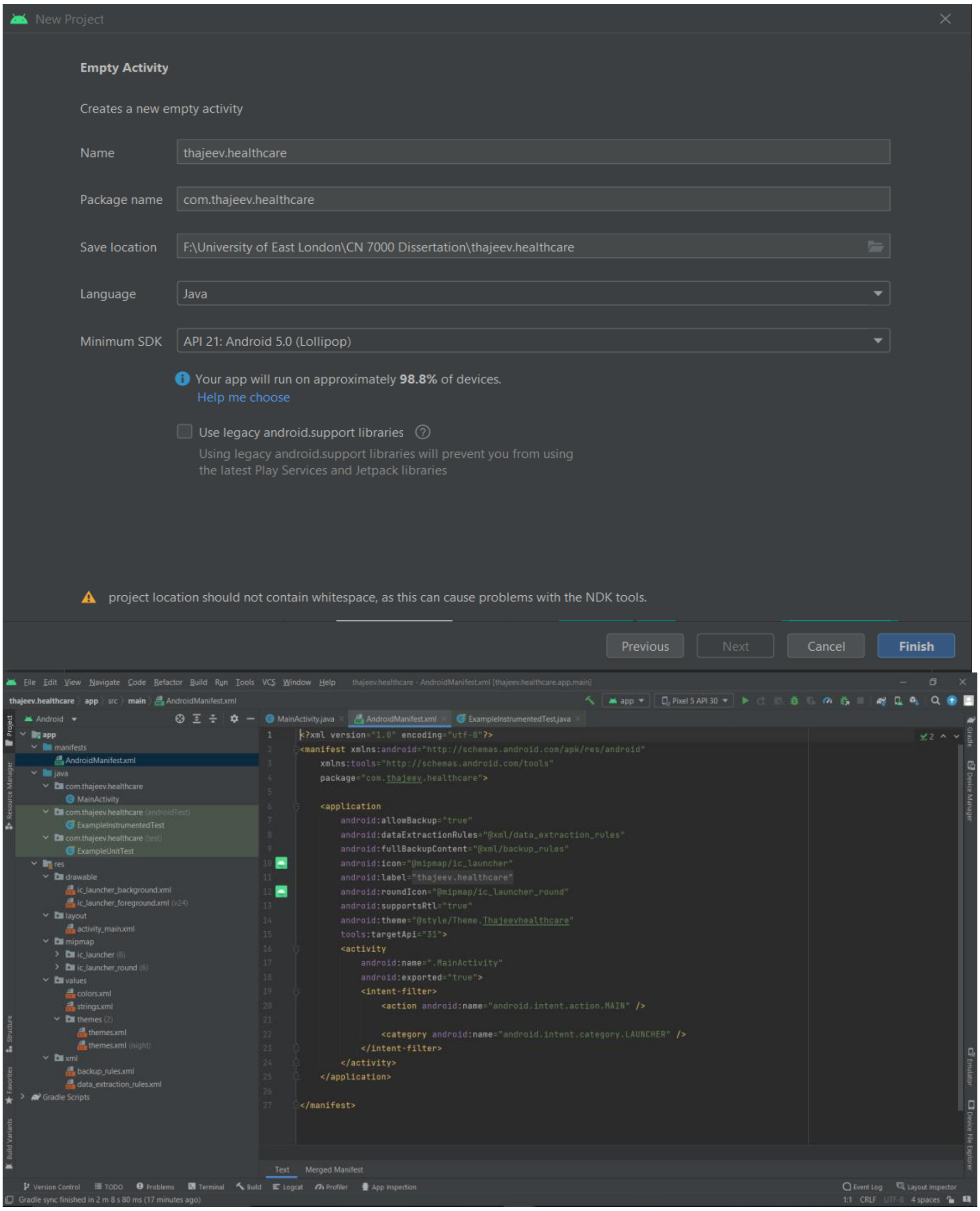


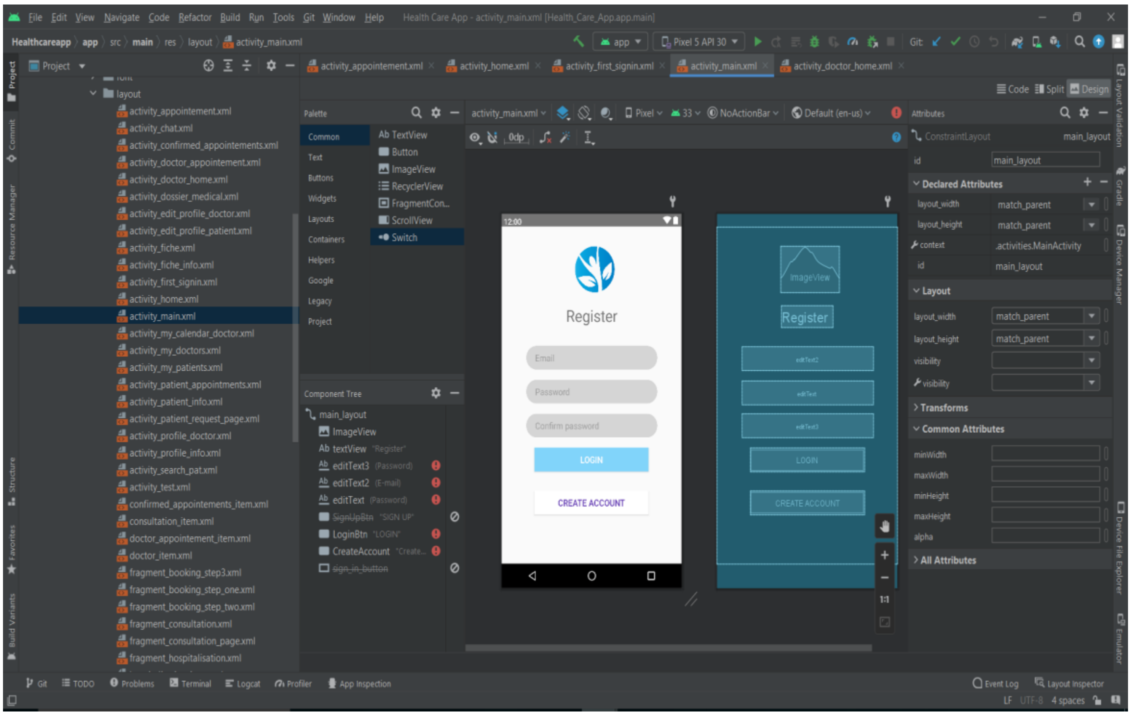
Figure 10 New Android Project

By choosing the empty activity, we are mentioning our project name to *thajeev.healthcare*. And we are setting the minimum software development kit (SDK) level to 5.0 of Lollipop version of API 21, which runs almost in all android devices.

After click finish it will automatically build the model with the following configurations. It builds the main activity and in the res folder there is a drawable folder which is used for designing the different types of images for building the application, layout folder which describes the structure of the User Interface (UI), mipmap folder is for storing the launcher apps icons and values folder is for storing the values of the resources which is used for creating the application.

5.1.2 Create an APP Layout:

The default application template creates a basic UI, so I created some layout for app functions.



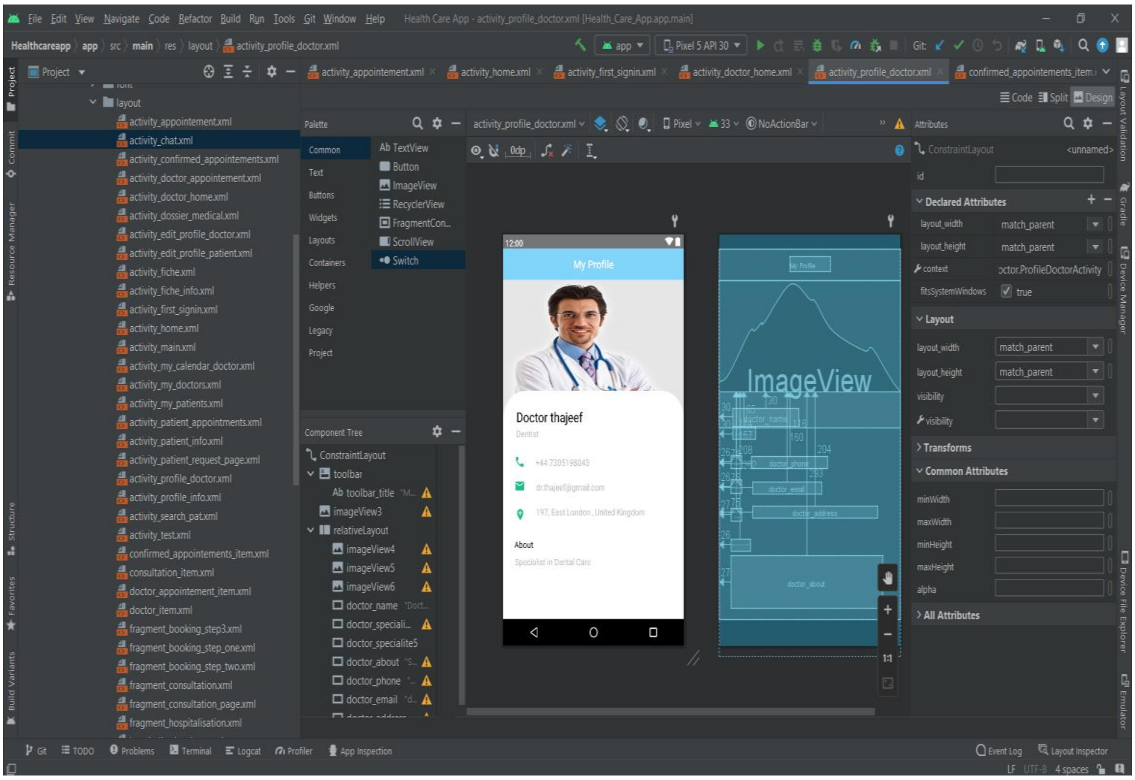
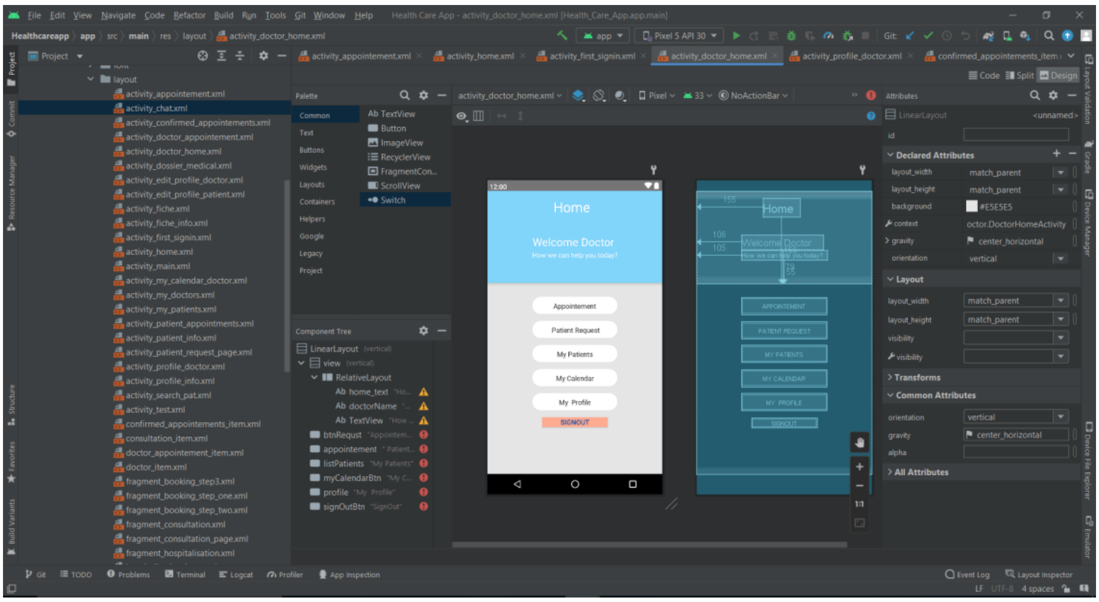


Figure 11 APP Layout

This is the Register and login screen for both doctor and patients for the use of the mobile applications. I have created a layout for a doctor's profile. By applying some default images and by adding some more information about the doctor.



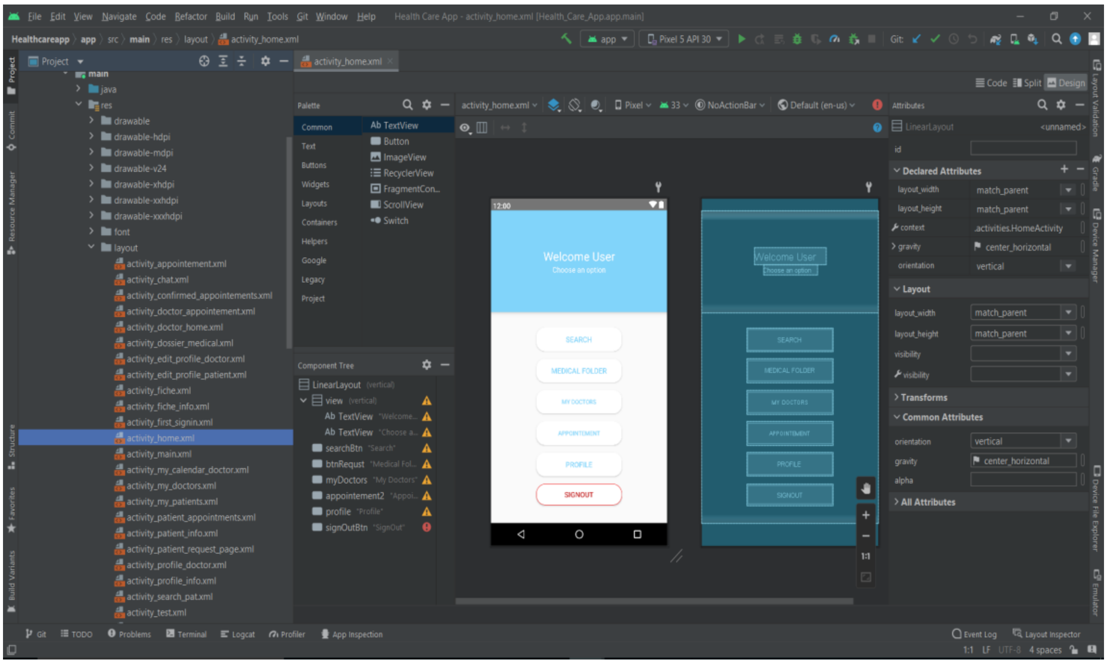


Figure 12 Doctor and Patient Home Screen Layout

This image shows the welcome page of the doctor which includes the appointment, Patient request, My patients, My calendar, and My profile folder and at last sign out button for the applications. Another image illustrates the patients welcome page after signing into the app which includes the contents like search, medical folder, my doctors, appointment, profile and sign out button for the app.

These are the layouts for my android applications. Layouts are the best visuals for the users. I have created a register and login screen, doctor, and patients' profile, choosing appointment time, visiting calendar, patients request, doctor approval and the activities of doctors and patients.

5.1.3 Android Firebase – Back End

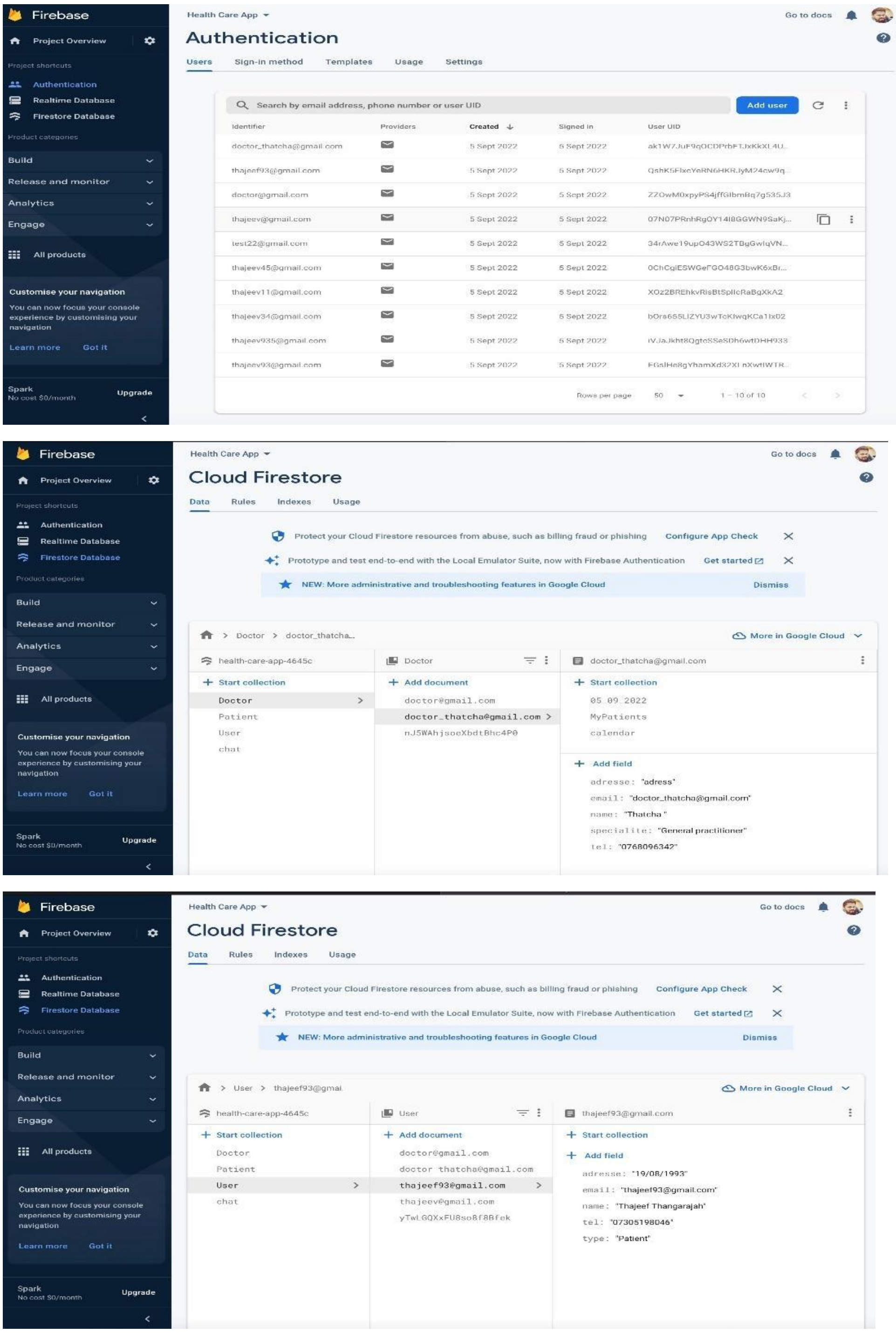


Figure 13 Android Firebase

Android Firebase is the open source for creating a database for storing the information of android application uses. This figure shows the authentication in which the users are made, and the doctor and patients' information are stored in cloud fire store database.

5.1.4 Android Emulator

Android emulator is a virtual device in which we can run the android applications. By selecting the required API level versions and the pixels of the app, we can make the app better and install the required Software Development Kit (SDK) component.

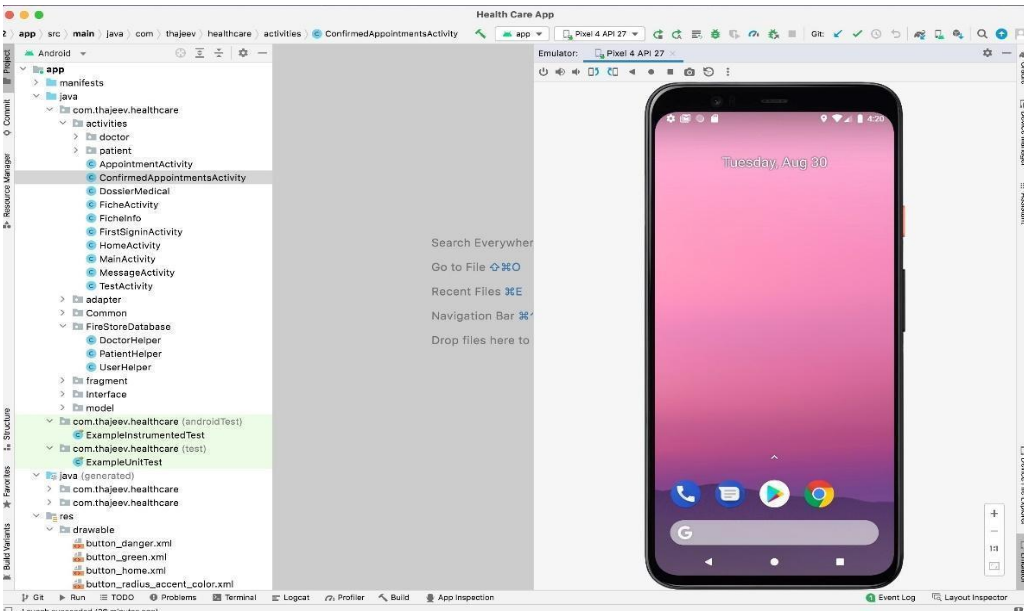


Figure 14 Android Emulator

5.2 Back End Application

5.2.1 Create a Resource Group

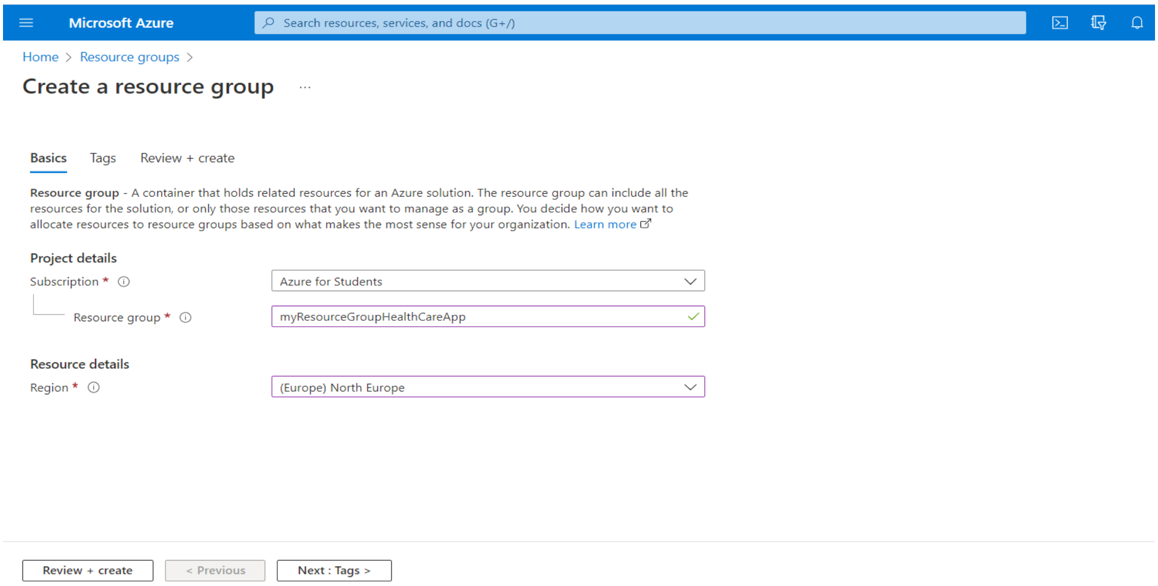


Figure 15 Azure Resource Group

Resource group is the collection of resources in a cloud which acts as a Role based access control for security purposes identifying who can get access to the Azure resources, managing the administration costs and monitoring the activities performed by all cloud services.

For Back End Application we are using Azure Cloud Services for the Online healthcare application. For using Azure services, we must create an Azure resource group. Hence, we created a resource group which is named as *my Resource Group Health Care App* and by selecting our nearby region *North Europe*.

5.2.2 Azure App Service

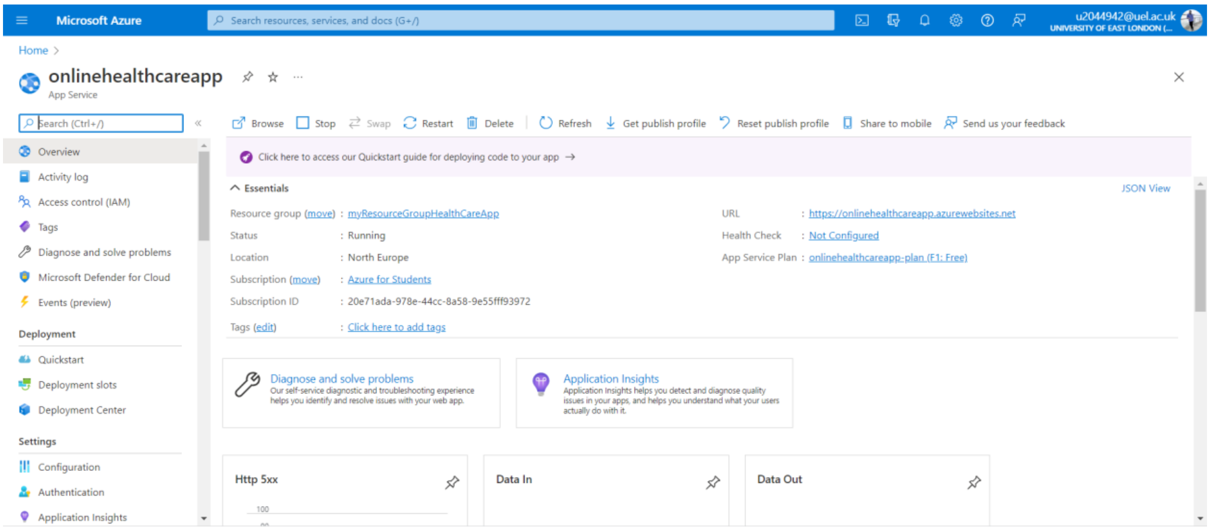


Figure 16 Azure App Service

For Creating Web applications easily and in a quicker way, Azure app service is one of the best Cloud Service which is Platform as a service (Paas) which makes deploying the code and the services automatically runs. By selecting the best operating system and a run time stack we can run web apps. There are three types of azure app services which are Web apps for creating Web applications and hosting websites, API apps for hosting Representational State Transfer api’s and Logic apps for automation of business processes and sharing the data over the cloud. By using the Deployment centre, we can easily deploy the app-on-app service via access controls like Git, GitHub, OneDrive and Dropbox.

5.2.3 Azure Cosmos DB

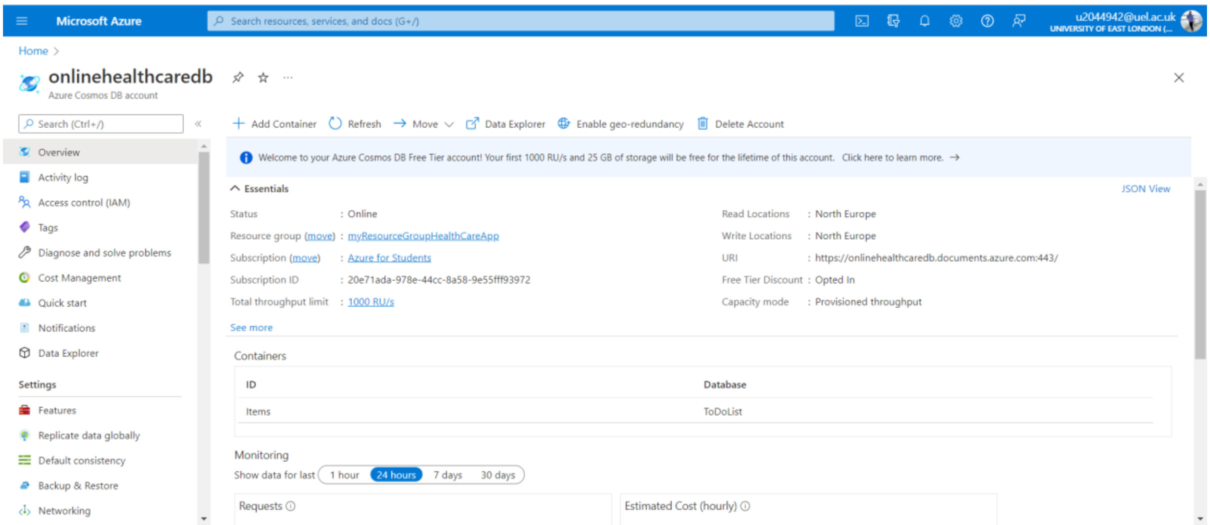
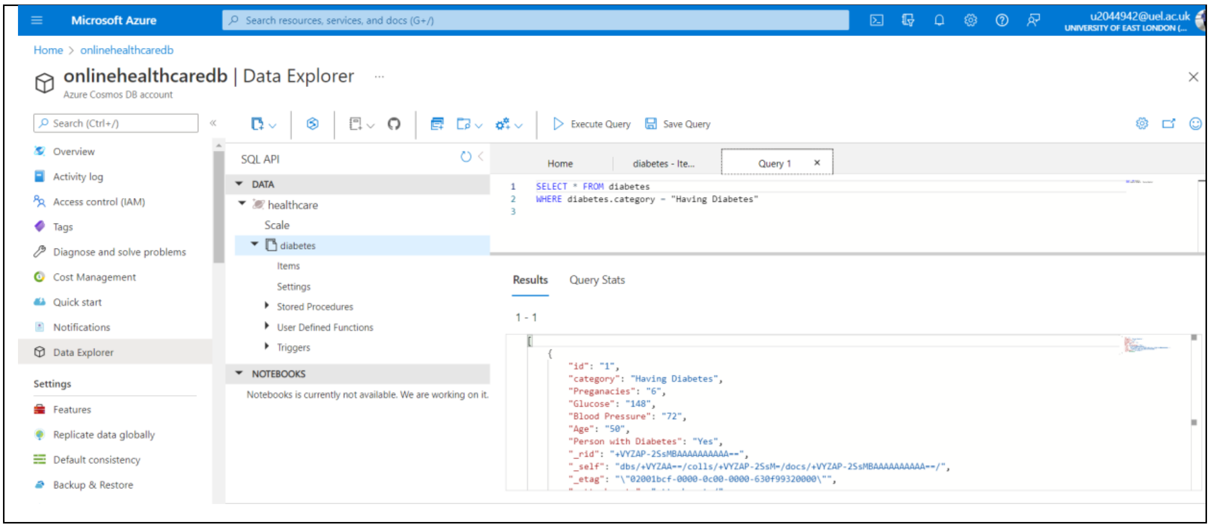


Figure 17 Azure Cosmos DB

Azure Cosmos DB is a NOSQL database that can store document type of files, we can set the data as a key-value set as JSON files and it has an analytical workload in Jupyter notebook and Apache Spark. It is a global distribution database used in a multi-region workload.



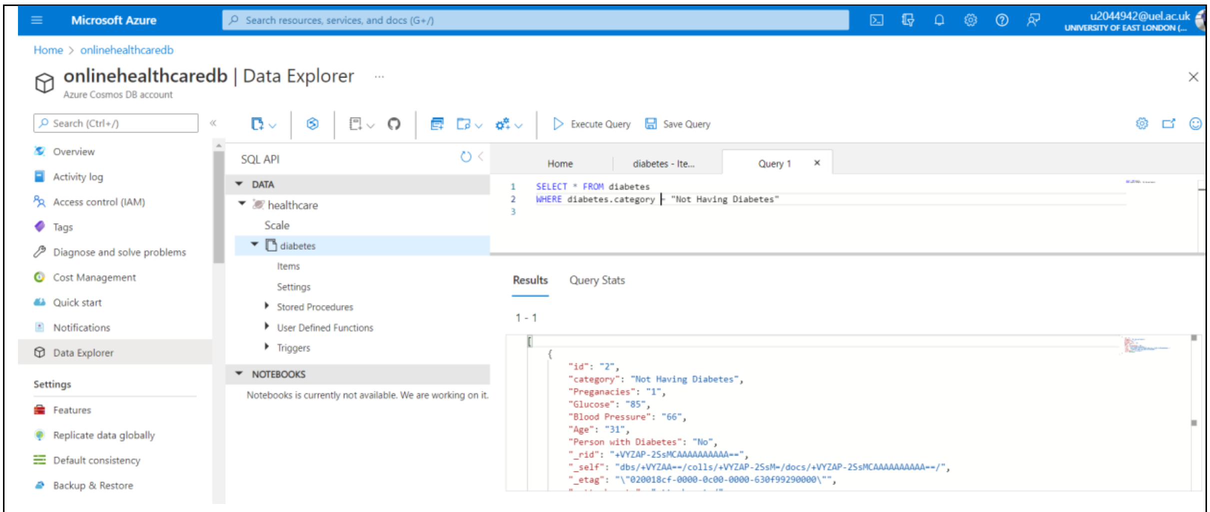


Figure 18 Querying Using SQL

In Cosmos Database, we have created a container named healthcare and, in the container, there is a JSON file in which there is information about the patients having diabetes or not. SQL API has been used which can access a local database server or a remote database server.

5.2.4 Notification Hub

Azure notification hub is a message sending service in azure. It automatically sends notifications about the device running.

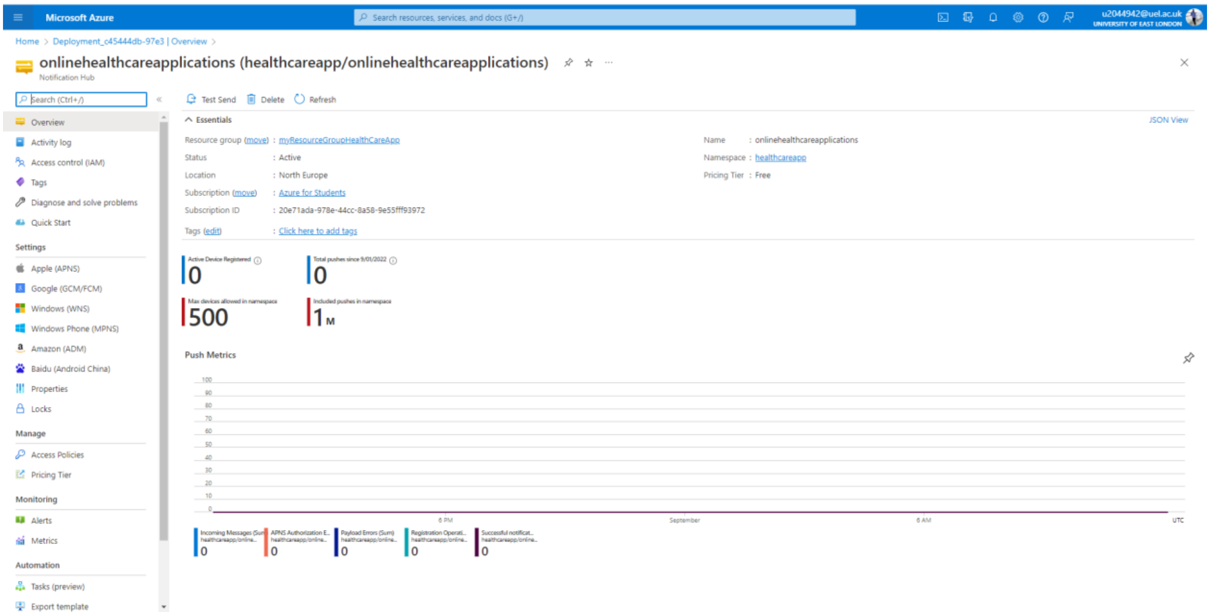


Figure 19 Azure Notification Hub

5.3 Machine Learning using Azure Databricks

5.3.1 Generate a Databricks workspace

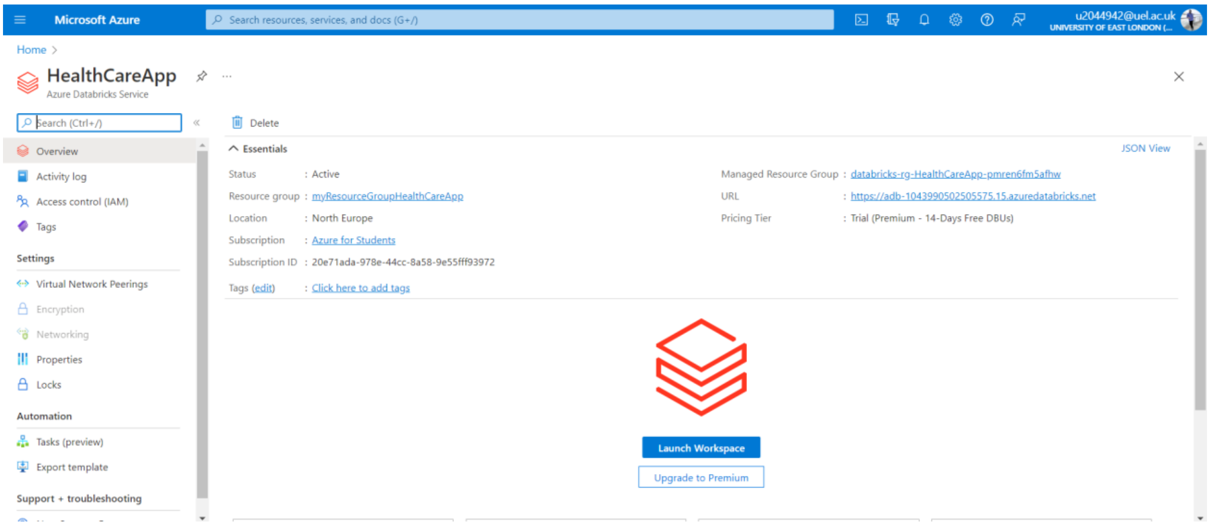


Figure 20 Azure Databricks Workspace

For Machine Learning we are using Azure Databricks. So, we are creating Azure Databricks service in our resource group by mentioning our Workspace name as *Health Care App* and by selecting a pricing tier for 14 days free trial. We have constructed a data bricks workspace in our Resource group and are ready for launching.

5.3.2 Design a Cluster

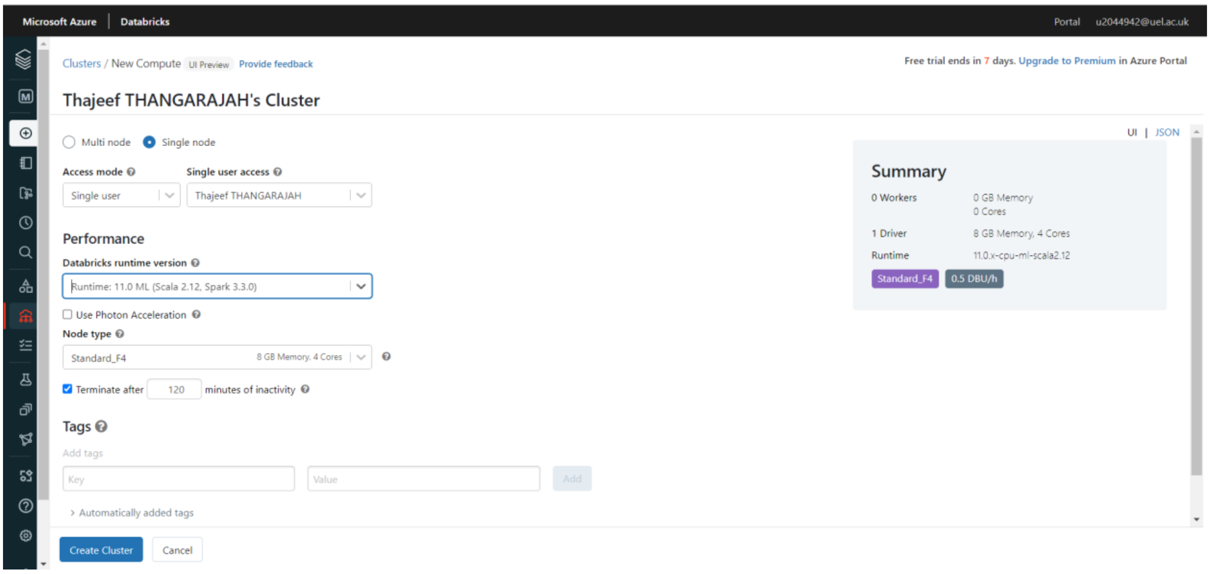


Figure 21 Cluster Computing

Following the launching, for using computing we must create a cluster for running the machine learning notebook. So, for our machine learning, I'm using

Pyspark for coding, so I have selected the 11.0 ML data bricks runtime version which includes all ML features of Pyspark. Standard_F4 node type which is 8GB memory with 4 cores machine which is enough for running the small dataset.

5.3.3 Create a notebook

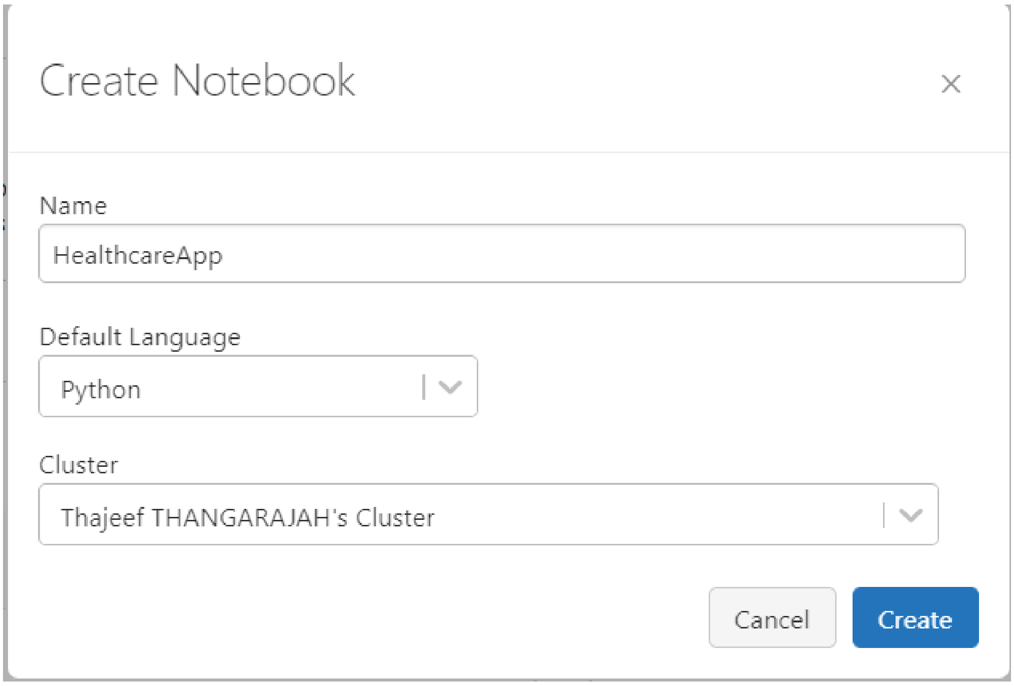


Figure 22 Create Python Notebook

Next to Clustering, we are creating a notebook for performing Machine Learning coding. For the name I have mentioned *HealthCare App,* Python is our coding language under Thajeef THANGARAJAH Cluster.

5.3.4 Azure Blob Storage

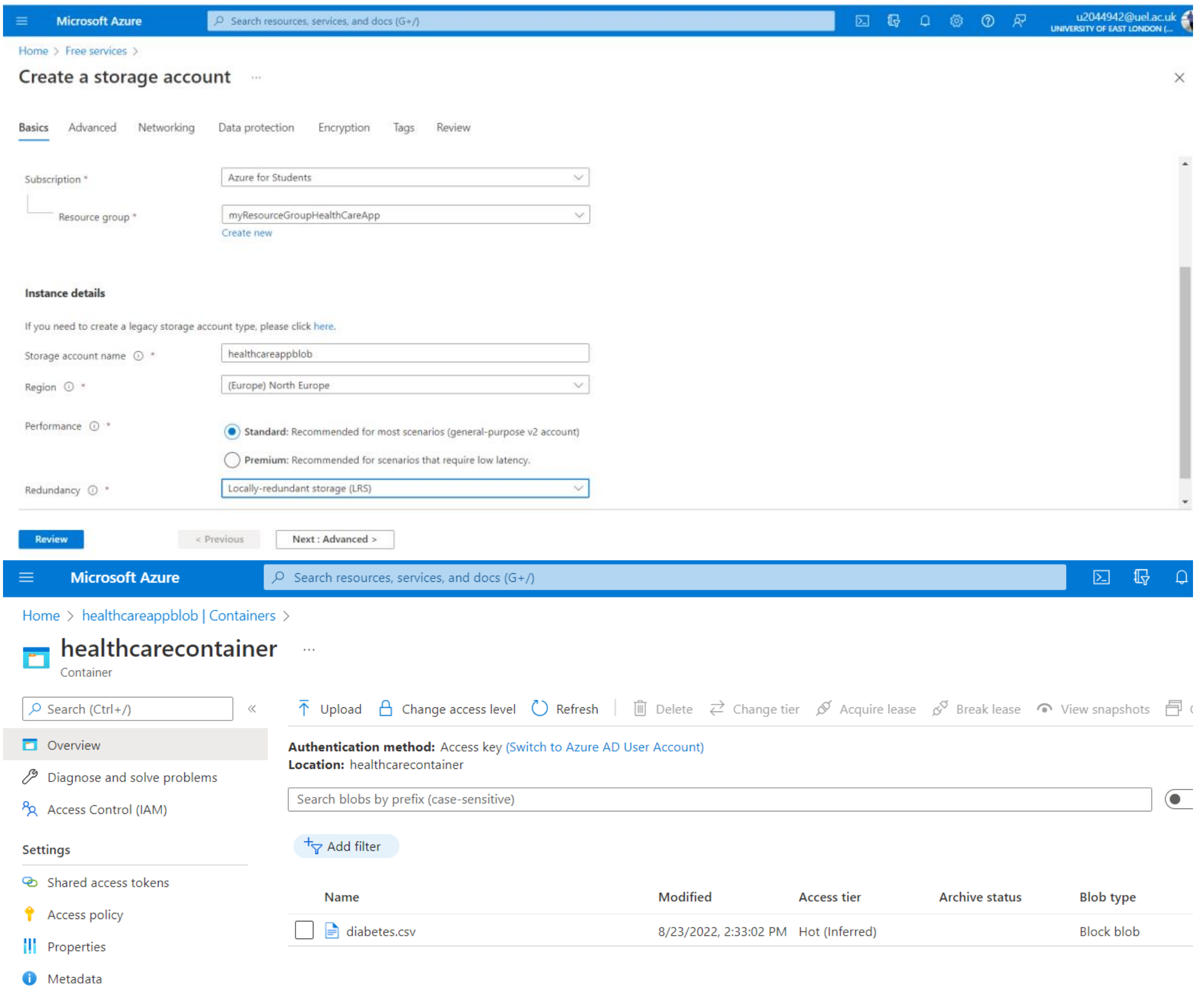


Figure 23 Azure Blob Storage

Azure blob storage is another azure service which is used for storage accounts. For storing the image types of files, JavaScript files and Cascading Style Sheets files. Blob storage has many features like soft delete, Custom domains and acts as a Content Delivery Network (CDN). We can upload pictures on blobs and easily categorise them.

In this process, the diabetes dataset taken from Kaggle is used for Machine learning using Azure Databricks, so in case of using data bricks we need storage for our data. Following up we created a storage account naming with the *healthcare app blob* in our resource group. And we created a container named *healthcare container* for storing data. I have uploaded a dataset of Diabetes containing a CSV file for Machine Learning.

5.3.5 Machine Learning with Pyspark

5.3.5.1 Load Dataset

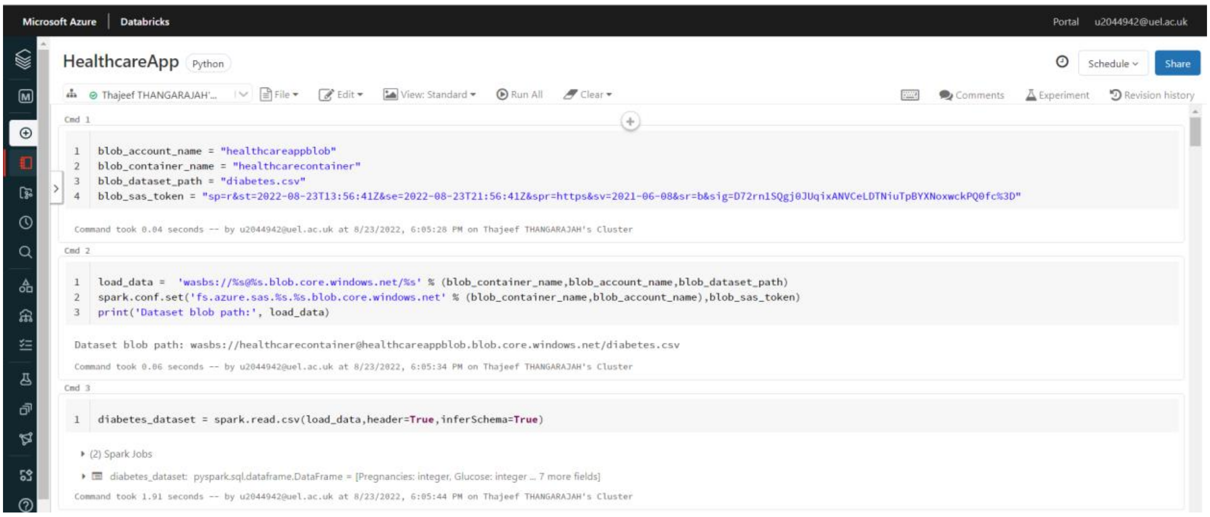


Figure 24 Load Dataset

To connect Azure blob storage with Azure data bricks we are using Windows Azure Blob Storage Driver (WASB). By mentioning our blob account name, blob container name, blob dataset path and blob sas token with driver we connected our notebook with Azure blob storage. Using read.csv in spark for loading our dataset into a data frame named diabetes dataset.

5.3.5.2 Features of Dataset

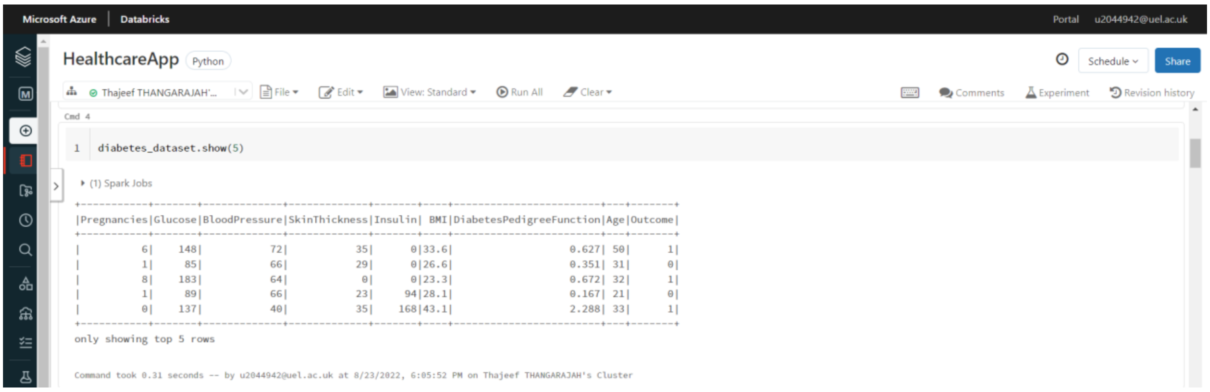
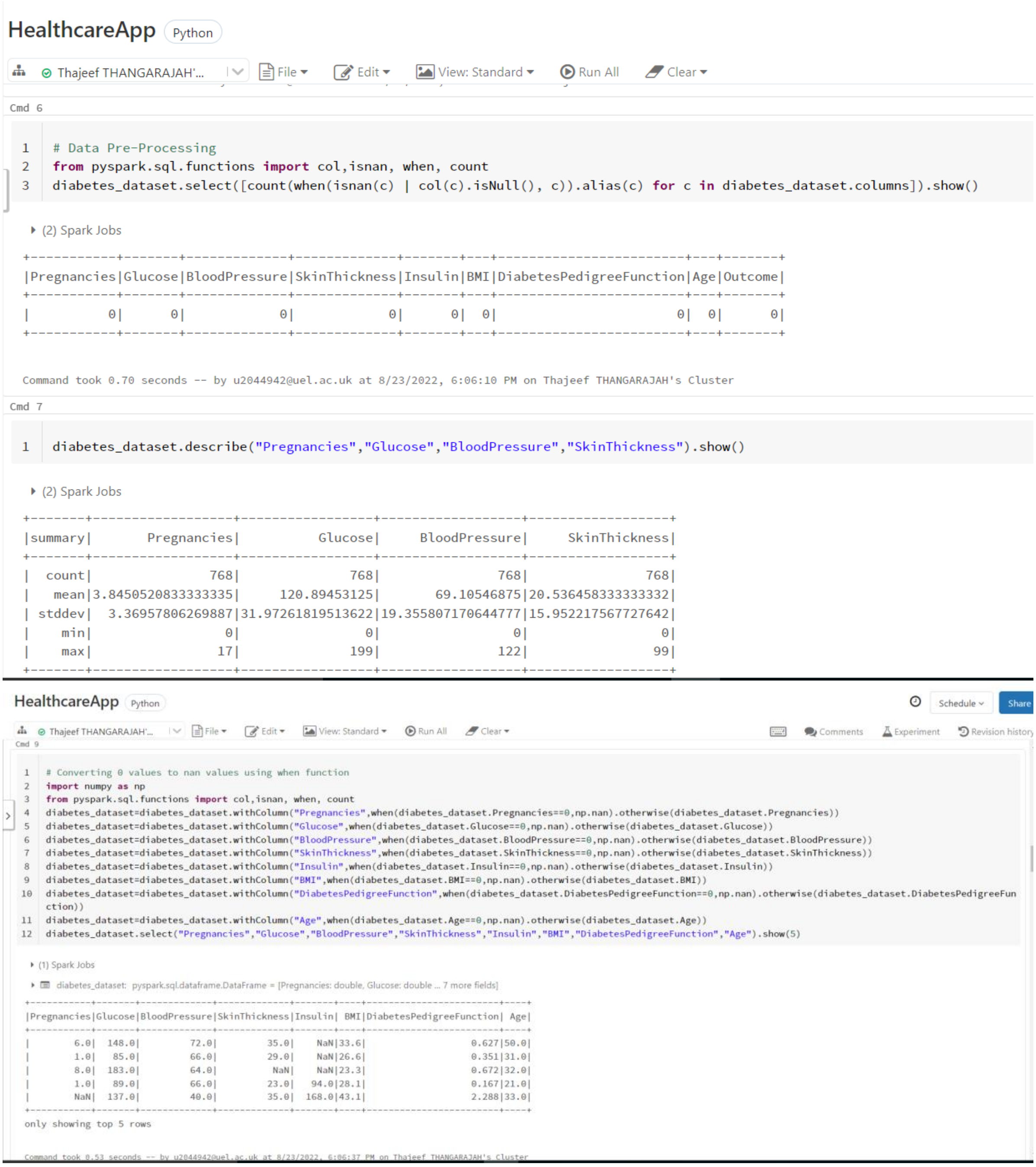


Figure 25 Features of Dataset

The features of our dataset containing Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Diabetes Pedigree Function, Age and at last the feature containing Outcome mentioning that the patients having diabetes or not. It is a binary classification dataset with 0 or 1 which is 0 for not having diabetes and 1 for having diabetes.

5.3.5.3 Data Pre-Processing



HealthcareApp Python

Cmd 6

```
# Data Pre-Processing
from pyspark.sql.functions import col,isnan, when, count
diabetes_dataset.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in diabetes_dataset.columns]).show()
```

(2) Spark Jobs

```
+-----------+-------+-------------+-------------+-------+---+------------------------+---+-------+
|Pregnancies|Glucose|BloodPressure|SkinThickness|Insulin|BMI|DiabetesPedigreeFunction|Age|Outcome|
+-----------+-------+-------------+-------------+-------+---+------------------------+---+-------+
|          0|      0|            0|            0|      0|  0|                       0|  0|      0|
+-----------+-------+-------------+-------------+-------+---+------------------------+---+-------+
```

Command took 0.70 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:06:10 PM on Thajeef THANGARAJAH's Cluster

Cmd 7

```
diabetes_dataset.describe("Pregnancies","Glucose","BloodPressure","SkinThickness").show()
```

(2) Spark Jobs

```
+-------+------------------+-----------------+-----------------+------------------+
|summary|       Pregnancies|          Glucose|    BloodPressure|     SkinThickness|
+-------+------------------+-----------------+-----------------+------------------+
|  count|               768|              768|              768|               768|
|   mean|3.8450520833333335|     120.89453125|      69.10546875|20.536458333333332|
| stddev|  3.36957806269887|31.97261819513622|19.355807170644777|15.952217567727642|
|    min|                 0|                0|                0|                 0|
|    max|                17|              199|              122|                99|
+-------+------------------+-----------------+-----------------+------------------+
```

HealthcareApp Python

Cmd 9

```
# Converting 0 values to nan values using when function
import numpy as np
from pyspark.sql.functions import col,isnan, when, count
diabetes_dataset=diabetes_dataset.withColumn("Pregnancies",when(diabetes_dataset.Pregnancies==0,np.nan).otherwise(diabetes_dataset.Pregnancies))
diabetes_dataset=diabetes_dataset.withColumn("Glucose",when(diabetes_dataset.Glucose==0,np.nan).otherwise(diabetes_dataset.Glucose))
diabetes_dataset=diabetes_dataset.withColumn("BloodPressure",when(diabetes_dataset.BloodPressure==0,np.nan).otherwise(diabetes_dataset.BloodPressure))
diabetes_dataset=diabetes_dataset.withColumn("SkinThickness",when(diabetes_dataset.SkinThickness==0,np.nan).otherwise(diabetes_dataset.SkinThickness))
diabetes_dataset=diabetes_dataset.withColumn("Insulin",when(diabetes_dataset.Insulin==0,np.nan).otherwise(diabetes_dataset.Insulin))
diabetes_dataset=diabetes_dataset.withColumn("BMI",when(diabetes_dataset.BMI==0,np.nan).otherwise(diabetes_dataset.BMI))
diabetes_dataset=diabetes_dataset.withColumn("DiabetesPedigreeFunction",when(diabetes_dataset.DiabetesPedigreeFunction==0,np.nan).otherwise(diabetes_dataset.DiabetesPedigreeFunction))
diabetes_dataset=diabetes_dataset.withColumn("Age",when(diabetes_dataset.Age==0,np.nan).otherwise(diabetes_dataset.Age))
diabetes_dataset.select("Pregnancies","Glucose","BloodPressure","SkinThickness","Insulin","BMI","DiabetesPedigreeFunction","Age").show(5)
```

(1) Spark Jobs

diabetes_dataset: pyspark.sql.dataframe.DataFrame = [Pregnancies: double, Glucose: double ... 7 more fields]

```
+-----------+-------+-------------+-------------+-------+----+------------------------+----+
|Pregnancies|Glucose|BloodPressure|SkinThickness|Insulin| BMI|DiabetesPedigreeFunction| Age|
+-----------+-------+-------------+-------------+-------+----+------------------------+----+
|        6.0|  148.0|         72.0|         35.0|    NaN|33.6|                   0.627|50.0|
|        1.0|   85.0|         66.0|         29.0|    NaN|26.6|                   0.351|31.0|
|        8.0|  183.0|         64.0|          NaN|    NaN|23.3|                   0.672|32.0|
|        1.0|   89.0|         66.0|         23.0|   94.0|28.1|                   0.167|21.0|
|        NaN|  137.0|         40.0|         35.0|  168.0|43.1|                   2.288|33.0|
+-----------+-------+-------------+-------------+-------+----+------------------------+----+
only showing top 5 rows
```

Command took 0.53 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:06:37 PM on Thajeef THANGARAJAH's Cluster

Figure 26 Data Pre-Processing

To perform a good Machine Learning model, data cleaning is the first step. We must check the null values or any other missing values in our dataset using SQL functions in py-spark by importing isnan for checking the null values, count is for counting the number of missing values. As a result, we have found there are no missing values in our dataset. Describe function is used for identifying the mean, standard deviation, minimum and maximum values and count the amount of data in our dataset. In our dataset there are minimum values as 0. So, we have converted the 0 values to nan values by using the Column method. First in Pregnancies column using with column when in the dataset containing number equal to 0 to be converted to nan or otherwise it will be as it is. By applying this technique zeros are converted into nan in our dataset.

5.3.5.4 Applying Imputer Function

HealthcareApp Python

Thajeef THANGARAJAH'... File Edit View: Standard Run All Clear

Cmd 11

```python
from pyspark.ml.feature import Imputer
imputing=Imputer(inputCols=["Pregnancies","Glucose","BloodPressure","SkinThickness","Insulin","BMI","DiabetesPedigreeFunction","Age"],
                 outputCols=["Pregnancies","Glucose","BloodPressure","SkinThickness","Insulin","BMI","DiabetesPedigreeFunction","Age"])
model=imputing.fit(diabetes_dataset)
diabetes_dataset=model.transform(diabetes_dataset)
diabetes_dataset.show(5)
```

(5) Spark Jobs

(1) MLflow run

Logged 1 run to an experiment in MLflow. Learn more

diabetes_dataset: pyspark.sql.dataframe.DataFrame = [Pregnancies: double, Glucose: double ... 7 more fields]

```
+-----------------+-------+-------------+------------------+-----------------+----+------------------------+----+-------+
|      Pregnancies|Glucose|BloodPressure|     SkinThickness|          Insulin| BMI|DiabetesPedigreeFunction| Age|Outcome|
+-----------------+-------+-------------+------------------+-----------------+----+------------------------+----+-------+
|              6.0|  148.0|         72.0|              35.0|155.5482233502538|33.6|                   0.627|50.0|      1|
|              1.0|   85.0|         66.0|              29.0|155.5482233502538|26.6|                   0.351|31.0|      0|
|              8.0|  183.0|         64.0|29.153419593345657|155.5482233502538|23.3|                   0.672|32.0|      1|
|              1.0|   89.0|         66.0|              23.0|             94.0|28.1|                   0.167|21.0|      0|
|4.494672754946728|  137.0|         40.0|              35.0|            168.0|43.1|                   2.288|33.0|      1|
+-----------------+-------+-------------+------------------+-----------------+----+------------------------+----+-------+
only showing top 5 rows
```

1

Command took 3.74 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:07:00 PM on Thajeef THANGARAJAH's Cluster

Figure 27 Applying Imputer Function

Therefore, in our dataset, zeros values are converted into nan values. By using the Imputer function we can convert the nan values into any other random values related to our dataset. For example, in the Insulin column nan values are converted into random values as 155.54.

5.3.5.5 Applying Vector assembler and Standard scaler

HealthcareApp Python

Thajeef THANGARAJAH'... File Edit View: Standard Run All Clear

Cmd 12

```python
columns=diabetes_dataset.columns
columns.remove("Outcome")
# Import vector assembler
from pyspark.ml.feature import VectorAssembler
builder = VectorAssembler(inputCols=columns,outputCol="assembled_features")
# Transform the dataset
diabetes_dataset=builder.transform(diabetes_dataset)
diabetes_dataset.select("assembled_features").show(5,truncate=False)
```

(1) Spark Jobs

diabetes_dataset: pyspark.sql.dataframe.DataFrame = [Pregnancies: double, Glucose: double ... 8 more fields]

```
+---------------------------------------------------------------------+
|assembled_features                                                   |
+---------------------------------------------------------------------+
|[6.0,148.0,72.0,35.0,155.5482233502538,33.6,0.627,50.0]              |
|[1.0,85.0,66.0,29.0,155.5482233502538,26.6,0.351,31.0]               |
|[8.0,183.0,64.0,29.153419593345657,155.5482233502538,23.3,0.672,32.0]|
|[1.0,89.0,66.0,23.0,94.0,28.1,0.167,21.0]                            |
|[4.494672754946728,137.0,40.0,35.0,168.0,43.1,2.288,33.0]            |
+---------------------------------------------------------------------+
only showing top 5 rows
```

Command took 0.69 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:07:12 PM on Thajeef THANGARAJAH's Cluster

HealthcareApp Python

Thajeef THANGARAJAH'... File Edit View: Standard Run All Clear

Cmd 13

```python
from pyspark.ml.feature import StandardScaler
ss=StandardScaler().setInputCol("assembled_features").setOutputCol("Scaled_features")
diabetes_dataset=ss.fit(diabetes_dataset).transform(diabetes_dataset)
diabetes_dataset.select("assembled_features","Scaled_features").show(5)
```

(3) Spark Jobs

(1) MLflow run

Logged 1 run to an experiment in MLflow. Learn more

diabetes_dataset: pyspark.sql.dataframe.DataFrame = [Pregnancies: double, Glucose: double ... 9 more fields]

```
+--------------------+--------------------+
|  assembled_features|     Scaled_features|
+--------------------+--------------------+
|[6.0,148.0,72.0,3...|[2.01653909662368...|
|[1.0,85.0,66.0,29...|[0.33608984943728...|
|[8.0,183.0,64.0,2...|[2.68871879549824...|
|[1.0,89.0,66.0,23...|[0.33608984943728...|
|[4.49467275494672...|[1.51061388947989...|
+--------------------+--------------------+
only showing top 5 rows
```

Command took 1.55 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:07:20 PM on Thajeef THANGARAJAH's Cluster

Figure 28 Applying Vector Assembler and Standard Scaler

Accordingly, we are selecting the columns that we are going to assemble. And in the column, we are removing the outcome column which is our target column for prediction. By using the Machine learning Vector Assembler feature we can assemble all columns into one column. Hence all columns are transferred into the assembled features column. Consequently, the Standard scaler feature is used for scaling the data between 0 and 1. For scaling the data we are setting the output column as Scaled features.

5.3.5.6 Feature Selection using Filter method

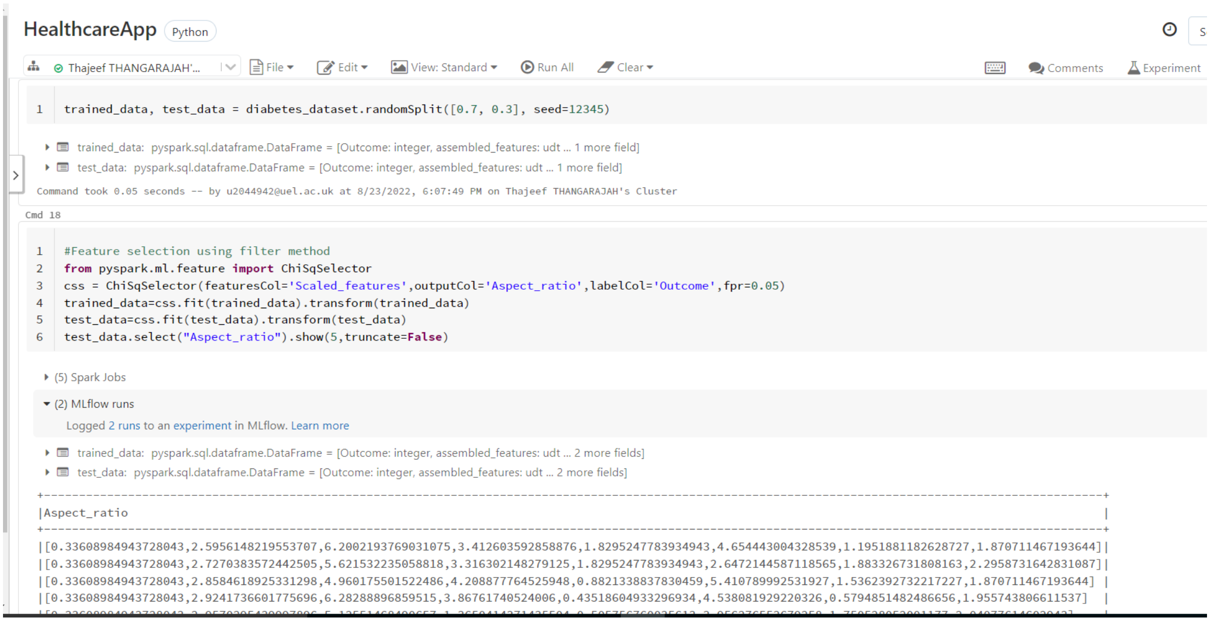


Figure 29 Feature Selection

Therefore, in the machine learning model we must split the data into training and testing data. For training almost 70% of the data and for testing 30% of the data consumed. Following up, using the filter method for feature selection in our dataset. In this model ChiSq selector filter method is performed. This method is for identifying the topmost features in the dataset which performs categorical features to predict the outcome.

5.3.5.7 Classification using Logistic Regression

Cmd 19

```python
from pyspark.ml.classification import LogisticRegression
logistic_R = LogisticRegression(labelCol="Outcome", featuresCol="Aspect_ratio", maxIter=10)
logistic_R_model=logistic_R.fit(trained_data)
test_prediction = logistic_R_model.transform(test_data)
test_prediction.show(5)
```

(19) Spark Jobs

(1) MLflow run

Logged 1 run to an experiment in MLflow. Learn more

test_prediction: pyspark.sql.dataframe.DataFrame = [Outcome: integer, assembled_features: udt ... 5 more fields]

```
+-------+--------------------+--------------------+--------------------+--------------------+--------------------+----------+
|Outcome|  assembled_features|     Scaled_features|        Aspect_ratio|       rawPrediction|         probability|prediction|
+-------+--------------------+--------------------+--------------------+--------------------+--------------------+----------+
|      0|[1.0,79.0,75.0,30...|[0.33608984943728...|[0.33608984943728...|[3.15920597208480...|[0.95926993417353...|       0.0|
|      0|[1.0,83.0,68.0,29...|[0.33608984943728...|[0.33608984943728...|[4.10746343949383...|[0.98381675869599...|       0.0|
|      0|[1.0,87.0,60.0,37...|[0.33608984943728...|[0.33608984943728...|[2.07745367512527...|[0.88869240456035...|       0.0|
|      0|[1.0,89.0,76.0,34...|[0.33608984943728...|[0.33608984943728...|[2.95425058789128...|[0.95046399903246...|       0.0|
|      0|[1.0,90.0,62.0,12...|[0.33608984943728...|[0.33608984943728...|[2.80224692656010...|[0.94279712307415...|       0.0|
+-------+--------------------+--------------------+--------------------+--------------------+--------------------+----------+
only showing top 5 rows
```

Command took 4.29 minutes -- by u2044942@uel.ac.uk at 8/23/2022, 6:08:05 PM on Thajeef THANGARAJAH's Cluster

HealthcareApp Python

Thajeef THANGARAJAH'... File Edit View: Standard Run All Clear

Cmd 20

```python
from pyspark.ml.evaluation import BinaryClassificationEvaluator
evaluation = BinaryClassificationEvaluator(rawPredictionCol="rawPrediction",labelCol="Outcome",metricName="areaUnderROC")
area_under_ROC = evaluation.evaluate(test_prediction)
print("The area under ROC Curve is:",area_under_ROC)
```

(3) Spark Jobs

```
The area under ROC Curve is: 0.8374757460962758
```

Command took 1.89 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:13:05 PM on Thajeef THANGARAJAH's Cluster

Figure 30 Logistic Regression

For binary classification models, Logistic regression is the perfect classification Machine learning feature to predict the outcome. Logistic regression model predicts the dependent variable by analysing relationships between the various independent variables. By choosing our label column as Outcome and our features column to be what we achieved from the feature selection method as aspect ratio. By fitting the model and to transform the dataset. For Evaluation, Binary classification evaluator ML techniques are followed. Area under the ROC curve is the metric name for binary classification evaluator. Higher AUROC will be preferable; the model is predicting the negative classes as 0 and positive classes as 1. In this model 83% of the AUROC is predicted which is a good one.

5.3.5.8 Finding Accuracy

Cmd 21

```
True_positive = test_prediction[(test_prediction.Outcome==0)& (test_prediction.prediction==0)].count()
print("True positive rate is :",True_positive)
True_negative = test_prediction[(test_prediction.Outcome==1)& (test_prediction.prediction==1)].count()
print("True negative rate is :",True_negative)
False_positive = test_prediction[(test_prediction.Outcome==1)& (test_prediction.prediction==0)].count()
print("False positive rate is :",False_positive)
False_negative = test_prediction[(test_prediction.Outcome==0)& (test_prediction.prediction==1)].count()
print("False negative rate is :",False_negative)
```

▸ (8) Spark Jobs

```
True positive rate is : 123
True negative rate is : 45
False positive rate is : 34
False negative rate is : 14
```

Command took 1.83 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:13:17 PM on Thajeef THANGARAJAH's Cluster

HealthcareApp Python

Thajeef THANGARAJAH'... File Edit View: Standard Run All Clear

Cmd 22

```
#Calculating accuracy
accuracy = float((True_positive+True_negative)/(test_prediction.count()))
print("The Accuracy of the model is:",accuracy)
```

▸ (2) Spark Jobs

```
The Accuracy of the model is: 0.7777777777777778
```

Command took 0.46 seconds -- by u2044942@uel.ac.uk at 8/23/2022, 6:13:27 PM on Thajeef THANGARAJAH's Cluster

Figure 31 Accuracy of the Model

Another metric used for predicting the model is accuracy. The term accuracy is defined as the number of accurate predictions to the total number of predictions. Accurate predictions which are considered as correct predictions of positive and negative, and the total number of predictions are identified as correct predictions of positive and negative and incorrect predictions of positive and negative.

In this model,

Correct positive prediction = 123

Correct negative prediction = 45

Incorrect positive prediction = 34

Incorrect negative prediction = 14

For this dataset, we got 77% accuracy which is almost a good model. By using machine learning models, we can easily predict the patients results with the required datasets. A cloud-based platform called Azure Data Bricks Machine Learning makes it easier to create, implement, and maintain predictive analytics systems. You can predict behaviour, results, and trends using these models.

5.4 Summary

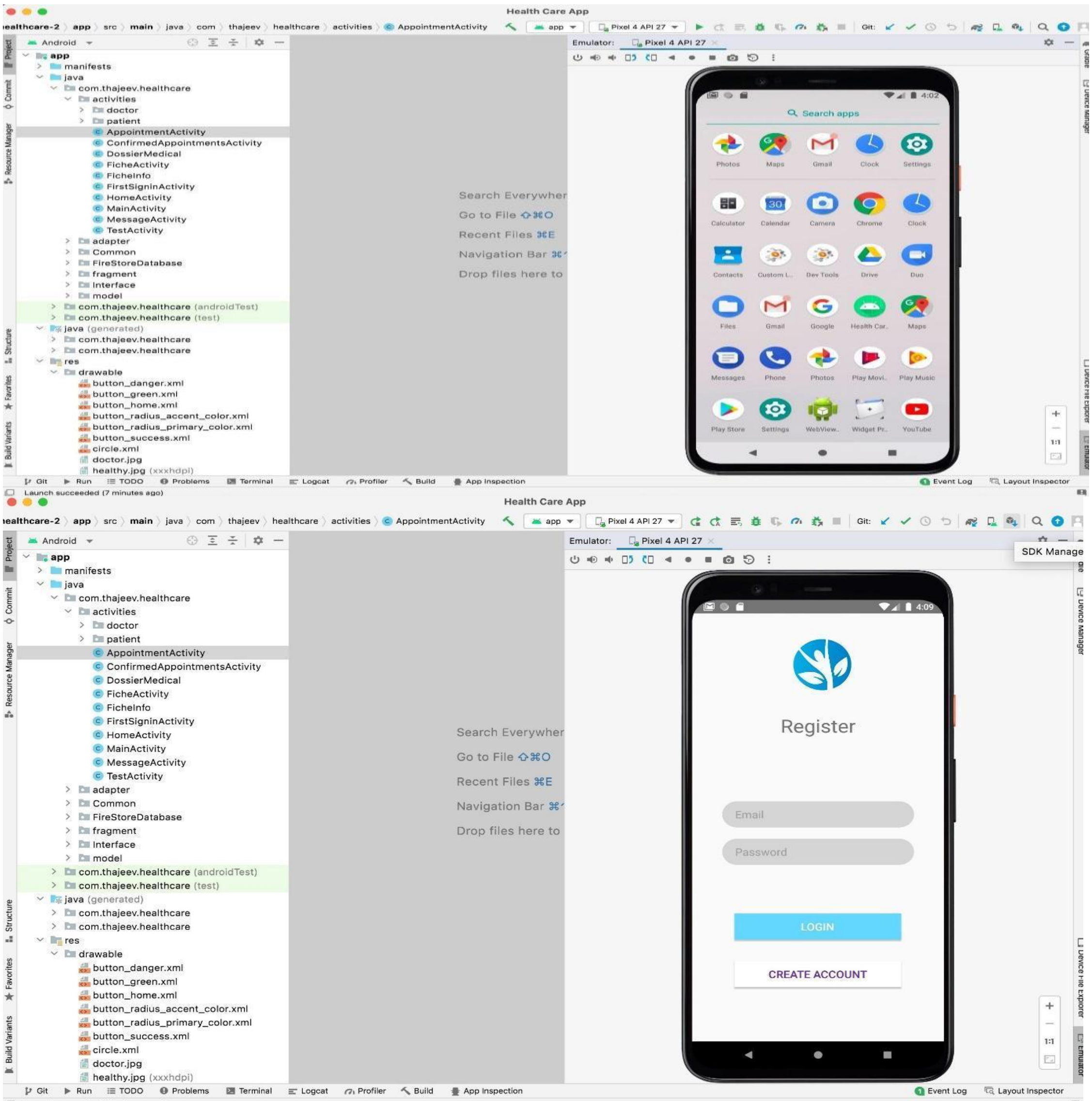


Figure 32 App Running on Android Emulator

By running the app on an android emulator in API level 27 and our healthcare app is running. Android Emulator is a virtual device in which we can run the applications virtually.

Patients Dashboard:

This is the final running app for patients. It indicates the patient's home screen, patient's profile, searching the available doctors for booking appointments, selecting the appointment time and date, what is the purpose of the appointment and at last the confirmation of the appointment.

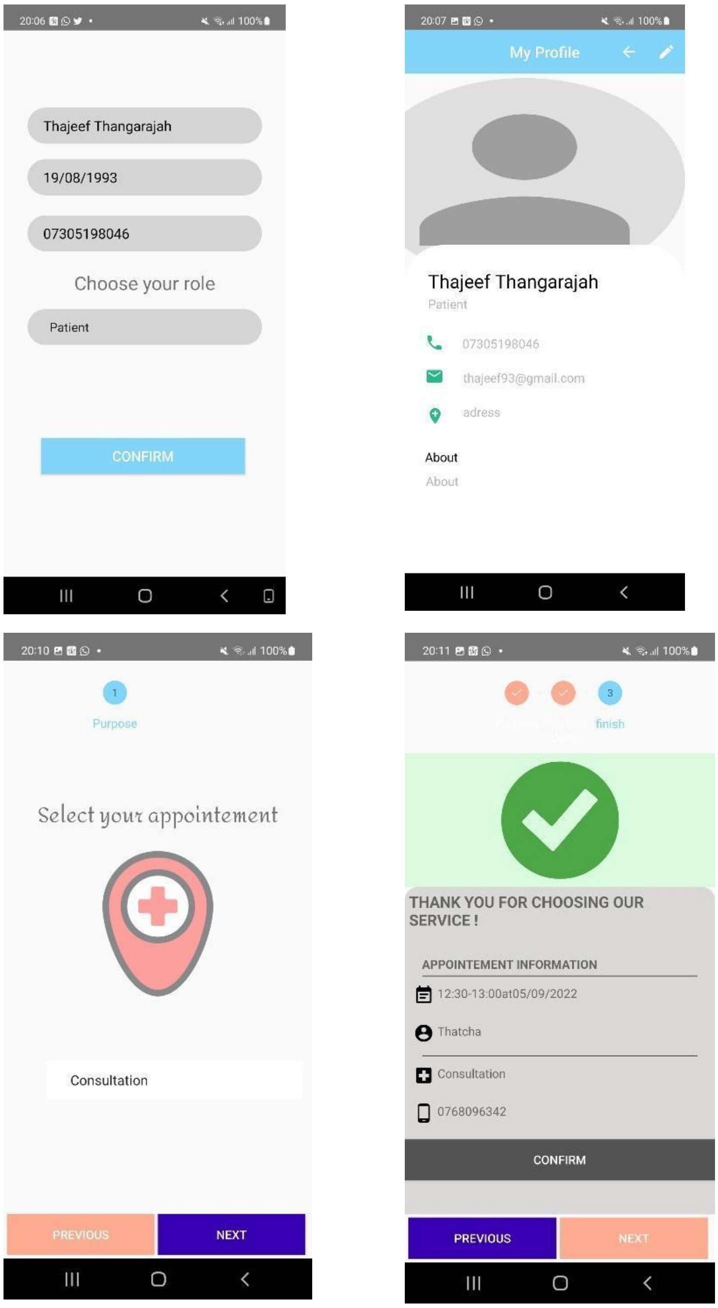


Figure 33 Patients Dashboard

Doctor Dashboard:

Final doctor dashboards list the doctor home screen, doctor's profile, requested appointments from the patient's screen, my patients list, my calendar for doctor's availability, and the confirmation screen of appointments.

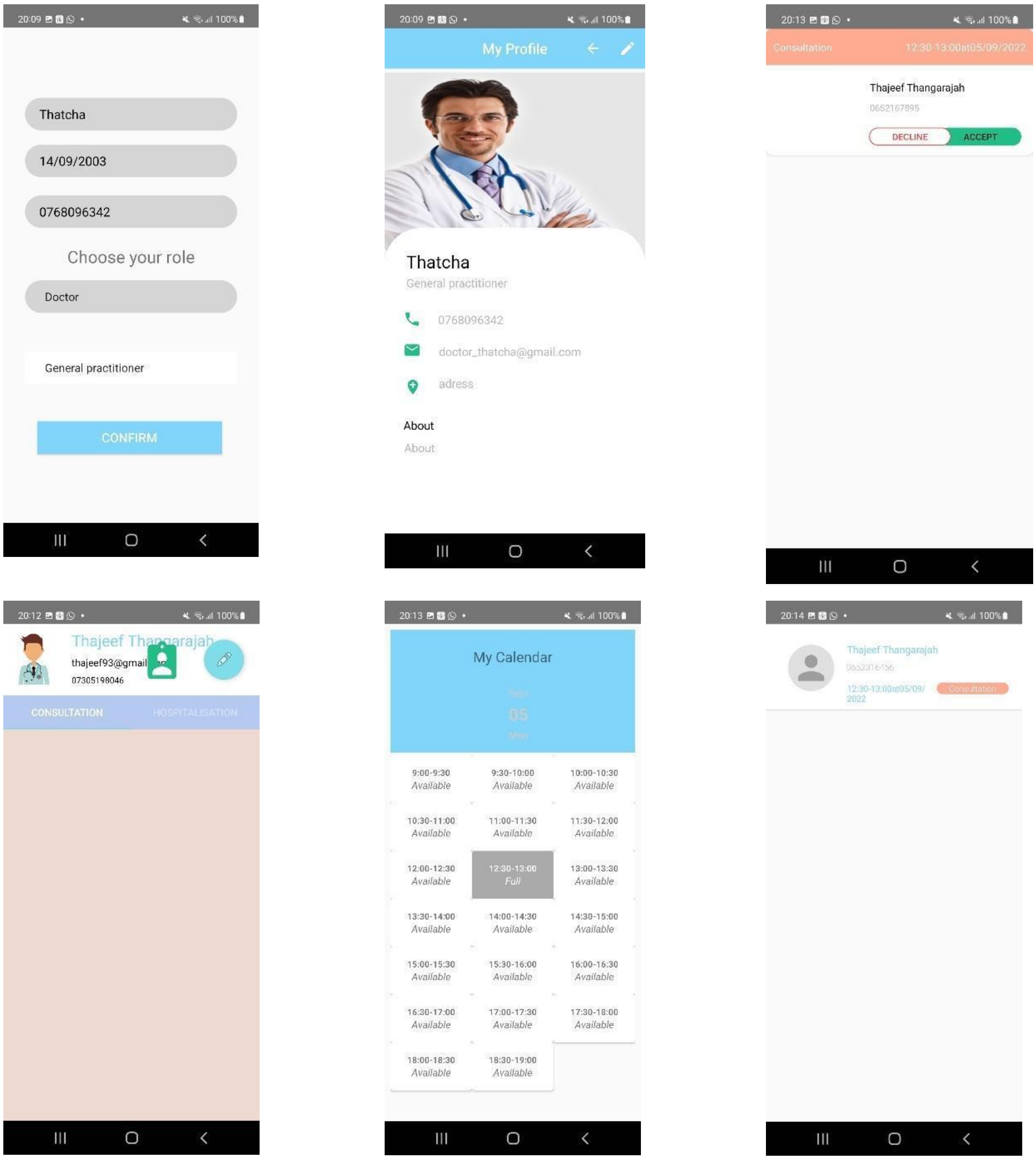


Figure 34 Doctor Dashboard

CHAPTER 6: DISCUSSION

500 billion Euros in yearly revenue are generated by measuring devices in Europe that are regulated by law, and they play a key role in the economy by fostering confidence among all stakeholders. This paper addresses both needs and duties in the Legal Metrology framework and presents a secure cloud approach architecture for measuring equipment. A new position of a Cloud Service Provider must be created with the use of cloud computing networks in legal metrology. To establish if cloud computing may be included into the legal framework, the general access of the achieved architecture must be assessed. Each layer of the cloud is handled and meticulously examined against the fundamental standards for Legal Metrology using a bottom-up methodology.

My Research Questions was:

RQ1: How will integration of machine learning help to secure end-to-end encryption of communication modes between patient-doctor?

RQ2: How can cloud computing architecture be integral in securing data encryption within the communication matrix?

It becomes more difficult to ensure the security including integrity of the measurements when a well-contained measuring device is divided into a dispersed measuring system. Technologies like completely homomorphic encryption, which addresses these issues, are assessed, enhanced, and deployed to allow computations on encrypted measurements. To meet the need for integrity of encrypted measures throughout their lifespan, a secure communication protocol for encrypted data is also described. Finally, a continuous monitoring strategy is provided to identify abnormalities and classify system behaviour into three categories—green, yellow, and red—based on their severity and effect.

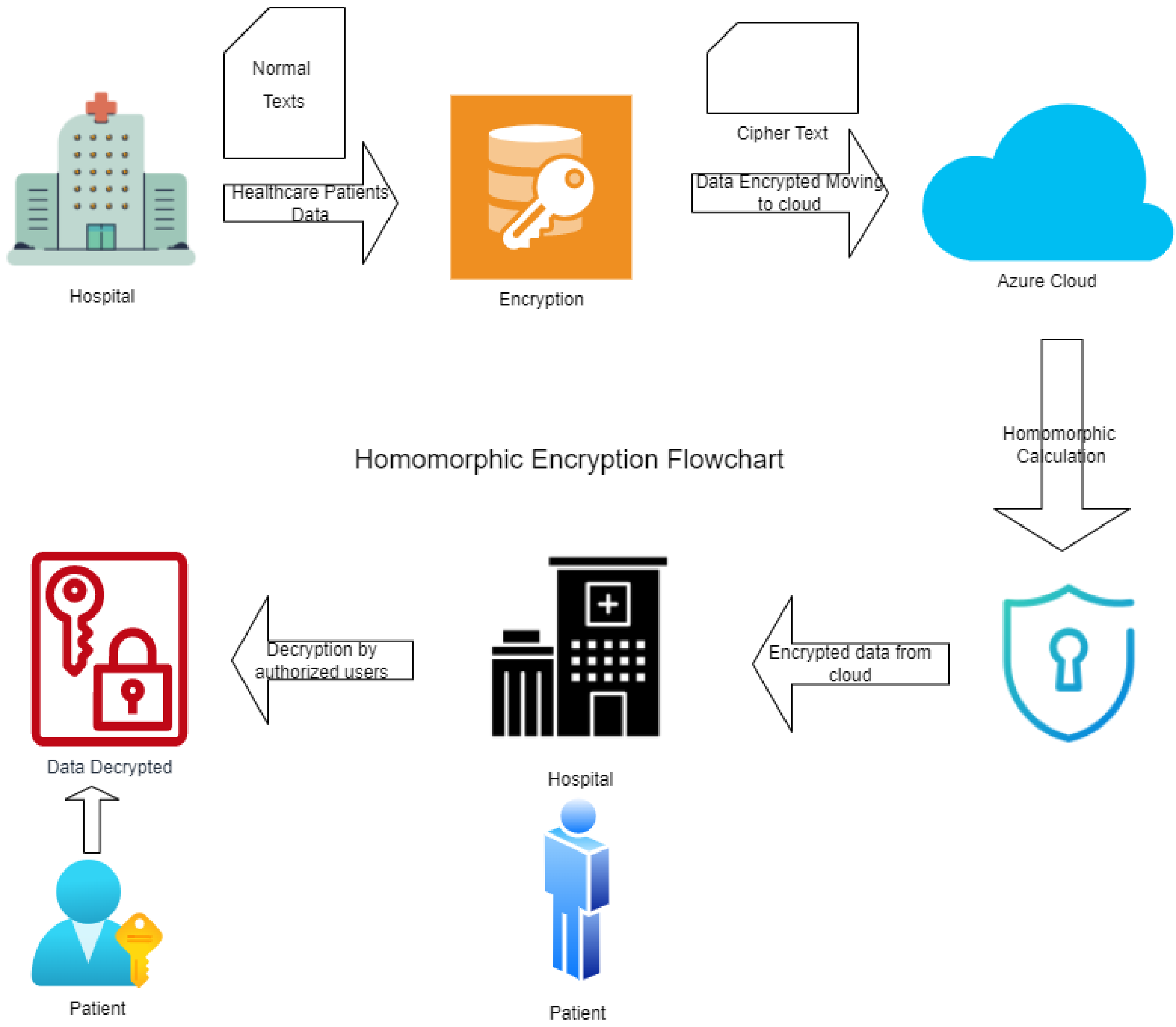


Figure 35 Flowchart of Homomorphic Encryption

A patient's history and other pertinent information are contained in their patient health record (PHR), which is fundamental and significant data. The platform for sending as well as receiving patient health data is regarded as the digital healthcare system. The digital healthcare systems that are now in use, however, rely on centralised servers that are more effective for security breaches. As a result, due to its many uses and enhanced security, blockchain technology integration is the most straightforward option. More crucially, blockchain offers decentralised and peer-to-peer (P2P) network solutions. Generally, blockchains fall into one of three categories: private, public, or consortium blockchains.

All the parties concerned may have confidence and security because of this. For building contracts and network applications, Hyperledger Fabric supports Java, Node.js, etc. and is not domain specific. In industrial applications, the field of healthcare is regarded as crucial. Patients' bodily characteristics, including heart rate, diabetes, electroencephalogram, and other essential biomedical signals, may be monitored in addition to a traditional medical diagnostic by integrating a variety of medical sensing devices for diagnosis and health quality improvement. Sharing information for policy making, biological research, and medical diagnostics may be done securely and with ease. The Internet of substances has been suggested to raise industry standards, overcome geographic barriers for remote monitoring, carry out autonomous manufacturing, and provide consumers with real-time information.

For instance, the healthcare sector may frequently benefit from the IoT, where wearable devices made of industrial sensors including actuators are utilised to gather users' physiological data including temperature, electrocardiogram (ECG), blood pressure, and other measurements. These physiological groups are often transferred to the user's local devices or servers for additional data gathering and aggregation before being sent over an open channel, or the Internet, for diagnosis and input to an industrial supplier. However, because the nodes in an IoT network are always connected, it is susceptible to security problems including message tampering, eavesdropping, including denial of service assaults.

Numerous searchable encryption (SE) techniques exist to address the issues raised above, but they are less effective in terms of adaptability and anonymity. Several factors, including single write (SW), single read (SR), multiple write (MW), including multiple read (MR) techniques, can be used to divide SE into several categories. When used with server-based architecture or the cloud, however, all SE methods are less effective. Secure searchable encryption (SSE), that enables users to encode the data networks on their own service without the participation of a third group, is one of the most promising and safe solutions to overcome these challenges. Asymmetric SSE including Symmetric SSE are the two categories into which secure searchable encryption may be separated. The Obvious Cross Tag searching technique was suggested by the authors. OXT aims to maximise the benefits of the protocol by dispersing all master keys across all users. The issue with OXT is that it is more vulnerable to attacks using key loss or cooperation. Our suggested strategy is more resistant to instances including active collusion attacks and key loss. Additionally, the solution we've suggested is adaptable enough to be used with a variety of platforms, including social networking, fog computing, including other IoT-based services. They have put out an enhanced multi-user-extended SSE that enables users to safely query the distributed ledger using whatever keywords they want. The patient initially encrypts the data before uploading it to the cryptographic ledger.

Cloud computing, which is renowned for its adaptability including accessibility, is a multifaceted pathway for data safety. Because the owner of the data has little control over it, outsourcing data to the cloud may be viewed as insecure because this might lead to further security concerns. In a similar vein, when it approaches to the healthcare sector, security concerns take precedence. Dealing with medical dataset is a common worry because the most of contemporary healthcare data including patient information are kept in the cloud. Sensitive patient information included in digital health records is among the most valuable and secured data, but it is also effective because of the cloud-dependent platform, that provides shady third parties greater opportunities to access or creep the data because of the market value. Even though access control frameworks and schemes have advanced, there are still problems with the suggested systems. These include identity dependence, role- and purpose-based approach control methods, and the lack of measurement granularity in authorization. The only approaches used by the current access control system are identity-based, role-based, and attribute-based. It has been determined through a group of comparative analyses that ABE is the best suitable access control approach out of the options currently available. The security limitations of attribute-based encryption are not solved by public-key encryption. As a result, we adopted Attribute Based Signature in the suggested solution since it ensures the signer's anonymity and unforgeability.

CHAPTER 7: CONCLUSION

In this work, we leverage blockchain and DL to create a digital healthcare system with a secure phrase search facility for end users. This facility is made possible by a unique extended approach to homomorphic encryption. By ensuring that data is immutable, tamper-resistant, and securely delivered, our suggested approach helps to reduce the number of security breaches that occur in the healthcare industry. DoS, DDoS, and collusion-resistant assaults may now be predicted and monitored thanks to the use of deep learning to train the model. Our data set has been split into two parts for the purposes of training and classification: the training data set, which comprises 70% of the total, and the testing data set, which comprises 30% of the whole. In addition, with our unique technique, blockchain users may encrypt data locally before adding it to the distributed ledger. Homomorphic SSE allows users to look for encrypted health information without needing to decode it. We have compared our results to those of established models.

Due to the adaptability of the proposed policy revocation, it is immune to aggressive collusion and replay assaults. In addition to these benefits, distributed data, resilience, in digital systems and fault tolerance are all facilitated by blockchain technology. The suggested research addressed and resolved existing issues facing the digital healthcare sector in the existing literature. To ensure the confidentiality and security of PHR data, we have suggested a framework including algorithms that implement an access control rule for users. The suggested technique promotes greater user autonomy and allows for both broad and specific keyword searches. Using the Hyperledger fabric tool, we ran simulations to prove the efficacy of our suggested research techniques and policies. For the purpose of data analysis, we employed PyCharm. Our method is the most recent strategy, and it has been used successfully in healthcare including blockchain technology as a pilot project. When compared to reference models like Medrec, Medchain, and Medbichain, we have enhanced privacy and anonymity. Future work might include incorporating more deep learning techniques, such as categorization approaches, into the proposed model.

As breakthroughs in computer vision have occurred simultaneously with other areas of AI, medical imaging has probably seen some of the most significant progress. However, security and privacy concerns are not unique to the medical imaging industry, as evidenced by the 2020 SARS-CoV2-widespread, which raised global access about the political, legal, and ethical, precedents that could be set by large-scale automated contact tracing as well as movement tracking and prompted a push for the secure and privacy-securing technical implementation of such systems. All AI applications, notably those involving sensitive data, play out in a multi-marketer tension field characterised by competing priorities. More people's private information is being used without their consent than previously thought, and this trend is only expected to accelerate, especially when it comes to commercial gain. However, the proposed methods provide a chance to avoid having stakeholder relationships devolve into a lose-lose situation (Richter K, 2005).

We believe the following areas of multi-disciplinary study and investment are necessary for the mainstream deployment of safe and private AI. The recent success in medical imaging and genomics demonstrates that decentralised data storage and federated learning systems have the greatest capacity to enable privacy-protecting cross-institutional research across a variety of biomedical fields in the upcoming future. More efficient cryptography and privacy primitives, including neural network searches based on methods such functional encryption, including quantization, and optimization policies, including encrypted transfer gaining approaches are needed to address the limitations of the currently available methods. Thirdly, there must be investigation into the privacy-utility trade-offs including measures of precision, interpretability, fairness, bias, and anonymity. For example, in radiology, intermediate outputs may be obfuscated and difficult to decipher in an encrypted context, yet assessment of trained databases on new pictures or investigation of the input data are still possible (Anderson J, 2020).

This problem can be solved by the interpretable private algorithms that are now the subject of intense study. Expertise in cryptography is needed for the design and implementation of safe and valuable systems that are resistant to (or at least disclose) faults due to technical strategies and are also resilient to semi-honest or maybe dishonest participants/adversaries trying to weaken the system. Fifth, it might be challenging to keep an eye on and potentially fix deployed models for temporal instability if the data or methods involved are encrypted. Research must address the topic of how the right to be forgotten (such as GDPR) may be accomplished, including through machine unlearning until truly safe and private solutions become the norm. The broad adoption of safe and private AI solutions by individuals and politicians will be facilitated by the success of auditable including objectively secured systems (which is, not dependent on subjective assertions—such as, by governments). In a data economy that is in flux due to an oversupply, the idea of personal data as a scant including valuable resource will be reinforced by innovative ways to quantify and track the supplementary measure of data groups regarding algorithm performance, and the technological capacity supplied by secure including private AI solutions to keep sovereignty over one's identity (Neppe V, 2008).

Recommendations:

Utilising optical character recognition (OCR) technology on doctors' handwriting to streamline data input is one use of machine learning in healthcare. Decision-making and medical treatment can benefit from further analysis of this data using other machine learning applications. The term "artificial intelligence in healthcare" (or "AI in healthcare") refers to the application of machine learning algorithms including other cognitive strategies in the healthcare industry. Simply explained, artificial intelligence (AI) is the ability of computers and other machines to learn, understand, and make decisions or take actions in ways that are like human beings (Lanke E, 2008).

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