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T. Jayasree, M. Vaibhavadarani, K. Oviya

Department of Biomedical Engineering,
College of Engineering Guindy, Anna university,
Chennai, India.

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AI DRIVEN TALKING HEALTH MANAGEMENT SYSTEM

T. Jayasree[1*], M. Vaibhavadarani[2], K. Oviya[3]

Department of Biomedical Engineering,
College of Engineering Guindy, Anna university, Chennai, India.
[1]jai_t@annauniv.edu,[2]email2vaibz@gmail.com, [3]oviyalatha00@gmail.com
Corresponding Author

Abstract. *The proposed work introduces a novel approach to healthcare monitoring, leveraging voice-enabled technology to provide real-time health status updates in local languages. While telemedicine has been implemented in certain rural areas, this system goes a step further by integrating voice-based communication, making it accessible to all groups of people, regardless of literacy or language proficiency. The system uses IoT-based sensors to monitor vital signs such as heart rate, blood oxygen saturation (SpO2), body temperature, and respiration rate. These data, combined with user-reported symptoms, are processed using machine learning algorithms to predict diseases and provide actionable insights. The system delivers real-time feedback, health education, and emergency assistance through voice output, making it particularly beneficial for individuals in remote and underserved areas. This paper discusses the design, implementation, and evaluation of the system, highlighting its potential to improve healthcare access and outcomes.*

Keywords: *Health monitoring, SpO2, Respiration rate, Telemedicine, Machine learning Algorithm.*

1. Introduction

The proposed work represents a new approach in healthcare monitoring, where voice-enabled technology is used to provide real-time health updates in local languages. Although telemedicine is introduced in some remote places, this methodology is not area-specific or subject-specific. The voice command and output can be customized to any language, benefiting all groups of people in distant places. This system ensures that all clusters of society can monitor their health status at any time, empowering individuals to take control of their well-being.

Many researchers have proposed various ideas for remote health monitoring, but audio-based alertness or communication has not been widely implemented. As the world moves to remote monitoring, real-time data collection, and quick disease identification, remote healthcare is becoming a growing research area. Remote healthcare includes subclasses

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such as telehealth and mobile health, all of which refer to using technology to monitor patients outside of a hospital setting [1]. The benefits of remote patient monitoring include:

- Continuous monitoring of patients.
- Early detection of illnesses in real-time.
- Reduction of hospital costs and hospitalizations.
- Accurate readings while patients get to go about their routine lives.
- Improved healthcare service efficiency through telecommunications.
- Emergency medical care and support for patients.

Voice-based output has been implemented in medical robots that assist patients admitted to hospitals [2]. Robotic technology is now used for a variety of delicate medical procedures, including minimally invasive and open surgery, the replacement of amputated limbs, neuro-rehabilitation therapy for stroke patients, and the administration of medications. This proposed work focuses on developing a medical gadget with a simple sensor arrangement that allows individuals to monitor their health without doctor support. The system communicates the user's health condition in their preferred language (e.g., Tamil), making it accessible and user-friendly.

2. State of Art

The primary goal of this project is to develop an intelligent, voice-enabled health monitoring system that provides real-time assistance to people, particularly those in remote areas, in their native language. The system is designed with enhancing Accessibility to Healthcare by integrating speech-based output, the system ensures that individuals from diverse backgrounds, including those with limited literacy, can receive vital health information in a language they understand. The system raises awareness about disease prevention, early detection, and effective treatment strategies, empowering users with knowledge to take proactive steps in managing their health [3]. By offering real-time monitoring of key vital signs, the system motivates individuals to engage in routine check-ups, screenings, and early symptom detection, ultimately improving health outcomes [4].

3. Methodology

The proposed work makes several notable contributions to the field of healthcare technology, particularly in the integration of IoT, artificial intelligence, and accessibility features [5]. The Talking Health Management System is structured around three core components. IoT-Based Sensor Integration, Machine learning for disease prediction and multilingual voice output for accessibility [6] [7]. The system utilizes the MAX30100 pulse oximeter sensor to measure heart rate and saturation (SpO2). The DS18B20 digital temperature sensor records body temperature. A respiratory sensor is incorporated to track breathing rate. The sensors are connected to an ESP32 microcontroller, which processes the data and transmits it to a mobile application via Wi-Fi. The system employs a soft voting classifier, which merges predictions from two robust machine learning models Support Vector Classifier

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(SVC) and Random Forest (RF) [8] [9]. By analyzing a combination of user-reported symptoms and real-time vital signs, the model predicts up to 17 different diseases with high accuracy [10]. To accommodate users with varying literacy levels, the system provides health insights through both text and audio formats [11]. The voice output is available in English and regional languages like Tamil, ensuring clear communication and guidance [12]. The block representation of the work is shown in Figure. 1 and the sensors integrated with the microcontroller is shown in Figure.2.

The system follows a structured process to collect, analyze and present health insights to users. The data collection is carried out in two ways, the users will manually input their symptoms based on their health condition in the mobile application and simultaneously, the IoT sensors collect the vital signs (heart rate, SpO2, temperature, and respiration rate) in real time [13]. The microcontroller gathers the sensor data and transmits it to the mobile application using the MQTT protocol [14]. The ensemble learning model process the user inputs and sensor data to generate a disease prediction [15]. Where the soft voting classifier ensures that predictions from the SVC and RF models are combined to enhance accuracy and reliability. The system presents the predicted disease along with possible remedies. The information is displayed in text format and also delivered through voice output in the user's preferred language.

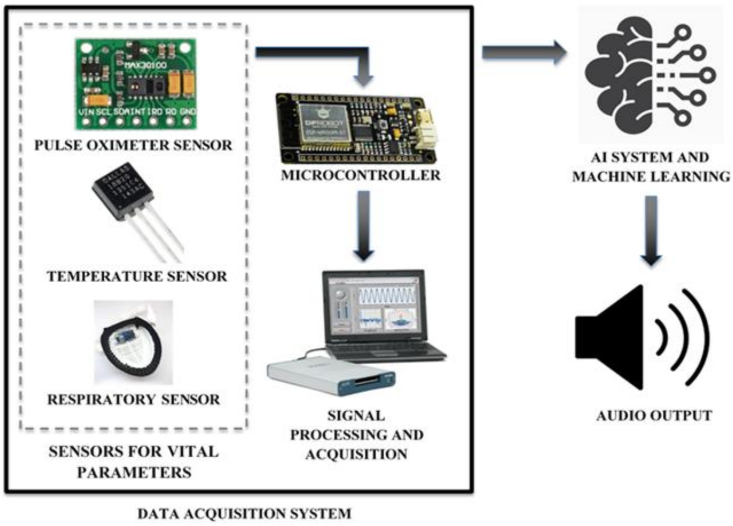

Figure. 1. Block representation of the proposed work

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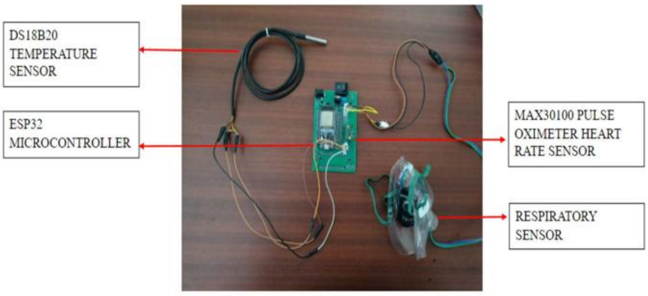

Figure. **2.** Sensors integrated with the microcontroller

In case of disease prediction, the Support Vector Classifier (SVC) is designed for both binary and multiclass classification tasks [16]. It operates by identifying a hyperplane within a multi-dimensional space that maximizes the margin between different data points, ensuring optimal separation based on equation 1 and equation 2

$$\min_{\omega,b,\tau} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \tau_i \quad (1)$$

$$y_{i(w^T \emptyset(x_i) + b)} \geq 1 - \tau_i \quad (2)$$

Where τ_i denotes the distance to the correct margin with $\tau_i \geq 0$, i = 1, n, C denotes a regularization parameter, wT w = $\|w^2\|$ denotes the normal vector, $\emptyset(x_i)$ denotes the transformed input space vector, b denotes a bias parameter y_i denotes the i-th target value.

Random Forest is an ensemble learning algorithm that enhances the performance of decision trees by combining multiple trees to make more accurate and robust predictions [17]. It operates by creating multiple decision trees during training and outputs the mode of the classes (for classification tasks) or the mean prediction (for regression tasks) of individual trees. The process begins by generating several bootstrapped datasets through random sampling with replacement from the original training data. Each of these datasets is used to train a separate decision tree. During the construction of each tree, a random subset of features is selected at each split point, ensuring that the trees are decorrelated and diverse. This randomness helps in reducing overfitting and improves the model's generalization capabilities [18] [19].

$$P(y = i|X) = \frac{Number\ of\ trees\ predicting\ class\ i}{Total\ number\ of\ trees} \quad (3)$$

Where P(y=i/X) is the probability of the input, X belonging to class I and number of trees predicting class i is the count of trees in the forest that predict class i for the given input. The final prediction is determined by a majority vote among all the trees. The class with the most votes becomes the predicted class for the input. It calculates the probability of an input (X) belonging to a specific class (i) based on the proportion of trees in the forest that predict that class, as shown in equation 3.

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Soft voting is an ensemble learning technique where multiple classifiers provide probability estimates for different classes, and the final prediction is based on the weighted average of these probabilities [20]. The class with the highest weighted average probability becomes the ensemble's final prediction which is calculated using equation 4.

$$\hat{y} = \underset{i}{\operatorname{argmax}} \sum_{j=1}^{m} \omega_j p_{ij} \tag{4}$$

Where y represents the final predicted class, argmax selects the class index that maximizes the weighted sum of probabilities, ω_j represents the weight assigned to the j-th model's prediction, and p_{ij} is the probability assigned to class i by the j-th model. The flow representation of the disease prediction is shown in Figure.3.

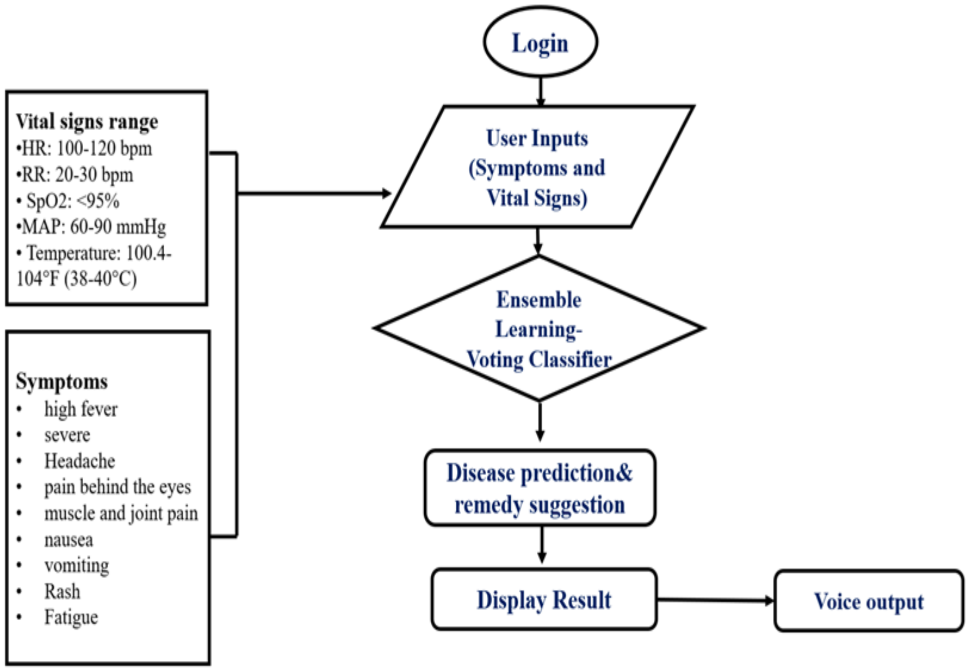

Figure. 3. Flow diagram for disease prediction

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4. Results

A disease prediction app has been developed with a user-friendly mobile interface, as shown in Figure.4.

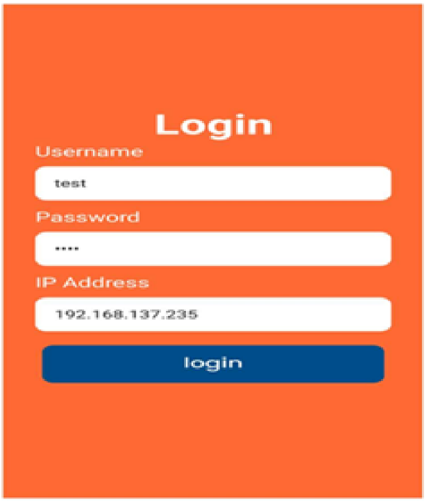

Figure. 4. Login page

In the login page, the user need to enter their username, password, and IP address. The system then checks whether the entered username and password match the stored credentials. If the details are incorrect, an alert message appears, informing the user that the username or password is invalid.If the login is successful, the system moves on to validate the IP address format. This is performed using a regular expression (regex)given in equation 5

/^(?:[0-9]{1,3}\.){3}[0-9]{1,3}$/ **(5)**

This ensures that the IP address follows the standard IPv4 format, which consists of four numbers (each between 0 and 255) separated by dots. If the format is incorrect, the user will receive an alert message notifying them that the IP address is invalid. By implementing these checks, the app ensures that users log in securely and inputs are validated to proceed further.

Once the user successfully logs in, the main screen of the app, will be displayed. This screen allows users to enter their health details by selecting from 28 symptoms and tracking 5 vital signs heart rate, temperature, respiration rate, blood pressure, and SpO_2 (oxygen saturation). Based on their health status the user manually selects symptoms, while real-time vital signs are automatically collected from sensors. After entering the necessary details, they tap the "Submit" button to initiate the analysis, the developed homepage for entering the symptoms is shown in Figure.5. And the real time data collection is shown in figure 6. The vital parameter from the sensors will be recorded for 60 seconds, and the readings will be appeared on the app’s screen. At this point, the user simply taps the "Submit" button", and the app analyzes the data to predict possible health conditions. If a disease is detected, the app displays both the diagnosis and recommended remedies. To make things even more accessible, the results are not only shown as text but also read out loud through voice output [21].

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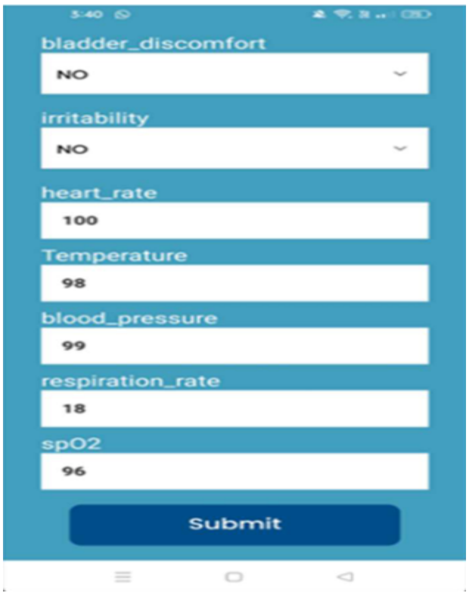

Figure. 5. Home page representing vital parameter and submit button

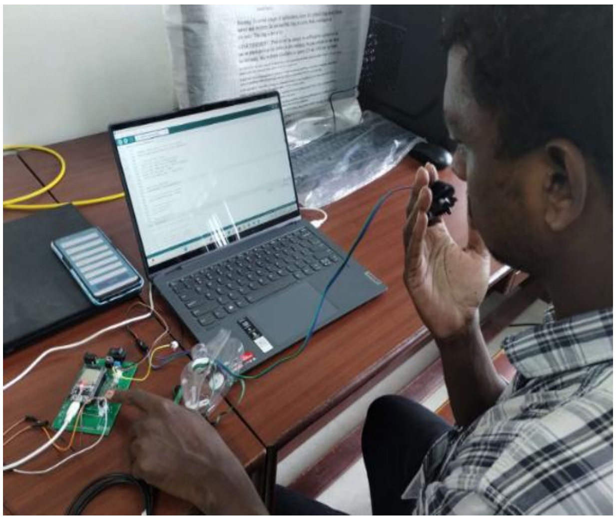

Figure. 6. Real time data collection

The Figure.7 illustrates a person's vital signs recorded using the developed module. In this instance, the readings show a body temperature of 34°C, a heart rate of 72 beats

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per minute (bpm), an SpO_2 level of 95%, and a respiration rate of 14 breaths per minute. The mean arterial pressure is entered manually.

The app features a list of 28 symptoms, including fever, shortness of breath, and fatigue. Users can indicate whether they are experiencing each symptom by selecting "Yes" or "No." To assess the app's accuracy, it was tested on a healthy individual with no symptoms. Based on their normal vital signs, the app correctly identified them as healthy and provided general health advice. A complete list of symptoms available in the app is shown in Table 1. Table 2 presents real-time vital sign data collected from 10 subjects, including heart rate (HR), SpO_2, temperature(Temp), and respiration rate (RR). Additionally, blood pressure(MABP) readings and symptoms were manually entered. Based on these inputs, the app analyzed each condition and correctly identified all subjects as being in a healthy state.

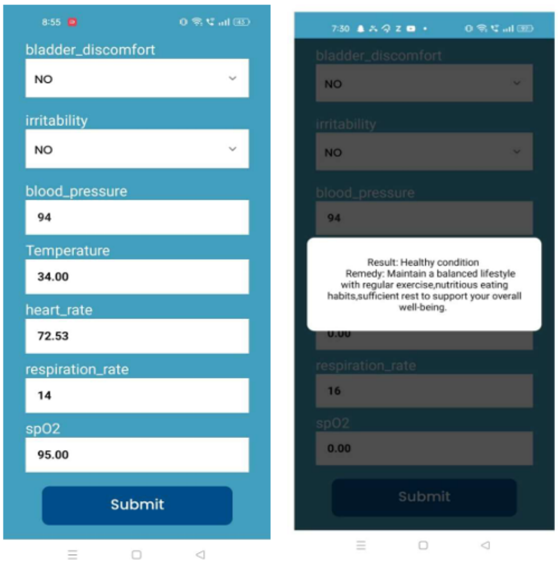

Figure. 7. Predicted condition: Healthy

Table 1. List of Symptoms

Symptoms		
High Fever	Stomach pain	Nausea
Severe headache	Acidity	Vomiting
Pain behind the eyes	Ulcers on the tongue	Abdomen pain
Muscle and joint pains	Burning micturition	Fatigue
Skin rash	Weight loss	Dehydration
Breathlessness	Yellowish skin	Enlarged thyroid
Chest pain	Blurred and distorted vision	Indigestion
Rapid heart rate	Patched in throat	Bladder discomfort
Irritability	Yellowing of eyes	Nodal skin eruptions

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Table 2. Experimental result of a person's vital signs

Subjects	Vital Signs						
	Symptoms	**HR**	**SpO2**	**Temp**	**RR**	**MABP**	**Result**
1	NO	74	96	34	15	94	
2	NO	84	96	35	12	93	
3	NO	92	95	35	15	95	
4	NO	78	97	34	14	96	
5	NO	88	96	36	13	92	
6	NO	76	95	35	16	98	**Healthy**
7	NO	85	94	36	13	91	
8	NO	80	97	34	15	93	
9	NO	93	96	35	12	99	
10	NO	87	95	36	14	94	

Similarly, to check the response of the application developed few symptoms for condition like hypertension and hypotension is entered in the app, the developed algorithm successfully identifies hypertension by analyzing the user's symptoms and the values of their five vital signs and the corresponding result is shown in Figure.8.

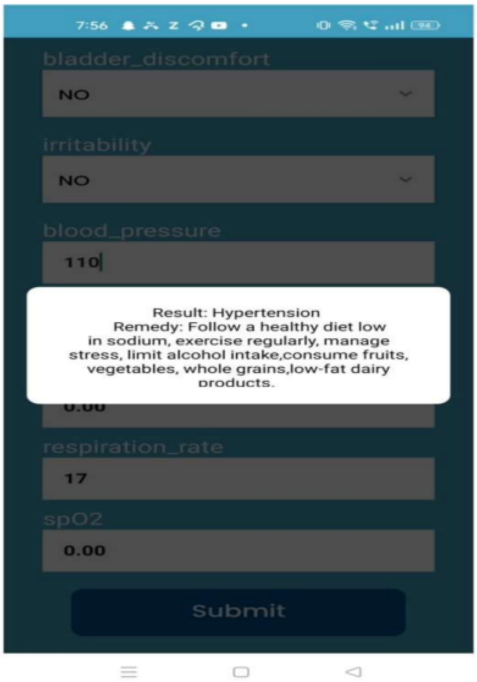

Figure. 8. Predicted disease: Hypertension

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The diagnosis is displayed along with recommended remedies, helping users understand their condition and possible next steps. A sample of specific ranges of vital signs used for the disease prediction of hypertension are detailed in Table 3. By thoroughly evaluating user inputs along with continuously monitored real-time health data, the app delivers highly accurate predictions and provides insightful, actionable health recommendations through text as well as voice output in the user comfort language [22]. This comprehensive approach makes it an invaluable tool for early disease detection, proactive self-monitoring, and overall health management, empowering users to take control of their well-being with confidence. Additionally, it enhances personalized healthcare by identifying potential health risks before they become critical, enabling timely medical intervention. The app also supports users in maintaining healthier lifestyles by offering tailored wellness plans, dietary recommendations, and fitness tracking. By seamlessly integrating with wearable devices and medical records, the app promotes a comprehensive approach to well-being, enabling users to manage their health proactively with ease and assurance.

5. conclusion

The Talking Health Management System is a promising solution for improving healthcare access and outcomes in rural and underserved areas. By integrating IoT-based sensors, machine learning algorithms, and voice output in local languages, the system provides a user-friendly and accessible platform for disease prediction and health monitoring. The system's ability to predict 17 diseases with high accuracy makes it a valuable tool for early diagnosis and intervention. This advancement will enable the application to provide timely suggestions and treatment plans, delivered via voice output. Additionally, a data storage feature to maintain individual records for each patient upon registration can be implemented, as it allows healthcare providers to monitor patients remotely and respond promptly to any concerning changes in their health status.

Table 3. Symptoms for the predicted disease: Hypertension

Input parameters		Output
Symptoms	Headache Shortness of Breath Blurred Vision Chest Pain Fatigue Fast Heartbeat	Hypertension
Vital Signs	Heart rate: 94 beats per minute Respiration rate: 19 breaths per minute Temperature: 37° Mean arterial Blood pressure: 106 mm Hg	

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	SPO2: 97%	

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