Computer-aided automated detection of kidney disease using supervised learning technique

Navaneeth Bhaskar[1], Priyanka Tupe-Waghmare[2], Shobha S. Nikam[3], Rakhi Khedkar[4]
[1]Department of CSE (Data Science), Sahyadri College of Engineering and Management, Mangalore, India
[2]Symbiosis Institute of Technology, Symbiosis International (Deemed University), Pune, India
[3]Department of Electronics and Telecommunication Engineering, AISSMS Institute of Information Technology, Pune, India
[4]Department of Electronics and Telecommunication Engineering, Sinhgad Academy of Engineering, Pune, India

Article Info

Article history:

Received Feb 16, 2023
Revised Mar 10, 2023
Accepted Mar 28, 2023

Keywords:

Chronic kidney disease
Internet of things
Machine learning
Salivary diagnosis
Support vector machine

ABSTRACT

In this paper, we propose an efficient home-based system for monitoring chronic kidney disease (CKD). As non-invasive disease identification approaches are gaining popularity nowadays, the proposed system is designed to detect kidney disease from saliva samples. Salivary diagnosis has advanced its popularity over the last few years due to the non-invasive sample collection technique. The use of salivary components to monitor and detect kidney disease is investigated through an experimental investigation. We measured the amount of urea in the saliva sample to detect CKD. Further, this article explains the use of predictive analysis using machine learning techniques and data analytics in remote healthcare management. The proposed health monitoring system classified the samples with an accuracy of 97.1%. With internet facilities available everywhere, this methodology can offer better healthcare services, with real-time decision support in remote monitoring platform.

Corresponding Author:

Navaneeth Bhaskar
Department of CSE (Data Science), Sahyadri College of Engineering and Management
Mangalore, India
Email: navbskr@gmail.com

1. INTRODUCTION

The demand for remote health monitoring services has increased recently. Advanced sensors combined with machine learning techniques and data analytics can provide a perfect platform for implementing remote health monitoring systems. Many companies have come up with remote health monitoring setups. However, most of the commercially available health monitoring setup available today measures only physiological parameters like the heartbeat, electroencephalogram (EEG), body temperature, and blood pressure [1]. A health-tracking system based on salivary biomarkers is presented in this paper. Saliva samples can be used as an efficient diagnostic fluid to determine numerous disorders, just like any other body fluid [2]. Saliva, a composite biological fluid produced by the salivary glands is a valuable source of biochemical information [3]. Most of the compounds found in blood and saliva are the same, which makes the saliva test more equivalent to the blood test [4]. Saliva collection being non-invasive reduces pain and discomfort to patients making it more advantageous over other body fluids. There has been a rapid growth in the interest in salivary diagnosis in recent times, and for this reason, many saliva collection devices were developed in recent years. Major saliva collection devices commercially available are the Salivette tube, Quantisal saliva collector and Salivabio Oral Swab collection kit [5]. The amount of saliva secretion varies among individuals but the concentration of different salivary components normally remains within the specified range for a healthy individual. Concentration levels of salivary components will vary in patients according to the disease. By designing appropriate sensors, it is possible to detect this variation in the salivary compositions. Several research activities have successfully shown disease diagnosis using salivary compositions.

Around 10% of the world's population has chronic kidney disease (CKD), which causes millions of fatalities every year. Regular kidney monitoring is necessary as it is difficult to forecast how kidney functioning is decreasing. If suitable remedial measures are not followed to reduce its progression, CKD can advance to total renal failure [6]. In this work, we have checked the urea concentrations in the saliva sample for analyzing the functioning of the kidneys. As the urea filtering is done by the kidneys, the urea concentration in the body fluids, including saliva, will increase when the kidneys do not function normally [7]. Various devices and methodologies are available for estimating the urea values in the body. However, most of the existing techniques are lab-based analysis methods that use sophisticated machines like chemical analyzers. As we aim to develop an automated disease detection model, we have developed a new detection technique for measuring salivary urea concentration. This study also examines the correlation between the urea concentrations in saliva and blood samples. For analyzing the results, the obtained readings are processed and statistically evaluated. The concentrations of major electrolytes are also measured using chemistry analyzers [8]. Further, the flow rate and pH level of saliva are also assessed using conventional methods [9].

Remote health monitoring systems can measure different parameter values from the patient's location and transmit them to the cloud. Real-time data acquisition and monitoring of information are possible using the Internet of things (IoT) [10], [11]. Supervised learning algorithms can be used for real-time prediction and analysis of sensed values. In this work, we have used the support vector machine (SVM) classification model for performing the automated prediction [12], [13]. The sensor captures the raw data and is directly transferred to the processor. The processor will process the signals and transmits the information to the remote server. A database is created for each user on the server and details of the patients along with their medical history will be stored in the database. The user interface is created for the real-time monitoring of data. By continuously tracking patient data, doctors can provide immediate medical advice and timely diagnosis to patients. The proposed model can facilitate increased care for monitoring the health of elderly people, ensuring a feeling of safety and comfort among patients who are living independently.

2. SYSTEM ARCHITECTURE

The architecture of the remote health monitoring system comprises of hardware part and the cloud computing part. The sensing part consists of a urea sensor for measuring the saliva urea value. Different sensors can be connected to this architecture for sensing various parameters. Wearable on-body sensors can be used if continuous monitoring of the data is required. The information collected by the sensor is relayed to the processor. Bluetooth and Wi-Fi wireless standards are used for data transmission. Android mobile is used as an interfacing device between the user and the server. The data collected from the patient will be stored in the cloud server database for decision-making and long-term analysis. The cloud computing part consists of a health portal website wherein the data is fetched from the cloud. Medical experts and patients can log in to this website and can access the data in the cloud at any point in time. The architecture of the designed remote monitoring system using IoT is shown in Figure 1. The urea values obtained from the patient readings are checked against threshold values. Initial remedial actions will be given to the patient by the algorithm running locally in the processor. The mobile constantly alerts the status of the patient to doctors and the patient's family members from time to time. Data collected from the patients will be stored in the cloud where analytics play a major role in studying the medical behavior of the patients.

A sensing module, an Arduino Uno microcontroller board, and an Android smartphone make up the hardware components of the proposed system. The amount of urea present in the sample is computed by transforming it into ammonia gas. We have converted urea to ammonia using the traditional enzymatic reaction method where the urease enzyme hydrolyzes urea to produce ammonia [14]. The conversion reaction is conducted in a closed chamber, as the end product is a gas molecule. An input valve for dropping the sample is located at the top of the gas chamber. The urease enzyme is placed within the gas chamber, below the input valve. The sensing module contains the embedded gas sensor used for measuring ammonia gas. A metal oxide semiconductor (MOS) based MQ-137 sensor with high ammonia gas sensitivity is used to determine the amount of ammonia gas produced inside the chamber [15]. The sensor response is recorded using the Arduino Uno controller board.

As a gateway device, an Android mobile is used which displays the readings to the patients and also stores the values in the SQLite database. The mobile acts as the key interface between the patient and the server. The information captured by the sensor will be directed to the server. Coding is done to send feedback to the patient regarding the status of urea values through short message services (SMS) based on the threshold values. A database is created to load the data from the hardware part into the cloud. My structured query language (MySQL), which uses structured query language, is used to create the database. Data are retrieved through the health portal website coded in hypertext preprocessor (PHP). The website portal web page is developed using a hypertext markup language (HTML). Data stored in the SQLite is sent to the web server database using a hypertext transfer protocol (HTTP) request method [16].

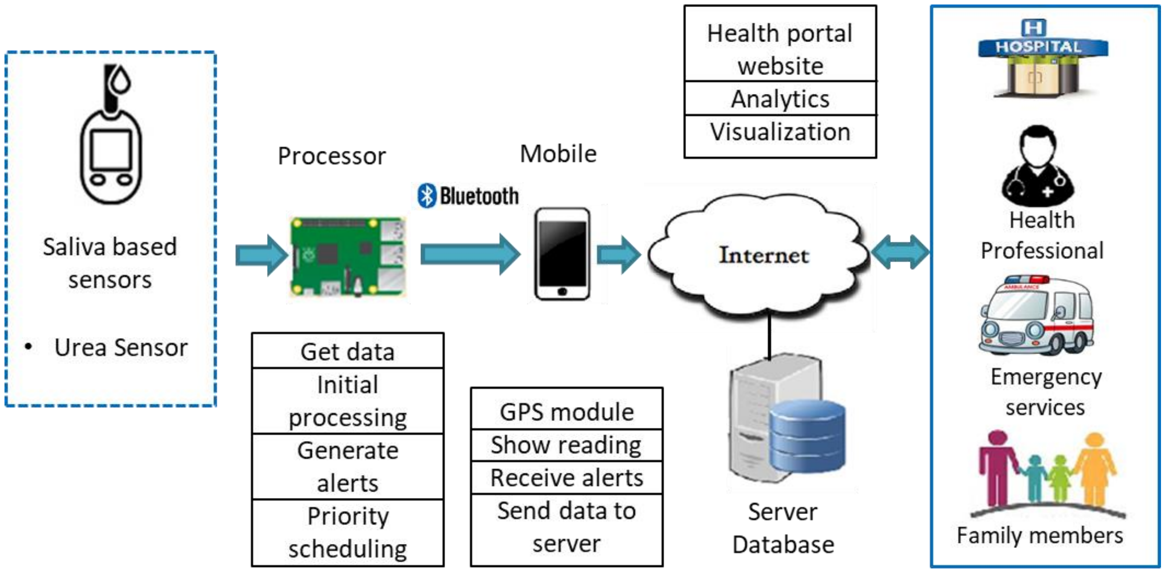

Figure 1. Architecture of proposed health tracking system

The use of analytics improves the overall operational performance of the system, allows fast decision making and helps in cutting down expenditure [17]. The sensor continuously transmits the data and the information will be collected by the cloud. The system should analyze and process the massive data volumes instantaneously. Data analytics plays a dominant role in analyzing these data instantly and by providing fast treatment options. Analytics uses techniques such as clustering and segmentation, classification, regression, neural networks, and artificial intelligence, for providing medical decision support [18]. Automated healthcare models are programmed to make decisions promptly with the help of machine learning techniques. During the training process, the network algorithms learn the information from the provided data set. This learned information is applied when the test set is provided for making predictions and for performing classification. A linear SVM algorithm is used in our analysis for the classification of sensed data. The classifier constructs the dividing hyperplane which linearly separates the received data values into different classes. SVM classifies the received sensor information as abnormal or normal based on a set of training data samples, which are already categorized and stored in records. This is done by checking whether the received value is above or below the hyperplane [19], [20].

3. METHOD

The subjects chosen for the study consisted of 32 CKD patients and 38 healthy individuals. For the analysis, 2 ml of saliva was collected from the subject by spitting approach. In salivary diagnosis, it is important to ensure that the consumption of food items does not impact the test results. Therefore, samples are taken at least two hours after eating or drinking any food materials. Saliva is collected after rinsing the mouth with distilled water to have good oral hygiene before the saliva collection. The guidelines stated in the Declaration of Helsinki were followed in the conduct of this study. A clinical analysis was conducted to find the correlation between the blood and saliva readings. The Beckman Coulter AU680 chemical analyzer is used to measure the concentration of urea in the blood and saliva samples [8]. The chemistry analyzer AU680 along with chemical reagents can quantify the amount of analyte present in the sample. This is an automated chemical analyzer which displays the reading directly on its display. The levels of major electrolytes like sodium, calcium, potassium, chloride, magnesium, bicarbonate, and phosphate are measured using an electrolyte analyzer. The flow rate of saliva is then estimated using a graded test tube through a visual examination [21]. A tabletop pH meter from Orion Star Thermo Scientific is used to determine the pH value of saliva [9]. The hydrogen ion concentration in the saliva sample is determined by the salivary pH value. The pH value reveals the body's capacity to maintain the acid-base balance. The acid-base balance in the body is primarily under the control of the kidneys. The normal pH value of saliva is 6.5. Increased salivary pH indicates the saliva is alkaline, and lower salivary pH value indicates acidic saliva.

For measuring the urea concentration with the proposed sensing approach, the saliva sample is dropped through the input opening of the chamber. As a result, the hydrolysis of urea will begin, which converts the urea in the sample into ammonia gas. The ammonia concentration induced in the chamber will determine the level of urea in the sample. The sensor's electrical conductivity changes in proportion to the ammonia gas induced. An electrical circuit converts the conductivity variations into a voltage. Using the Arduino board, the signal is transformed and the sensor output is acquired. The output variations of the sensor are recorded for 100 seconds for further analysis. Figure 2 shows the sensor response waveform obtained from the sensor output for a sample.

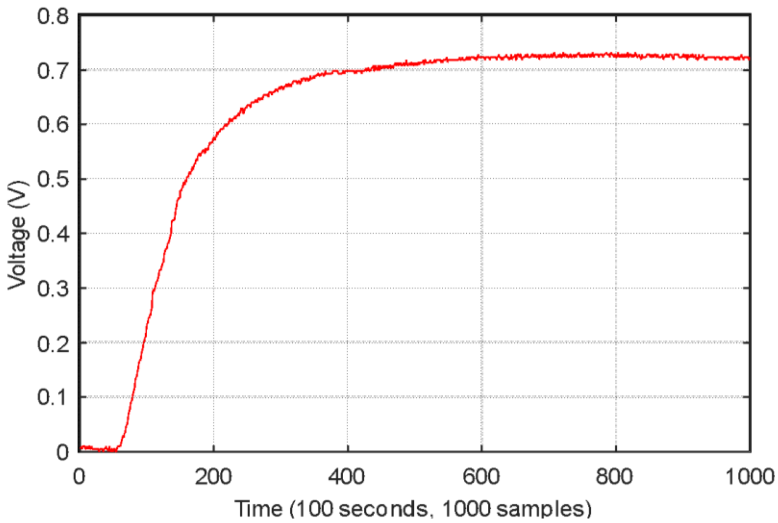

Figure 2. Sensor response voltage obtained from the sensing module

The SVM classification algorithm is used to classify the sensor response under healthy or abnormal classes. Programming of the classifier is done in MATLAB software. SVM was trained with training set values and then tested with new test values. The principal task of the SVM algorithm is to segregate the values into different classes by establishing a maximum margin hyperplane [22]. SVM builds a hyperplane for defining the boundary between the classes and for configuring the data inputs. Two features are extracted from the sensor response signal for performing the classification using the SVM classifier. The 'maximum voltage' and 'area under the curve' were detected from all the samples and these two features were used for classification. MATLAB tool is used for this analysis.

4. RESULT AND DISCUSSION

More and more researchers are showing interest in saliva-based diagnosis since various components present in it have the potential to provide valuable inputs for clinical diagnostic applications. The salivary diagnosis-based health tracking system presented in this paper is suggested as an efficient technique towards improving healthcare services. Patients will find this system more comfortable as the medical procedures are less in saliva-based sensing. Also, the patients can collect saliva samples easily without any help from medical professionals.

The concentrations of salivary sodium, potassium, bicarbonate, calcium, chloride, phosphate, and magnesium are analyzed using electrolyte analyzer [8]. Table 1 shows the concentration values obtained for both CKD patients and healthy individuals. When compared to healthy individuals, CKD patients had greater electrolyte concentrations. Salivary electrolyte levels typically vary from person to person, and compositions might change multiple times within a day. Research studies have shown that electrolyte imbalance in the body can occur due to multiple diseases [2]. Also, the flow rate might affect the values of the salivary electrolyte concentrations. Therefore, monitoring the levels of electrolytes in the saliva cannot provide accurate information for detecting kidney disease.

Table 1. Concentration of electrolyte levels in saliva

Salivary electrolytes	Healthy individuals	CKD patients
Sodium	13.61±3.43	19.63±7.34
Potassium	23.53±6.89	39.2±12.62
Calcium	1.37±0.98	1.67±0.93
Bicarbonate	3.57±1.65	11.42±2.98
Chloride	23.55±7.51	33.8±8.63
Phosphate	7.45±2.36	11.56±1.62
Magnesium	0.57±0.27	0.67±0.27

The saliva flow rate is seen to be lower in CKD patients than in healthy people. Our analysis recorded mean flow rates of 0.368±0.2 and 0.216±0.13 for healthy and CKD patients, respectively. The salivary flow rate values obtained for different test sets are shown in Figure 3. Compared to healthy persons, CKD patients have lower flow rates and pH levels. As kidney function deteriorates, the kidney's ability to manage acidity weakens, resulting in low pH values in CKD patients. Compared to healthy male individuals, the salivary flow rates in healthy female subjects were found to be a bit lower. Our comparative analysis did not reveal any appreciable gender-related differences in the pH levels. When compared to the younger groups, the flow rates and pH values were a little lower in the elderly people. This variance, though, is acceptable and falls within the usual, healthy range. Therefore, it can be inferred that the pH and flow rates of saliva may not be significantly affected by age.

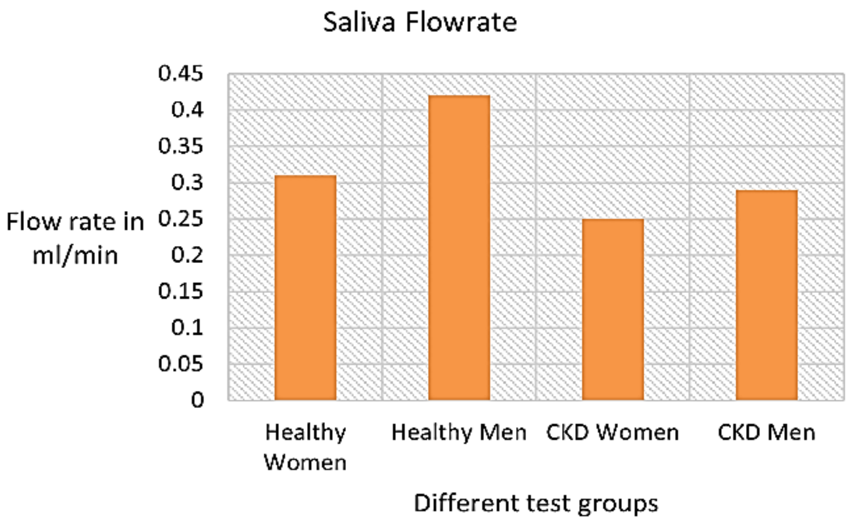

Figure 3. Saliva flow rates for different test groups

The medically accepted biomarkers for CKD detection are urea and creatinine. The mean values of urea levels recorded for healthy people and CKD patients are 24.13±3.45 and 69.13±16.56 mg/dL, respectively. Similarly, the blood urea levels were estimated as 35.63±7.89 and 98.55±25.51 mg/dL in healthy individuals and CKD patients, respectively. As expected, the urea concentrations were higher in CKD patients. Urea concentration will be higher in kidney patients as their concentrations are directly associated with kidney functioning. The results of the clinical study are statistically analyzed to make predictions. The correlation between salivary and blood urea levels is assessed using Pearson's correlation approach. Pearson correlation coefficient will determine how strongly these two parameters are correlated with each other. A correlation of 0.81 was attained for salivary and blood urea levels.

To explore the connection between saliva and blood urea concentrations, regression analysis is carried out [23]. Regression is used to predict how a dependent variable will behave in relation to an independent variable. Regression analysis uses statistics to forecast a reaction based on past data. This knowledge aids in creating a regression model to forecast the result. For urea concentration, the regression equation y=35.676+0.875x is obtained. The values of y can be inferred from the values of x using the resulting equation. This suggests that the linear regression line equation can be used to determine the urea concentration in the blood from the saliva readings. The coefficient of determination R^2 achieved for this regression analysis is 0.6561. The scatterplot of the regression analysis of urea concentrations in saliva and blood is shown in Figure 4.

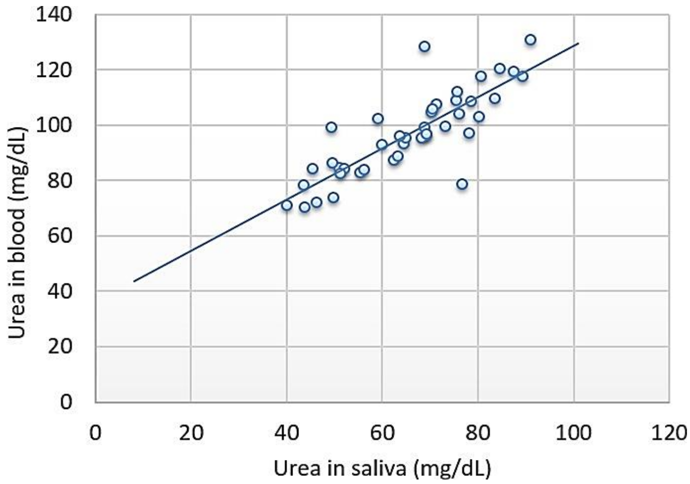

Figure 4. Scatter plot of urea levels in saliva and blood

To evaluate the performance of the model, saliva samples collected from the participants were analyzed using the SVM classification algorithm. The SVM classification algorithm is employed to categorize thesamples into two classes, which are ‘Healthy’ and ‘Abnormal’. The SVM classifier is used in our study as it isthe commonly used data classification algorithm, and also it gives good output for both linear and non-linear input sets. The classifier’s performance is assessed by calculating the key performance indicators, including accuracy, precision, specificity, sensitivity, F1 score, and error rate [24]. The test samples were classified by the SVM classifier with an accuracy of 95.71%. The SVM plot showing the classification of analyzed sampleswith the two manually selected features is shown in Figure 5.

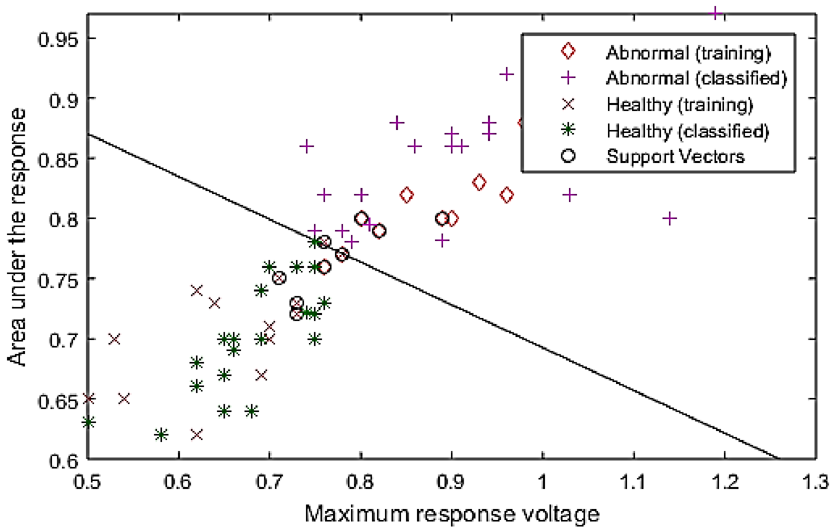

Figure 5. SVM plot showing the classification of samples

We have trained and tested the classifier with 70 samples. In this work, we employed a 10-fold cross validation approach [25]. The test set for each fold consists of 7 samples, and the training set is made up of the remaining 63 samples. The overall performance of the system is then evaluated by averaging the performances recorded in all ten iterations. Even though the SVM classifier obtained a decent accuracy value, it can be improved further by optimizing the classifier. We have optimized the classifier by incorporating a particle swarm optimization (PSO) algorithm. The optimal values of the regularization parameter ‘C’ and the Gaussian kernel parameter ‘γ’ are selected using the PSO algorithm. Table 2 displays the classifier performance metrics acquired for the analysis using conventional SVM and optimized SVM classification models. The optimized SVM attained a classification accuracy of 97.1%. The designed system was able to successfully transmit the urea values to the cloud and display the values in the Android app and website portal. This system was designed to generate alert messages to doctors and patients’ caretakers whenever the observed reading is not in the normal range.

Table 2. Performance metrics of classifiers

Performance parameters	SVM	Optimized SVM
Accuracy	0.957	0.971
Sensitivity	0.906	0.937
Specificity	1	1
Precision	1	1
F1 Score	0.95	0.968
Error rate	0.043	0.029
False positive rate	0	0
False negative rate	0.094	0.062
Negative predictive value	0.927	0.95
False discovery rate	0	0
False omission rate	0.073	0.05
Matthew’s correlation coefficient	0.916	0.944

Functions of the cloud computing part include data collection from the sensor, storage, data processing, making decisions based on the acquired readings, and sending data to devices connected to the network. A health portal website is created to display the readings and to keep track of the health conditions of the patient. Figure 6 shows the screenshot of the health portal website’s dashboard. This page provides a summary of patient details, medical history, and collected readings. Unique user ID and password are allotted to registered patients and health professionals to ensure data visibility to only authorized persons. The website portal allows the users to access the data and monitor the patient’s health status simultaneously by logging into the website. Patient details and collected readings can be accessed anytime by health professionals. Multiple doctors will be associated with this portal for diagnosing and monitoring patients. Initial remedial actions and diagnosis methods will be given to the patients by the doctors through this portal. Continuous monitoring makes it possible for doctors to study the behavior status of patients before and after drug intake, thus helping them to provide better treatments.

Security measures in IoT-based health care schemes are very essential because most of the communications are done wirelessly. Patient details and medical data should be secure and non-authorized access should not occur in IoT-based healthcare systems. By implementing technical safeguards and network securitymeasures it is possible to build a secure IoT system so that medical details are not leaked or impaired. The users are assigned unique user IDs and strong passwords for accessing the network. Data in the system is protected by encrypting it during storage and transmission. An anonymous authentication protocol can be used for implementing network security in IoT-based systems [19]. Password with hash function-based authentication protocols is generally used because of their easy implementation. An authentication protocol is implemented in this work, where the mobile and the server authenticate with each other before the data transmission. The global positioning system (GPS) facility of the patient’s mobile phone is used for identifying the current location of the patient in case of emergencies. Applications proposed in this project are well suited for monitoring the health of people and connecting patients with doctors and family members of patients. Security measures were taken to prevent unauthorized persons from assessing or altering the data. This technology will turn out to be an intelligent and efficient method especially for monitoring patients in remote areas and overcoming critical health conditions. Patients would find this idea hassle-free since they could skip travel to hospitals. Elderly people will find this concept more useful as they have to constantly monitor their health status. With such a model and advanced technologies, it is possible to improve healthcare and save lives by discovering associations and studying the patterns and trends of the recorded data.

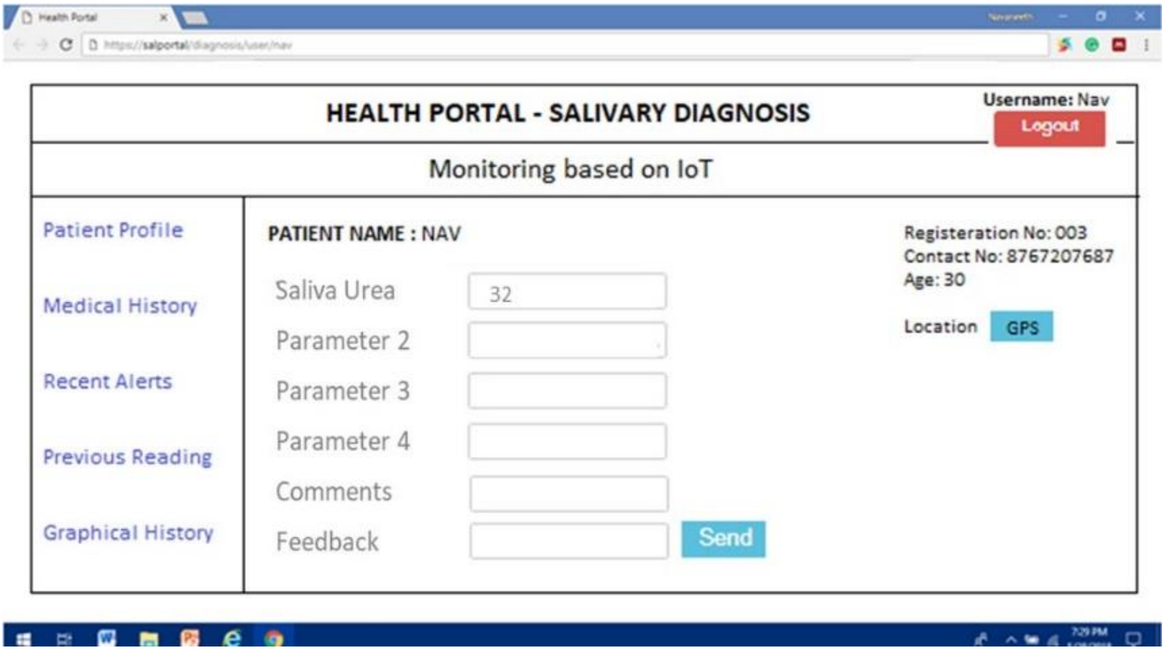

Figure 6. Screenshot of health portal website dashboard

5. CONCLUSION

An IoT-based remote health tracking system based on salivary diagnosis is presented in this paper. The experimental data are analyzed using correlation and regression analysis. We have obtained a positive correlation between saliva and blood levels of urea. The high correlation and regression coefficient values obtained in the analysis show how well blood and saliva concentration values are correlated. The proposed home-based model is implemented to detect CKD by checking the urea concentration in the saliva sample. As the readings are taken from the patient's home doctors would be able to monitor patients remotely without having to travel. Unnecessary hospitalizations and healthcare expenditures can be reduced with this model. Real-time sensor data is recorded and transferred to the system for predicting the disease. Classification of the features is carried out using the SVM classifier, and the results obtained are promising. With two manually extracted features, the optimized SVM classifier categorized the samples with an accuracy of 97.1%. The classification results imply that the proposed model is very efficient and can be considered for clinical practice for detecting CKD non-invasively. The proposed system can be extended for a wider application by connecting various sensors. The performance evaluation of the proposed system shows that saliva-based diagnostic techniques can be effectively used with the capabilities of machine learning methods and data analytics for providing cost-effective and accurate detection with good response time.

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BIOGRAPHIES OF AUTHORS

Navaneeth Bhaskar received the B.E. and M.Tech. degree in electronics from Visvesvaraya Technological University, and a Ph.D. degree in machine learning from VIT University, India. Currently, he is working as an associate professor at the Department of Computer Science and Engineering (Data Science) at Sahyadri College of Engineering and Management, India. His research interests include artificial intelligence, machine learning, data analytics, IoT, and signal processing. He can be contacted at navbskr@gmail.com.

Priyanka Tupe-Waghmare completed her master's in engineering in 2010 and currently submitted her Ph.D. thesis to Symbiosis International (Deemed University). She has been working as an assistant professor at Symbiosis Institute of Technology, Pune, since 2011. Her research area includes medical image analysis, artificial intelligence, and computer networks. She is a senior member of IEEE and an associate member of the Institution of Engineers (India) and the International Society for Magnetic Resonance in Medicine. She can be contacted at priyanka.tupe@sitpune.edu.in.

Shobha S. Nikam received her B.E.(E&TC) degree from the University of Pune, Maharashtra, India in 2007, her M.E. (E&TC-Microwaves) from Savitribai Phule Pune University in 2012, and her Ph.D. from Savitribai Phule Pune University in 2022. She has teaching experience of more than 13 years and research experience of 1.5 years. Currently, she is associated with AISSMS Institute of Information Technology, Pune as an assistant professor in Electronics and Telecommunication Engineering. She is a life member of ISTE, IETE, and member of IEEE. She can be contacted at shobha.nikam@aissmsioit.org.

Rakhi Khedkar completed her diploma from Government Polytechnique, Pune in 1998 and her B.E. degree in electronics and telecommunication engineering from North Maharashtra University in 2001. She completed her M. Tech degree in Electronics (Computer) Engineering in 2006 and her Ph.D. degree in electronics and telecommunication engineering in 2020 from the College of Engineering, Pune. Presently she is working as an assistant professor in the Department of Electronics and Telecommunication Engineering, Sinhgad Academy of Engineering, Pune. She has more than 20 years of experience in teaching and industry. She has been a life member of IETE since 2011. She can be contacted at rakhedkar.sae@sinhgad.edu.in.