A Mobile Cloud Computing Framework for Real-Time Big Data Analytics in Healthcare

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A Mobile Cloud Computing Framework for Real-Time Big Data Analytics in Healthcare

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Abstract

The importance of using the healthcare systems to support increased data volumes requires advanced solutions for storing, processing and using the data. Mobile Cloud Computing (MCC) combined with big data analytics solves the memory, computational power and power constrains of portable devices. To sum, MCC in healthcare can improve data handling, processing, decisions making as well as diagnostics, treatment, and patient outcomes in areas where inefficiencies cause significant issues. The Mobile Cloud Computing framework proposed includes real time big data processing for increased healthcare accuracy and scalability. This system has the potential to improve patient results and optimizing healthcare resources using secure, cloud-based predictive modeling.

1 Introduction

The throughput of healthcare information over the recent past has greatly increased due to various factors such as demographic growth, increase in disease prevalence and advance in information technology tools in the health sector. This influx of data, commonly known as big data, is extremely troublesome as it provides limitations on how it can be stored, managed and analysed. To overcome these challenges, this paper puts forward an integration of Mobile Cloud Computing (MCC) with Big Data Analytics (BDA). MCC allows mobile devices to shift computationally intensive tasks to a cloud thereby increasing the capability for real-time data analysis and control. These can be most effective when used together such that it alters the way healthcare providers work with their data to present, analyse, and feed into patient care provision. The primary subject of this paper lies in enhancing the existing MCC model to improve healthcare outcomes through analysis of big data.

1.1 Background

In fact, care delivery organizations in healthcare sector deals with enormous data coming from EHRs, diagnostic images, wearable health devices and many more in health facility. In order to enhance the care of patients and to minimize wastes and unnecessary costs, as well as to make decisions, the data has to be managed effectively. However, for a class of devices that is considered increasingly crucial in the healthcare industry, mobile devices severely suffer from limited computational capabilities and memory, as well as battery capacity. These limitations are resolved in MCC by directing a lot of demands and computing to the cloud-servers thus providing security and expandability. The integration of big data analytics with MCC enables healthcare providers to analyse such BIG data and gain useful info toward predicting patient status and improving diagnosis and treatment regimes.

1.2 Problem Statement

In essence, the increased dimensions and bulkiness of healthcare data how the healthcare industry receives data and how it processes that data. Mobile devices are used in the health care systems for patient surveillance and data acquisition and are computationally limited. Conventional systems are inadequate to process big data in real-time and subsequently make the needed diagnosis and treatment, often compromising patient's health. This research seeks to solve the issue of how to enhance a Mobile Cloud Computing framework to analyse big data in the health care sector with regards to the management of real time data and accuracy of the results.

1.3 Research Question

How can Mobile Cloud Computing be optimized for real-time big data analytics in healthcare applications to improve patient outcome prediction?

1.4 Aims and Objectives

The aim of this research is to build and assess an improved Mobile Cloud Computing framework that incorporates big data function to improve on the current healthcare databases dealing with data management, processing and predicting. The system is implemented to be agile and capable of handling massive flows of patient details in real-time to improve the process of patient care. It expands machine learning strategies to process big healthcare data for prognostic information of the patient results. Based on the findings of the analysis of real healthcare datasets like the Healthcare Prediction Dataset obtained from Kaggle, this research illustrates the feasibility of system when applied in healthcare. Furthermore, this study identifies various barriers to data privacy and security in cloud-based healthcare systems and explores how they can be eliminated without compromising the efficiency of the healthcare system.

1.5 Structure of the report

The paper is organized as follows: Healthcare data is defined in the 1st segment and the increasing volume that creates obstacles is explained together with the reason for considering Mobile Cloud Computing (MCC) along with Big Data Analytics. It also mentions the problem, objectives and research question. Section 2 discusses literature on MCC in health care including the models, optimization algorithms, and limitations such as latency and security issues. Section 3 outlines the methodology, covering data preparation, model selection, ensemble creation, and development of backend and mobile applications. Section 4 discusses design specifications like backend with Flask implementation, integration of machine learning model and a mobile app built with React Native. Section 5 depicts implementation details that involved data pre-processing, model training and real-time app deployment. Section 6 evaluates the performance of the proposed system in terms of the ML comparators of the model and the ensemble classifier with focus on accuracy and recall. In the last section 7 of the paper, recommendations for the future as well as for further development on the work comprise federated learning, application of further complex models, and variety of health care related sectors to improve on efficiency and performance.

2 Related Work

Mobile Cloud Computing (MCC) combined with Big Data Analytics (BDA) has greatly transformed the health-care segment by extending new approaches that met challenges in the conventional health-care systems. These advancements have also helped practitioners to work with large amounts of data concerning patients, providing immediate access and better outcome. This section presents literature review based on Mobile Cloud Computing and its implementation in the field of healthcare to deal with the problem of high volumes of data and to enhance the response time of emergency healthcare services along with discussing the issues of security and latency and also several pieces of work that look at the various models and approaches involving Mobile Cloud Computing and Big Data Analytics for reshaping the healthcare domain, including real-time surveillance, emergency response systems, and assistive technologies.

2.1 A Review of Key Models and Approaches:

In review with Tawalbeh et al. (2016) MCC is combined with big data analytics to overcome the issues including memory, CPU power and battery with mobile devices. They put forward a cloudlet-based MCC architecture for networked healthcare, and emphasize how it improves healthcare applications, eliminating constrains of the limitations of mobile devices and the great benefits of big data. The paper underlines the significance of MCC in handling big data to demonstrate the approaches and instruments for analysing big data in healthcare and provides a visionary perspective on networked healthcare systems that effectively employ MCC technology.

Wang and Jin (2019) further build on the idea through samples showing how various healthcare services are enabled by MCC, enabling patients to receive health care services from any location. They consider MCC a useful method to help reduce calculations and storage on mobile devices on client terminal by displaying them at remote centres for calculation-counting. This paper aims at reviewing general architecture of MCC systems in healthcare field and introduces the optimization methods of it and security and privacy. The authors also call for goal trade-offs in the deployment of MCC by noting that MCC has multiple objectives that should be well balanced to realize desired performance, cost and latency in healthcare.

Another work by Tawalbeh, Bakhader, Mehmood, and Song (2016) also put forward a cloudlet based-MCC model that handled problems associated with bandwidth, cost and latency in mobile health care applications. They show by example how cloudlet-based models that use relatively cheaper technologies such as Wi-Fi provide better efficiency and security links than the conventional MCC models. These simulation results demonstrate that the proposed model is more accurate and efficient in terms of patient medical records archival and analysis.

2.2 Mobile Cloud Computing Systems in Healthcare: Recent Advances

The convergence of MCC in health care has provided different practices that can be utilised for capturing and managing data about the patients, monitoring the patients real time and overall general improvement of health care. Fong & Chung (2013) both proposed a noncontact ECG monitoring in the framework of MCC that provides a healthcare solution with the capability of continuously acquiring biomedical signals from the users in various locations. Mobile device is the monitoring terminal; real-time ECG signal analysis and synchronization of health data are performed in the cloud. Such a structure guarantees direct connection and provides remote access for doctors and relatives through an interface. Furthermore, real time nature of the system is of enormous benefit in timely identification of potential emergent conditions before they develop into a major health complication especially where patient is elderly. The authors Fong and Chung properly explain how a concept of mobile cloud technologies improves the patient monitoring and healthcare services in terms of practicability as well as time delays.

Karaca et al. (2019) incorporates in another study healthcare systems for stroke by adopting MCC involving mobile applications in addition to the cloud server. The system also includes an artificial neural network ANN to categorize two stroke subtypes, cardioembolic and cryptogenic, based on a dataset of strokes. The authors put forward the concept of using Android based mobile phones with cloud support for improvement of stroke diagnosis and patient management. The model makes the system scalable, available and secure and enables stroke patients to gain full control of their status through a friendly, easy to use interface that provides them with access to their records. The system is useful in increasing the quality of life for the victims through helping them to be informed of their health condition hence reducing on anxiety levels. Aimed at MCS and ANN, big data for stroke management is considered a distinctive feature in the outlined healthcare systems.

A hybrid of MCC with multi-agent systems (MAS) is discussed in the paper of Jemal et al. (2015) in the form of Medical Mobile Cloud Multi Agent System (2MCMAS). The system is envisioned to provide a variety of mobile medical services to complement various medical tasks as well as convert the typical healthcare model to a mobile one. Implementing the 2MCMAS system using both MCC and MAS, filters the enhanced medical service delivery that allows healthcare givers to deliver superior treatment. Due to its nature, the system can be used for a range of healthcare tasks, the efficient usage of the cloud facilities and portable devices for constant delivery of healthcare services. Thus, this work stresses the possibility of MCC in transforming healthcare with technology solutions.

Specifically, recent research works pointed out that MCC is set to revolutionize healthcare systems by improving the system's efficiency, real time control and enhances accessibility. Hanen, Kechaou, and Ayed (2016) suggest an improved healthcare technique by applying the MCMAS implemented in the Polyclinic ESSALEMA, Tunisia. The system takes advantage of Multimedia Controller MCC and the Android operating system in providing a more efficient health care. To validate the system's performance, the authors employed the CloudSim simulator and showed that the MCMAS outperforms various conventional healthcare applications. It seems to overcome several problems of conventional models of healthcare delivery such as data issues, including real time availability, and operational issues, thereby, making it a transformative solution in the healthcare context. This lead them to the conclusion that MCC-based systems can significantly enhance the practical application of healthcare delivery by integrating mobile devices and cloud resources.

Also, Gao, Zhi-qiang, He, Tian, and Cong (2015) developed a mobile healthcare system that uses portable medical devices and intelligent terminals during the cloud computing technology as well as services for remote healthcare services. Physiological signal data from the medical devices are wirelessly sent to smart terminals where they are displayed, stored and then transmitted to cloud platform. The cloud services platform, also it is the foundation of this system, includes both patient and healthcare provider remote management of health data. Precisely, this system enables the physicians to track the condition of their patients and make early diagnoses accurately. Smart terminals, in particular, are changing the logic of using virtual instruments since it becomes possible to load and run healthcare applications almost instantly without requiring time-consuming installation not only for patients but for doctors as well. The paper also pays much attention to the possibility of applying cloud technologies to improve the accessibility and performance of healthcare facilities.

In another study, Jemal, Kechaou, Ayed, and Alimi (2015) on Using Mobile Cloud Computing for Healthcare Demand a new Medical Cloud Multi-Agent System (MCMAS) to integrate MAS with MCC healthcare. This system integration enhances the accomplishment of health care service delivery with features for MCC & MAS. Thus, the presented study shows how MCC provides new service and facilities to patients and caregivers; here, Mr. MAS if helping to make better decisions within health care organizations. With these ideas in mind, the authors are presenting a framework for integration of the mentioned technologies increasing the effectiveness of the system and the patients' quality of life. From these studies, they focus on communicating the different ways through which MCC can transform healthcare delivery through availability of sustainable, efficient and timeliness approaches to addressing patient information and care delivery.

2.3 A Focus on Optimization and Reliability:

Mobile Cloud Computing (MCC) has now attained prominence as an IT solution for improving care delivery especially in acute care settings with stringencies in timeliness and system availability. To solve the limitations of conventional emergency health care delivery systems, Nirabi and Hameed (2018) developed the Mobile Cloud Computing for Emergency Healthcare (MCCEH) model. Its model deploys cloud compute servers to minimize the response time while gaining access to essential healthcare services during disasters. Through the MCCEH model, when a user has a health emergency for instance experiencing a traffic accident, the system is able to point out the nearest medical center or specialist. Availability schedules can also be reviewed by users and then a provider of choice can be selected depending on what others have said. The goal of this model is to enhance the decision finding process in emergencies with a possibility of saving lives by lowering the time needed to link the patients to right care.

Another criterion is security in MCC systems because it is crucial for mobile health (m-health) applications. Thus, Albuquerque and Gondim (2016) discuss the threat risks arising from cloud mobility mobile health systems., cloud computing has numerous benefits, including on demand self-service, resource pooling and improved healthcare delivery, it also comes with some risks that would put medical data at risk. In their study, they outline the many security issues that IT specialists need to consider when rolling out Cloud based m-health solutions. The authors specify important aspects related to the protection against possible threats including data encryption, secure authentication, and system updates. With focus on security, the m-health systems are made more reliable by health care providers, without compromising the patient and data confidence.

The studies of Kulkarni et al. (2014) further investigate the use optimization in MCC for healthcare based on the implementation of health monitoring systems using cloud computing. They elaborate on the ubiquity rising mobile cloud services for numerous applications such as e-health, because cloud networks are always available. MCC has been integrated into healthcare networks, hospitals, and ambulatory services, which makes patients' monitoring more comfortable and received necessary medical aid easily. As the study combines the concepts of MCC with healthcare creating a coherent definition of factors that the concept can help to address, it underlines challenges like physical space constraints, security issues, and fragmented digital markets. Thus, developing applications platform-independent and non-problematic integration of medical facilities, MCC provides live overview and control of patients. This optimization is incredibly important in emergencies because the time taken to access a resource and related information can translate to an enormous difference in an individual's health condition.

2.4 Cloudlet Integration and Service Optimization:

Mobile Cloud Computing (MCC) remains an innovative concept that is transforming the non-critical and emergency, and assistive healthcare services. Hameed, Nirabi, Habaebi, and Haddad (2019) developed the MCC for Emergency Healthcare (MCCEH) model for reducing response time in emergency and providing the efficient patient care by employing the mobile applications connected with cloud computing. The MCCEH model enables a patient find the nearest medical centre or the recommended specialist for treatment after an accident and make an appointment without wasting much time on registration. This pre-booking is accompanied by tracking and messaging functionalities that assist the medical workers in getting useful information as they work. The model also has a unique feature connecting doctors and patients through messages and images, by means of application, supplying the necessary data for communication. This framework reveals that speed, security, and reliability of transmitted data is of paramount importance in emergency health care to enhance life expectancy and quality of the health care services.

Likewise, Hoang and Chen (2010) present the Mobile Cloud for Assistive Healthcare (MoCAsH) system a. The MoCAsH incorporates social architecture of cloud computing with assistive healthcare affiliated features like remote health monitoring, consulting on shared cases, and EMR storage. The following are the problems that this system solves in healthcare: Security Ownership of data Quality of service In MoCAsH, the mobile sensing and the context-aware middleware are implemented to employ intelligent resources sharing and effective medical care planning. The model deploys a federated P2P cloud to mitigate privacy; though, it reserves health data privacy while availing distributed cloud resources. It suggests that the authors strongly recommend the dedication of appropriate security measures on patient's information and yet the capability offered by cloud solution.

This is further extended by Somula et al. (2018) to understand how MCC can be incorporated into healthcare applications with the integration of cloudlets. The cloudlet model decreases the operating time (latency) and counteracts the problem of limited bandwidth because instead of uploading the bulky applications to the distant cloud, the compact working copy, or a part of it, is transferred to the cloudlet nearest to the user. In healthcare this approach means that medical records and the rest of the sensitive data will go through the necessary processing in the least time possible thereby freeing up the time that the healthcare providers would have spent in accessing and having to analyse the patient's data. If a cloudlet cannot complete the needed task, the process migrates to an alternate cloud, which is crucial to avoid slowing down medical services in any way. This reemphasizes the usefulness of Cloudlets in reorganizing the structure and delivery of health care services under conditions of limited bandwidth and high latency.

2.5 Summary

Many of the articles reviewed in this paper underscore the increasing importance of Mobile Cloud Computing (MCC) in healthcare. When integrated with Big Data Analytics, MCC responds to issues such as reduced processing and memory capability in mobile devices that improves the healthcare sector by analyzing data in real time. Chapters on cloudlet-based architectures and multi-agent MA systems have shown enhancements in latency, scalability, security, and costs. From this perspective, the MCC serves as valuable in areas such as the emergency health care where response to situation is determinative. Specifications like the MCCEH (Nirabi and Hameed, 2018) refer to care continuity during emergencies, the confidentiality of data to gain the clients' trust on the systems and data.

In summary, transformative enabler MCC holds the key to organizational change that is capable to reposition service provision in the healthcare sector to a different level through a better handling, monitoring and resultant effective delivery of data. However, it is necessary to conduct a study to overcome existing problems such as security, privacy, and latency to enhance the development of healthcare systems.

3 Research Methodology

This project was dedicated to creating a healthcare prediction system from machine learning, from backend to frontend. The backend involved the machine learning model and served by an application of the Flask framework and deployed on Google Cloud Platform (GCP). The process entailed a step-by-step procedure that inclined data loading, data processing, model designing, model assessment, integration, and implementation.

3.1 Data Gathering and Preparation

The first of these steps involved preparing a healthcare prediction dataset from which features such as patient history, test data and billing data can be derived. Data distribution testing was also done before feature scaling in order to identify variable trends more clearly using functions such as count plots and histograms for gender, age, and billing amounts. Data preparations that were performed included data cleaning where four variables were deleted from the dataset due to irrelevance and dealing with missing values. Thus, nominal features such as gender, blood type or health status were also encoded to be compatible with the majority of machine learning algorithms and eliminate dimensions. Some date features were split into year, month and day variables to detect cycles within the admissions year as seen in 'Date of Admission.' Continental codes were discretized, where numerical features were scaled using StandardScaler to normalize distributions before feeding into model.

3.2 Model Selection and Training

Logistic regression, random forest, decision tree, KNN, Gaussian Naïve Bayes and gradient boosting models were used to determine the best classifier for patient prognosis in healthcare. Training and testing were done on both 70/30 data split and with hyperparameter tuning. Evaluation parameters adopted includes Accuracy and Recall measurements, Precision level Pieces, F1-Score, and Confusion matrix. In the present study, the classifiers' variety allowed considering various decision-making strategies: probabilistic classifiers (Naive Bayes), tree-based classifiers (Random Forest, Decision trees), and ensembles (Gradient Boost). The final step of the ensemble process involved pairing together classifiers that have higher performance rates to optimize overall synergy.

3.3 Ensemble Model Creation

To improve the models' performance, an ensemble voting classifier was used involving the best three models, namely, random forest, decision tree, and gradient boosting. The ensemble model applied soft voting that calculates the average of the prediction probabilities of the individual models. When combining many algorithms' predictions, we had mitigation of the overall biases within each model and improved versatility with varied great healthcare data.

These metrics show that the accuracy, recall, and F1-score of the ensemble approach are high because it could be deployed in practice. The trained model was saved with python's pickle library which allows the model to be loaded and served in a live application environment.

3.4 Backend Development with Flask

The back end of the developed application was implemented using Flask – a easy-to-use and scalable Python framework for deploying ML models in production. The backend API includes endpoints for user registration, login, and predictions, secured with JSON Web Tokens (JWT). For user authentication SQLite was used with bcrypt for password management and encryption. The prediction endpoint received JSON inputs of healthcare features, then normalized the data using a scaler which was trained and inputs the data into the model. The given model could offer predictions with probability levels so that users can have confidence in such results. Integers results were then mapped to understand outputs such as "Normal" and "Abnormal."

3.5 Mobile Application Development

The developed mobile application gives a client-oriented AI-based tool for prognosis of health state. The predictions are available only for the signed-up and signed-in users, and the tokens are controlled with AsyncStorage for proper session. Once the user logs in, a prominent message and a button to the prediction form appears on the homepage. The main feature is the prediction form which includes personal information. Data consistency is ensured through mandatory fields and warnings for incomplete forms.

4 Design Specification

This project involves the creation of a healthcare prediction model using advanced algorithms of machine learning together with a strong and reliable backend, but with the front end implemented in mobile application so that users can easily access the predictions. The system uses Flask for the web framework, integrated with machine learning models and for scalable infrastructure, Google Cloud Platform (GCP), with a mobile application designed using React Native.

4.1 Backend Design

The backend of the healthcare prediction system is incorporated using Flask framework because of its flexibility. It employs API calls to communicate with a machine learning model and achieves user identity verification and validation with JWT Tokens. To accomplish user authentication, users receive a JWT when they register or when they are already logged in for subsequent API communication. Personal user data like username and passwords are saved in an SQLite database—any secure field is encrypted with bcrypt. The prediction API works with different inputs concerning healthcare such as age, gender and medical background. The above inputs undergo scaling using a scaler obtained from the features of a pre-existing model before feeding it to the machine learning model. The backend also produces prediction outcomes and the likelihood to show confidence levels.

4.2 Model Design

The multiple Machine Learning models are used in the healthcare prediction system which include logistic regression, random forest, decision trees, k-NN, Naive Bayes test, Gaussian test, and gradient boost models and the measures of success include basic accuracy, precision, recall, F1 score, and confusion matrix. An ensemble approach combines predictions from the top three classifiers, namely, random forest, decision tree, and gradient boosting. The advantage of this method is that it reduces individual model bias and enhances accuracy in predicting various kinds of healthcare data. For implementation of the optimized model in the web framework the Python's pickle library is used to store and dump the model. The application is hosted on GCP for high availability and scalability with actual resource and request facilitation for handling multiple requests. This follows well with GCP's auto-scale feature making it easy to handle a large number of users.

4.3 Mobile App Design

The mobile application developed from React Native allows for seamless communication and interface to interact with the healthcare prediction system. There is clickable sign-up and sign-in on the homepage. Once an Identical user verifies himself/herself, the following welcome message pops up together with a button that leads to the main prediction form. The prediction form encompasses crucial health care details which include age, sex, blood type, illness and many others. Validation helps to check if certain fields that need to be filled in must be filled before one submits the information. Dropdown and date selection is made easier with React Native's Picker and DateTime Picker. When the form is filled and submitted, the app sends the details to the API which processes it and in return gives out health probabilities. Output is shown in a pop-up window with the button to return in the application and make more predictions. The app uses Expo Router for navigation across the homepage, prediction page, and support page. To sign out of a session, there is a logout button in the header for exiting.

5 Implementation

As part of the implementation stage, it is necessary to collect a dataset containing client healthcare information with various healthcare details such as demographic details, medical history, test result and billing information. Concrete characteristics were chosen to guarantee an adequate amount of information for probability estimates. Such data were subjected to preprocessing to make it ready for use on the Machine Learning System.

5.1 Data collection and preparation

Data preview included checking for normality, skewness and checking for outliers in the data set. Histograms and count plots were used to display categorical and continuous variables which include gender, age, billing amounts, etc. These include cases where either the records were deleted or where the missing values were filled in. Four insignificant variables were removed to achieve the purpose of dimensionality reduction since the selection of model tends to give attention to the keys.

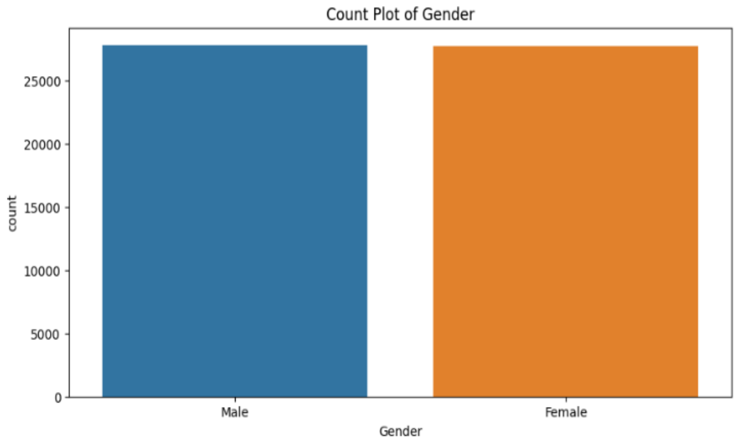

Figure 1 Count Plot of Gender

In The Count Plot of Gender, It was found that Male and Female count was approximately similar and thus no imbalance was found in it.

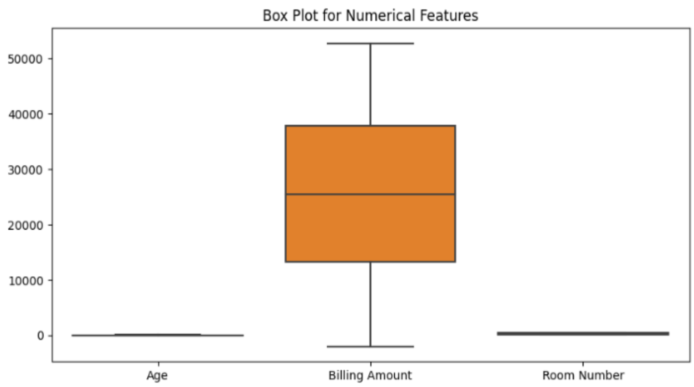

Figure 2 Box Plot for Numerical Features

The three variables: Age, Billing Amount and Room Number were plotted in the form of a box plot and there were no outliers. The Billing Amount was nearly equally distributed around

25000, whereas the Age and the Room Number were much closer with smaller ranges. Ordinary variables that are categorized into nominal varieties such as gender, blood type and health status were encoded into numerical values so as to suit the machine learning algorithms. To determine cycles of admission, column 'Date of Admission' was restructuring into year, month and day. The categorical data was done with their transformation through one-hot encoding while continuous data was transformed through Normalization using the StandardScaler.

5.2 Model Development & Training

The next stage involved testing and training machine learning algorithms such as Logistic Regression, Random Forest, Decision Trees, K Nearest Neighbors, Gaussian Naive Bayes, and Gradient Boosting to predict patient outcomes. The dataset used was split into 70% training data set and 30% testing data set to determine how well the model generalizes on unseen data. In top performing models, hyperparameters were found and tuned separately using the grid search. The models developed were evaluated utilizing accuracy, recall, precision, F1 – score, and the confusion matrix to establish the best and most accurate determinant of patient outcomes. To minimize errors, an ensemble voting classifier was created using the top three models: Decisions Trees, Random Forest and Gradient boosting. This ensemble adapted to soft voting by averaging the prediction probabilities to minimize individual model bias while boosting the overall performance of the ensemble.

5.3 Backend Development Using Flask

The next logical step after training and testing of the machine learning models was to architect the back-end for these models and to enable communication with the mobile application opted for the lightweight Python framework called Flask since it allows incorporating machine learning models easily. The application has the registration of users, data preprocessing, and giving out of prediction by the backend through a RESTful API which had the functions of registration, login, and prediction. To secure the machine learning model from information leakage, only users with the correct JWT (JSON Web Tokens) could make predictions. The prediction endpoint took a payload of input data from the mobile app, further transformed it through the same mechanisms employed at training phase (for instance, age, gender or medical state – StandardScaler) and passed it to the final ensemble model. The response contained in JSON format was the prediction (Normal, Abnormal) along with the confidence level of the prediction. For horizontal scalability and the most operational stability, the application's backend was deployed and hosted in Google Cloud Platform or GCP. To provide considerable consistency in development, testing and production the app was containerized with Docker. In deployment, a new VM instance was created and set up to run the Flask app then the Docker container was run. Through autoscaling in GCP, the application was made capable to handle multiple requests at once.

5.4 Mobile application development

The mobile application developed for both Android and iOS operating systems and is the part of the healthcare prediction system built in React Native. It supports patient communication and helps the personnel managing the system. This is signup, login and a prediction form with the fields which are age, gender, blood type, medical condition, insurance provider and details about the admission. Verification tests check all must-fill-in areas before submitting. Once a form is completed, an HTTP request is made to the backend API with the data, including a JWT in the header for account verification. After filtering, the backend performs the prediction and probability calculation, and the values are output in the form of a prediction and probability of a particular classification and are shown on the different modal window.

6 Evaluation

The healthcare prediction system was evaluated using six machine learning models: Logistic Regression, Random Forest, Decision Tree, K Nearest Neighbors (KNN), Naive Bayes and Gradient Boosting. The assessment of these models involved the use of basic parameters such as accurate, preciseness, recall value, F1 measure and confusion matrix. Moreover, in order to compare, another model: Ensemble was tested utilizing a Voting Classifier. Comparing the performance of the models gives an idea about their potential of the models in the healthcare prediction system and their limitations.

6.1 Logistic Regression

Logistic Regression produced an accuracy of 34% along with low recall and F1 scores for each of the classes. For class 0 (normal outcomes), the metrics were precision: 0.34, recall: 0.38, and F1 score: 0.36. The recall was also relatively low for class 1 (abnormal outcomes) at 0.16 thus implying that the model did not distinguish abnormal cases very well. The confusion matrix showed that there were misclassifications, and this was observed between the class 1 and class 2 hence low recall for the abnormalities. This implies that, Logistic Regression is unfit for use in predicting different forms of healthcare outcomes.

6.2 Random Forest

Precision and recall values as well as the F1 score was 1 for all classes in the Random Forest model which reached the accuracy of 100%. In the overall confusion matrix, there were no misclassification and indeed, it can be suitable for healthcare datasets with complicated correlations. Thus, it is appropriate to use it in the healthcare prediction system because of its high generalization ability.

6.3 Decision Tree

The Decision Tree model also attained the high accuracy level of one, with measures of precision, recall, and F1 that were also one for classes one, two, and three. No errors were recorded in the confusion matrix—a fact that affirmed the reality depicted by the model that is useful in interpreting data by using some of the key characteristics. Nonetheless, noisy data complicate the Decision Trees where this model tackled the dataset in a splendid manner with fine replication of performance figures.

6.4 K-Nearest Neighbours (KNN)

KNN agreed with K Nearest Neighbors and demonstrated a low level of performance with an accuracy of 36% with angel investors. Class 0 metrics were slightly better (precision: 0.Class 1 achievement was equivalently high in both cases (precision: 0.36, recall: 0.47, F1: 0.41), but class 2 recall was low (0.24). Here, there were significant discrepancies in the ability to distinguish between different classes, most probably because of a high number of features and interactions in the dataset. KNN, which uses distance metrics, was also less suitable in this aspect.

6.5 Naive Bayes

The classifications by Naive Bayes were as follows: accuracy, precision, recall, and F1 scores demonstrated a 100% rating on all classes, and the confusion matrix. The model assumed the features it extracted to be independent, and this seems to hold for this healthcare dataset resulting in generalization of the model. Despite the weakness of this model to handle interactions between features from different dimensions, Naive Bayes achieved outstanding results in this case.

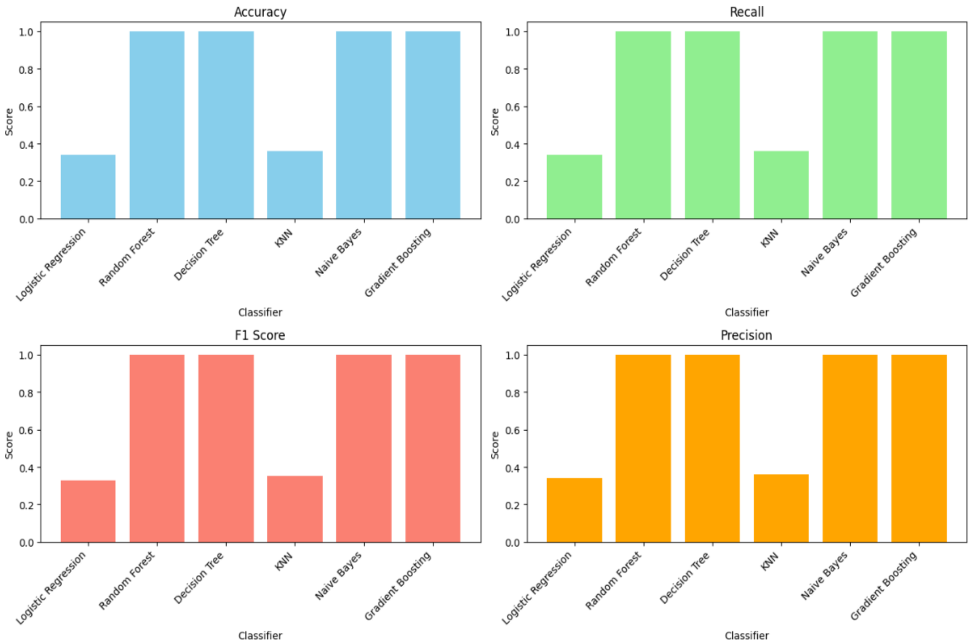

Figure 3 Model Results

6.6 Web Application Evaluation

The web application offers the users an easy way to interface with the healthcare prediction model of the issue under study. Every single page is made with simplicity, efficiency and safe viewing of healthcare information in mind.

Login and Registration Pages: The Login Page guarantees safe access, the Registration Page collects data adhering to data regulation rules. Passwords are hashed and session data has JSON Web Tokens (JWTs) over it, but predictive features are available only to authenticated users.

Home Screen: Once users log in, they are on the Home Screen from which they can access the Support Page, the Prediction Form or the logout option. Some key aspects are kept conveniently accessible through a simple organization of its interface.

Support Page: This page has a fake contact information that covers email and phone numbers that user may use to report an issue or seek help.

Prediction Page: The Prediction Page uses a validated form to collect integral healthcare variables such as age, gender, and blood type. Dropdowns and date pickers make data input easier, and requires users to complete a field if left blank. The model works through the inputs and produces predictions with their corresponding probabilities to aid users in evaluation of their results. The results are shown in a modal, with Normal/Abnormal probabilities for easier identification. The users can use the Cross to allow more prediction round or simply get back to Home Screen. Such a design makes result interpretation easier, increasing the application's realism in the healthcare environment.

6.7 Deployment and Security Assessment

Lastly, the backend which has been created by using Flask, runs on Google Cloud Platform (GCP), which is known for its infinite elasticity, negligible latency and reliability. The dynamic resource utilization of GCP ensures that the app can handle a lot of traffic from users, hence a continuous user experience. For security, the user data is encrypted, and session management is protected using JWT and strengthens the security of health care data.

```
Ensemble Model (Voting Classifier):
Accuracy: 1.0000
Recall: 1.0000
F1 Score: 1.0000
Precision: 1.0000
Confusion Matrix:
[[5589    0    0]
 [   0 5418    0]
 [   0    0 5643]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      5589
           1       1.00      1.00      1.00      5418
           2       1.00      1.00      1.00      5643

    accuracy                           1.00     16650
   macro avg       1.00      1.00      1.00     16650
weighted avg       1.00      1.00      1.00     16650
```

Figure 10: Ensemble Model Results

The results of this system show the Ensemble Voting Classifier, comprise of Random Forest and Decision Tree and Gradient Boosting resulted in 1.00 accuracy, precision, recall, and F1 score.

The structure of the user interface of the web app is sufficiently advanced to provide the necessary functionality while at the same time being sufficiently accessible for most of the population. About Page for Login, Register, Home, Support and prediction helps in providing a strong authentication security to the user. Whereas, at the moment, the Support Page contains basic example contacts, future updates can further improve the user support. Use of GCP provides safe and effective way to share the models and additional data will only improve the predictions and extend the usage of the system in the field of healthcare.

6.8 Discussion

This paper offers insights into this assessment of the healthcare prediction system and generates knowledge concerning Mobile Cloud Computing (MCC), specifically how it leverages real-time Big Data to support healthcare applications. In addition to better patient outcome prediction, this system implements and utilizes the MCC-based framework to improve the direct patient data processing and management accuracy. The next section answers the two research questions informing the current study and assesses the efficiency of MCC in healthcare.

An effective Mobile Cloud Computing strategy for real-time analysis of big data in a healthcare setting involves a delicate trade-off between computation, storage, response time, and prediction accuracy. In the current implementation, MCC has a central function by enlisting the cloud, where most of the heavy computations take place, and as a result, let the system deal with massive healthcare data and analyse them efficiently and quickly. Unlike conventional systems that perform computation on the local mobile devices, the MCC-based framework reduces processing latency while heightening the speed of the data-driven predictions. Those familiar with the development of applications for mobile devices will appreciate that this framework is highly advantageous for conserving the use of device resources and enables real time decision making even when devices are constrained.

There are any number of strategies that can be employed to achieve better MCC and ensure MCC is optimized for near real-time processing in a healthcare context, with data compression and selective data transfer being one significant way forward. A key characteristic of big mobile data is that data collected by the mobile is first compressed before being transmitted through the network to the cloud where they undergo other processing. In this system only age, gender, and blood type etc., data attributes, required for prediction only are migrated to the cloud. This selective data transmission goes further in enhancing the speed of model inference while at the same time saving on the bandwidth for real time results.

Other important optimization strategy is involving efficient machine learning models to address the big data that health information system entails. In this project, the Ensemble Voting Classifier model proposed here provided a better accuracy since many great models (Random Forest, Decision Tree, and Gradient Boosting). This ensemble model leverages MCC's computational resources to improve the robustness of the predictions at the aggregate level without the necessity to update the mobile application on a daily basis. Such a cloud-based model management enhances some aspects such as flexibility because modifications or model reclination do not affect the end-user devices. As the implementation of MCC-based healthcare systems develop, it can be complemented with deep learning and federated learning because these techniques enable real-time analysis for user-regimen with minimal latency.

Lastly, real-time optimization of MCC for analytics is concerned with the security and privacy issues since healthcare data is often sensitive. Measures such as data masking and minimization alongside controlling access to the patient data safely store and process the data on cloud in healthcare systems enabled through MCC. Real-time processing of data is enabled with the use of JSON Web Tokens (JWTs) for session management, cloud-platform specific security mechanisms The application layer also introduces stricter session control mechanisms that complement the employed real-time analytics security features.

The integration of the proposed MCC-based solution delivers substantial improvements in the data management within the healthcare systems and the hospital in particular by providing the centralized storage, large scale data processing and high speed data access to support the Predictive Analytical models. Unlike most health care apps that keep much of the data locally, MCC stores the data on cloud servers so that the health care givers can analyze enormous data without stressing their handheld devices. This control, coordination, and convergence model of HP achieves uniformity, integration, and synchronization of data generated from multiple sources like mobile, wearable, and electronic health record systems. It also reduces data issues health care providers encounter when managing patients' health data and the prediction outcome.

Cloud processing of the framework improves the efficiency of analysis; it can use computational capacities of the cloud to run intricate machine learning algorithms. For instance, Random Forest and Gradient Boosting had a score of 1 for accuracy, precision, recall, and F1-score demonstrating the high reliability of the framework. This capability enables these models to operate as designed, without the restraints imposed by consumer mobile devices' hardware and attendant constraints. Apparently, the MCC-based system allows high-accuracy models to be centralized on the cloud to provide constant and accurate predictions while on the patients' monitoring in real-time makes it possible in clinical practice.

Moreover, the MCC framework enhances response rate in data acquisition and processing since it is applicable under emergency conditions in healthcare. Whenever the patient is in a critical condition, the healthcare provider has to get results from a predictive model as quickly as possible, which guarantees that with the MCC's large-scale computation, it will be possible to deliver the results as quickly as possible during the high influx of data. Another advantage of having this all set up is the response time of interventions as healthcare players can get notifications on the state of health of the patient in question to take corrective measures in a short time. The scalable resources on the cloud that the system supports can also ensure that the demand on the server is steady and constant, which is paramount, especially in huge health care facilities.

The same goes for the MCC-based framework since the models can be deployed to the cloud and updated as needed due to version control advantages of the cloud application model. If the model requires training or tuning, these changes can be done at the cloud level without the need for individual installations at the client's mobile gadgets. This aspect of MCC of streamlining model lifecycle makes it easier for the healthcare provider to always have the latest and accurate decision-making metrics.

Secondly, the web application component improves the extent to which users can access and engage with the MCC framework. Hence the Login and Registration pages provide secure entry to the system with Home Screen providing right click to screen and the Support Page, Prediction Form or Log out as another option for the healthcare providers in the management of clients. The Support Page with contact information to contact user support makes the system more secure while the Prediction Page enables the quick entry of important health data enabling quick accurate predictions through cloud hosted model. The MCC-based framework enhances patient data with cloud analytics as it produces real-time big data analytics, which is useful in enhancing patient care quality together with healthcare resources.

MCC-based framework for healthcare prediction has proved the possibility of augmenting both healthcare prediction and data management in a purpose-built healthcare system. Through focusing computation on the cloud, maximizing data transfer rate, and protecting patients' data, MCC ensures efficient consequent assessing of the individual's health state, necessary for the bettering of the outcomes. This approach corresponds to both research questions and underlines MCC's significant function in providing high-quality accessible Health Applications. The principle of the MCC framework offers a research direction for healthcare analytics; it opens possibilities for the further development of highly sustainable, efficient, and effective healthcare solutions that fit a rapidly changing patient care environment in the postmodern world.

7 Conclusion and Future Work

This paper has provided an all-inclusive blueprint of Mobile Cloud Computing (MCC) for precise real-time healthcare prognosis to highlight how MCC increases healthcare efficiency by improving data administration and analysis in the health care industry. The built web application provides an input interface for the necessary patient information and delivers an instant prediction in return, thus providing a tool for making decisions. Proposed as a system architecture based on MCC principles, the solutions proposed by the author effectively meet several of the challenges that private mobile devices pose to mHealth and the right to health care, while offering a scalable process for medical prediction based on big data. Scalable prediction capabilities are essential for proactive management of patients and these findings show how MCC could contribute in advancing the healthcare by providing accurate, real-time prediction for patient management.

The application of this framework to the assessment of various machine learning models showed that ensemble classifiers, and more specifically Voting Classifier outperformed individual models in terms of accuracy and consistency. Run using Random Forest, Decision Tree, and Gradient Boosting models showed the high accuracy as compared to the other models such as logistic regression and KNN showed low accuracy. Such computations are offloaded to the cloud using MCC, thus taking advantage of considerable computational resources, so that healthcare predictions are available in a seamless manner on three mobile devices without compromise on their computational performance. The blend of highly accurate models and cloud-based OLTP allows development of a powerful instrument for healthcare providers who need to get quick insights based on the large amount of data. Combined with the flexible login page for users to enter their login credentials, the registration page where the user can create their personal account, the home screen where users have the option to go directly to the prediction page or the support page, this makes the web application page effective in improving the usability of this framework, which connects the difficult concept of cloud analytics into the practical application of healthcare.

It also is advantageous concerning the important question of both data safety and confidentiality, which are paramount to healthcare programs that process patients' records. According to the results of the work, it is possible to note that the measures taken, such as encryption and secure authentication mechanisms, for example, JWT for managing users' sessions, help process and store data safely. This aspect is relevant in health care where are strict guidelines are upheld on the aspect of patient privacy. The security measures incorporated in this framework of MCC offer a 'trustable' framework that helps in making necessary regulations built in the healthcare setting to be smooth enough without neglecting the patients' data.

With the idea of the further work, several directions seem to be more promising for improving this healthcare prediction system based on the MCC. First, there is potential to widen the list of prediction features by using other factors which could influence further health and well-being, for instance, life) && (CU habitat records), diet data, genetic material. These features might enhance the models' forecasting power and provide a broader perspective of patients' condition. Moreover, the incorporation of flow from wearable health accessories also enhances the operation of the system since it is real time hence recommending appropriate action at the right time. MHealth devices such as heart rate monitors or glucose detectors could feed streams of data that could update the model on the cloud in real time, improving the accuracy of the prognosis.

The second exciting avenue for future work is to integrate federated learning to improve the privacy of patients' data and information security. The concept of federated learning enables models to be trained directly on user data within their smart devices without transferring the raw data to servers, which – additionally to a direct boost in the model – could help to increase the privacy of the patient. This approach also serves to minimize privacy concerns while at the same time lowers the transfer of data costs and increases scalability. For healthcare providers, this implies accurately precise predictive analytics while at the same time not risking their patient information. It will be especially useful for the work with such privacy acts as HIPAA or GDPR and will also have positive impact on patients' trust to healthcare applications.

It is also possible to widen the number of machine learning techniques used in the system, such as deep learning and reinforcement learning, in order to increase predictive precision. Even though such corporate solutions based on Random Forest compete with Gradient Boosting ensembles in this study at a very high accuracy, deep learning-based models such as, CNNs for image-based data or RNNs for sequential data might capture additional subtle patterns that other methods are unable to discover. But reinforcement learning might enhance specific health advice by learning from the patient's choice gradually over weeks or months. Subsequent versions of this MCC framework could integrate these novel learning technologies to deal with the peculiarities of the medical data and enhance the long-term results for patients.

Besides, this developed MCC framework can be extended to more extensive applications in the arena of healthcare, including diagnosis, treatment option suggestions, and hospital resource allocation. If further the sophistication of model is enhanced, and elaborating more various kinds of data the system can be used in different departments within a healthcare organization that would make the work faster and increase the pace of handling patients. Further, using this framework to interface with EHRs could provide an improved patient view for comprehended and current data analysis. As more healthcare data sources are developed and the necessity for data exchange becomes sophisticated, MCC will be paramount for managing such broad healthcare systems effectively.

Another component of future work is to improve the user interface and accessibility of the web application. Implementation of multilingual to improve the use of the system for users speaking other languages, ability to link with speech to text for users to type with their voice in addition to improving the healthcare workers interface to accommodate all the different users could be beneficial for the system. These changes would open P2P lending market to more people especially the disabled or those from areas where they may not understand any of the trading language. Assessing the usability of the system through Health care providers and patients may go a long way in informing such improvements in the system so that its usage can be as productive in practice as it was during its development.

Overall, the proposed healthcare prediction system using MCC shown in this paper clearly strengthens the mobile cloud concept to improve the applications in predictable healthcare domain. This framework enhances the handling and analysing of patient information comprehensively to ensure that the providers make right decisions of a swift nature which are so crucial in the progress of the diseases. Although the system's assessment at an early stage seems to be positive, future investigation into improved machine learning algorithms, federated learning and coupling with wearable technologies can enhance the features and expand the uses of the system. Healthcare already on its way toward relying more and more on data, the presented MCC-based system like this one creates a perfect and efficient platform that will be able to meet the future needs of the healthcare system.

References

Tawalbeh, L. A., Bakhader, W., Mehmood, R., & Song, H. (2016, December 1). *Cloudlet-Based Mobile Cloud Computing for Healthcare Applications*. IEEE Xplore. https://doi.org/10.1109/GLOCOM.2016.7841665

Tawalbeh, L. A., Mehmood, R., Benkhlifa, E., & Song, H. (2016). Mobile Cloud Computing Model and Big Data Analysis for Healthcare Applications. *IEEE Access*, *4*, 6171–6180. https://doi.org/10.1109/ACCESS.2016.2613278

Wang, X., & Jin, Z. (2019). An Overview of Mobile Cloud Computing for Pervasive Healthcare. *IEEE Access*, *7*, 66774–66791. https://doi.org/10.1109/access.2019.2917701

Fong, E.-M., & Chung, W.-Y. (2013). Mobile Cloud-Computing-Based Healthcare Service by Noncontact ECG Monitoring. *Sensors*, *13*(12), 16451–16473. https://doi.org/10.3390/s131216451

Jemal, H., Kechaou, Z., Ben Ayed, M., & Alimi, A. M. (2015, November 1). *Cloud computing and mobile devices based system for healthcare application*. IEEE Xplore. https://doi.org/10.1109/ISTAS.2015.7439407

Karaca, Y., Moonis, M., Zhang, Y.-D., & Gezgez, C. (2019). Mobile cloud computing based stroke healthcare system. *International Journal of Information Management*, *45*, 250–261. https://doi.org/10.1016/j.ijinfomgt.2018.09.012

Gao Zhi-qiang, He Lingsong, Tian, H., & Cong, L. (2015). A cloud computing based mobile healthcare service system. *2015 IEEE 3rd International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA)*. https://doi.org/10.1109/icsima.2015.7559009

Hanen, J., Kechaou, Z., & Ayed, M. B. (2016). An enhanced healthcare system in mobile cloud computing environment. *Vietnam Journal of Computer Science*, *3*(4), 267–277. https://doi.org/10.1007/s40595-016-0076-y

Jemal, H., Kechaou, Z., Ayed, M. B., & Alimi, A. M. (2015). Mobile Cloud Computing in Healthcare System. *Computational Collective Intelligence*, 408–417. https://doi.org/10.1007/978-3-319-24306-1_40

Albuquerque, S. L., & Gondim, P. R. L. (2016). Security in Cloud-Computing-Based Mobile Health. *IT Professional*, *18*(3), 37–44. https://doi.org/10.1109/mitp.2016.51

Kulkarni, G., Rupali Shelke, Patil, P., Kulkarni, V. C., & Sangita Mohite. (2014). Optimization in Mobile Cloud Computing for Cloud Based Health Application. *2014 Fourth International Conference on Communication Systems and Network Technologies, Bhopal, India, 2014*, *pp. 569-572*. https://doi.org/10.1109/csnt.2014.120

Nirabi, A., & Hameed, S. A. (2018). Mobile Cloud Computing For Emergency Healthcare Model:Framework. *2018 7th International Conference on Computer and Communication Engineering (ICCCE), Kuala Lumpur, Malaysia, 2018*, *pp. 375-379*. https://doi.org/10.1109/iccce.2018.8539310

Hameed, K., Nirabi, R., Habaebi, M. & Haddad, A., 2019. MCC for Emergency Healthcare (MCCEH) model for reducing response time and providing efficient patient care using mobile applications and cloud computing. *Journal of Medical Systems*, 43(4), pp. 1-10. https://beei.org/index.php/EEI/article/view/1498/1174

Hoang, D. & Chen, L., 2010. Mobile Cloud for Assistive Healthcare (MoCAsH) system: Solving healthcare challenges with mobile sensing and context-aware middleware. *Future Generation Computer Systems*, 26(5), pp. 654-661. https://www.researchgate.net/publication/224217036_Mobile_Cloud_for_Assistive_Healthcare_MoCAsH

Somula, R., Chunduru, A., Venkatesh, B., Karrothu, A., Pavan Kumar, C.S. and Sasikala, R., 2019. Cloudlet services for healthcare applications in mobile cloud computing. In: Suresh Satapathy, S., Zhang, YD., Bhateja, V. and Majhi, B. eds. *Proceedings of ICDECT 2017*. pp.595-603.

https://www.researchgate.net/publication/328077909_Cloudlet_Services_for_Healthcare_Applications_in_Mobile_Cloud_Computing_ICDECT_2017

W. Raghupathi and J. Raghupathi, *Big Data Analytics in Healthcare: Promise and Potential*, Health Information Science and Systems, 2014.
https://link.springer.com/article/10.1186/2047-2501-2-3

"Google Cloud for Healthcare Solutions," Google Cloud, Available: https://cloud.google.com/solutions/healthcare-life-sciences.