Smart Wheel Chair for Elderly People

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Abstract— Healthcare is a labour intensive industry. A substantial amount of money and resources are spent on hiring caretakers and nurses for patients who need constant attention for their sustenance. The proposed system can be used for a broad spectrum of patients but specifically focuses on the elderly, the bedridden, and the ones with limited mobility. The proposed work provides a solution to get a full-fledged working system that automates every aspect of patient monitoring to reduce errors introduced by human intervention. It provides a framework of seamless interaction with the patient and, finally, to deliver external assistance for mobility. This proposed system relies on embedded computers, ECG, IoT, RTC, HMM, machine learning, and other sensors used in the healthcare industry.

Keywords—Embedded Computing, ECG, RTC, IoT, HMM, Healthcare, labour, machine learning, mobility, patient monitoring, automation, sensors.

I. INTRODUCTION

The spurt in technology in every sector has paved the way for more reliable healthcare management through seamless co-operation between programmed machinery that performs tasks efficiently and doctors who carry the power for advanced treatment of the patient [1]. The speed, efficiency and error correction capability of the conceived healthcare system is greatly enhanced by this synergy between humans and machines [2]. In the domain of medicine, machine monitoring has especially helped do the monotonous, repetitive work that humans don't necessarily need to waste time in chores that can be done by such robots. We explore avenues that can make a patient's life safer, healthier, and much more comfortable. Moreover, doctors and relatives enjoy realtime information on the patient remotely. With the surge in population and increased demand for a proficient healthcare system, it has become more and more critical for robots and artificial intelligence (AI) based systems to take up jobs to ensure continual care. The amount of money spent on managing a manual workforce has directly translated into exorbitant bills for a minimum requirement. Additionally, the number of nurses in hospitals has decreased over the years, and a large percentage of the current nurses crossed the age of 50.The nursing field is generally underpaid and comes with taxing labour and an unhappy work style. Given that the number of elderly and disabled people are consistently on the rise, any automation concerning their healthcare is of prime importance [3].

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Introducing such devices to take care of labour intensive and time-consuming tasks help direct resources towards areas that require such tasks to be finished briskly, effectively, and without wastage of space and time.
There have been several iterations of the same idea, but the approaches are different. In some iterations, devices are interfaced through wireless connections, but being a wearable contributes to its high costs and thus makes it uneconomical for a large section of the demographic [4]. Machine to Machine (M2M) communication is possible in devices such as Electrocardiogram (ECG) Monitoring, Blood Pressure Monitoring, Oxygen Saturation Monitoring, Temperature Monitoring, etc. to keep track of the patient's vitals. Wireless Body Sensor Networks use to keep track of the patient [5] health and observe ECG, heart rate, and pressure. But this prototype is for temporary wheelchair users, and for people permanently wheelchair ridden it is not economically viable. Several works proposed the smart wheelchairs in which they are voice-controlled by robots [6]. But their work is either very expensive or not practicable or have minimal functionality [6]. Conventionally these systems use Bluetooth to handle all the communication. Bluetooth is known to be safer and less power-consuming [7]. It also ensures wireless data transfer without physical connections like cables and wires. But with such a model, the radius of communication is limited, and so is not sufficient for remote manipulation reported by Kumar and Rahman [8]. Even though power consumption is reduced, the data transfer is restricted and inadequate for the application. Cloud computing technology is used to overcome this [9]. After going through various research papers, it was clear that multiple shelf sensors are used that are readily available online. Microcontrollers like PIC and Arduino controlled these. But none of these interprets the data by themselves – the only display raw data. E.g., when reading a heart pulse, only the pulse is projected, but no analysis is done about the patient's condition.

The MedBed as they call it, the nurses stationed have constant updates on the patient without them having to be physically present [10]. Their Web Servers cope with all devices, forward commands, and update websites on the UI. A similar feature included that helps the concerned doctors come to know if the patient has either asked for them or, in case of a failure, intimates them of the cause and asks them to rush immediately. The aim is to get a fraction of the enlisted sensors working in the proposed work, with all the data transferred to a shared database and linking all the required sets of machinery to form an independent network. This implementation also ensures malleability, as with time, new and advanced technology is introduced into this prototype. The patient is also mobile, and so the bed made can transform into a wheelchair. The implementation of this is sure to cost a little extra, but in the long run, it serves the purpose more cost-effectively.

Most prior systems had an inherent flaw concerning user-friendliness. Even though the patient is monitored and assisted in the right manner, the patient is not comfortable and finds the device hard to control. Thus there have been several attempts at making such systems much easier to use. Voice control and communication seem the most natural choice after physical buttons. There have been several attempts that use a variety of speech recognition algorithms like MFCC-DTW [11], Neural Networks, and Hidden Markov Models (HMM).

Across the country, many remote areas lack basic medical aid, so the aim is to reach out to the masses with this product. Back-end server coding techniques are implemented with supervised/unsupervised learning algorithms using the Internet of Things (IoT). This work encompasses various aspects of engineering, such as Mechatronics, AI, Networking, Natural Language Processing (NLP), and Signal Processing. Data management and neural networks are used to implement cloud computing [12]. The proposed work focuses explicitly on

constructing a real-life prototype that concerns the bedridden older people with limited mobility. Section II deals with hardware implementation, section III relates the proposed methodology, Section IV is related to results and discussion, and the conclusion part is given in section V.

II. HARDWARE IMPLEMENTATION

The hardware implementation part is discussed in detail in this section. The integrated units such as voice control, the medical dispenser unit are shown in Fig.1 and Fig. 2, respectively, and the final wheelchair part is depicted in Fig.3. The main hardware components are explained in the subsections, namely Arduino Uno, mini pulse oximetry and heartrate monitor MAX30100. Besides, integrated signal conditioning unit AD8232, humidity and temperature sensor DHT11, realtime clock, Servo motor and Raspberry Pi are discussed in this section. A prototype is developed for demonstrating the features mentioned above, is shown in Fig.3. Lithium-ion batteries power the smart wheelchair.

Fig.1. Voice Control and Sensors

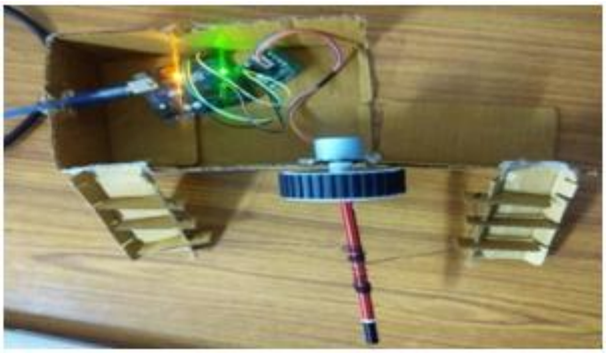

Fig.2. Medical Dispenser

Fig.3. Convertible Wheel Chair/Bed

A.Arduino Uno

Arduino Uno is an open-source platform that consists of a programmable board, software, or an IDE that helps to write the code as per our requirements and upload it to Arduino UNO. The Arduino Board has the following components:

- Power Jack: Every Arduino needs to be connected to the power connection to run it. In this case, a USB cable is used that connects the computer to act as a source of power.
- PINS: Various pins include the 5V or 3.3V power supply. There are 6 analog pins and 7 digital pins. There are also PWM pins present in the Arduino board.
- Reset Button: The reset button stops the current functioning of the code and starts running the code from the beginning.
- Power LED: There is a power LED that indicates whether the Arduino UNO is switched on or off.
- Microcontroller: This is the main IC that processes the code and runs it and controls the entire working of the model.

B. MAX 30100

The MAX30100 is mini pulse oximetry and heartrate monitor. A pulse oximeter provides a non-invasive method of estimating the saturation of peripheral oxygen (SpO_2). It essentially measures the percentage of hemoglobin (Hb) saturated with oxygen [13].

A light signal reacts with the tissues, and the changes are recorded based on time are used to calculate oxygen saturation [14]. The light immersion is calculated from Beer-Lambert law (equation number 1) and the percentage of oxygenation is found from the arterial network. The value usually denoted as % SPO_2.

The sensor is placed at a position where the skin is not too fat and light frequencies can easily pass the tissue, e.g. the finger, the earlobe. Depending on the % of the oxygen that flows through our blood, the fraction between absorbed red light and infrared (IR) LED differs, giving us oxygen levels. Taking only the IR data is not enough as it has a DC offset that needs to be filtered. To get precise readings of the heart rate, SpO2 DC part of the signal must be removed, and only the AC part is extracted using equations *(1)-(2)*. The following equations help with that:

$$w(t)=x(t)+\alpha \times w(t-1) \qquad (1)$$
$$y(t)=w(t)-w(t-1) \qquad (2)$$

Where,

y(t) is the output of the filter
x(t) is current input/value
w(t) is the intermediate value that acts like the history of the DC value
α is the response constant of the filter
If α = 1 then everything passes through
If α = 0 then nothing passes through

Our ability to detect pulses is enhanced after the DC filtering signal is passed through a statistical filter and it takes the derivative of the signal, so show the sudden changes in the pulse. The resulting signal is similar to a cardiogram.

The high-level harmonies give noise, so to get rid of it, Butterworth filter is needed. To apply a Butterworth filter sampling rate and cut-off frequency is required. For MAX30100 sampling rate is set as 100 Hz. The upper value of 220 BPM is set for the heartrate sensing, and the lower level is set as 50 BMP.

The fastest frequency allowed is calculated by equation (3):

$$f = \frac{220BMP}{60} = 3.66\ Hz \qquad (3)$$

The lowest frequency allowed is given by Eqn. (4):

$$f = \frac{50BMP}{60} = 0.83\ Hz \qquad (4)$$

Oxygen concentration is checked by taking the fraction of absorbed light given by the IR LED, and the Red LED. SpO_2 is defined as the ratio of oxygenated hemoglobin level over the total hemoglobin level given by (5).

$$SpO_2 = \frac{HbO_2}{Total\ Hb} \qquad (5)$$

Two different wavelengths are used for LED's, the first one is IR (950nm), and the other one is RED (650nm). These two wavelengths emit towards the user's finger in an alternating fashion. The ratio R between these two wavelengths define by equation (6).

$$R = \frac{log(I1AC)\times\lambda 1}{log(I2AC)\times\lambda 2} \qquad (6)$$

I_{1AC} is the light intensity (from IR), and I_{2AC} is the light intensity (from red light) where only the AC is present. In this, we use the light wavelengths as 650 nm and 950 nm for λ_1 and λ_2, respectively. Finally, the Oxygen content is found from equation (7).

$$\%SpO_2 = 110 - 180 \times R \qquad (7)$$

C. AD3282

The AD8232 is used as an integrated signal conditioning setup for ECG and other bio-potential measuring applications. It is designed to identify, amplify and remove the small bio-potential signals in a noisy situation, such as the ones created by movement or electrode placement. Fig. 4 depicts the circuit for monitoring ECG waveform with the external connections. This analog-to-digital converter (ADC) is a low-power device that receives the output signals quickly. The AD8232 is also a microcontroller that acts as a two-pole high-pass filter for removing motion artifacts and electrode potential. This filter is added with the instrumentation architecture of the amplifier to let both significant gain and high-pass filtering in every single stage, therefore saving space and also cost.

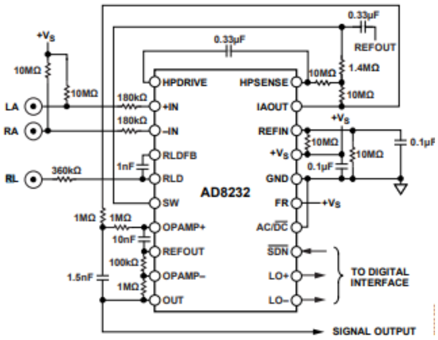

Fig.4. AD3282 Circuit for ECG Waveform Monitoring

This configuration is used for taking the shape of the ECG waveform. It is assuming that the patient remains almost still during the process, and thereby, the motion is not a big issue. The AD8232 is matched with a 0.5 Hz two-pole high-pass filter followed by a two-pole, 40 Hz, low-pass filter to obtain a waveform with minimum distortion. The frequency response of the cardiac monitor is shown in Fig. 5. A third electrode is driven for optimum common-mode rejection.

Next, a total gain of about 1100 is achieved in this OpAmp stage with 40 Hz filtering for a gain of 11. The gain level is flexible, depending on the input signal (which varies with electrode placement) and the ADC input scope to optimize the range of this system.

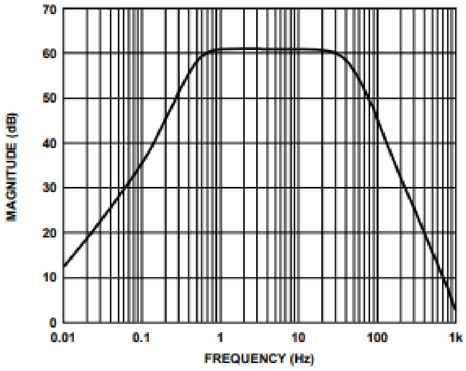

Fig.5. Frequency Response of Cardiac Monitor

D. DHT11- Digital Humidity and Temperature Sensor

DHT11 sensor gives moisture and temperature readings in the form of a digital signal. The moisture is calculated using a condenser sensor, and the temperature from a thermistor. One big profit of this is that it gives digital output, built inside as a single wire interface, needing no analog pins to usage. The sensor best works when accuracy is not essential, and the scope of use is least. It gives temperature reliability of about ±2°C and samples at a rate of about 1Hz (providing a reading every second).

E. Realtime Clock (RTC)

The clock chip DS1307 acts as RTC and uses the I2C protocol. It has a Lithium cell battery (CR1225). The calendar gives seconds, minutes, hours, day, date, month, and year data. The month-end date is automatically calibrated for months with less than 31 days, including accuracy for leap year. The clock works in either the 24-hour or 12-hour mode with AM/PM gauge.

F.Servo Motor

A metal-geared servo motor is used that can easily withstand the pressure of the chair and rotate it 90 degrees to change its shape into a medical bed.

G. Raspberry Pi

Raspberry Pi is a small single board computer. It is exceptionally famous for other branches such as robotics, cloud computing, and the Internet of things. The Foundation provides Raspbian, a Debian-based Linux distribution for download, as well as third-party Ubuntu, Windows 10 IoT Core, Reduced instruction set computer (RISC) Operating System (OS), and specialized media centre distributions. It is used in home automation, industrial automation and now even in space options.

III. PRINCIPAL METHODOLOGY

This paper provides maximum support to older people with an affordable cost with multiple functionalities. The proposed work is divided into the construction of three individual blocks, namely the sensor box, the convertible bed/wheelchair, and the medical dispenser. The workflow of the proposed work is displayed in Fig 6. A full-scale prototype is integrated after the successful implementation of three tasks. For improving the patient interface with the automated system, some user-friendly interaction system is needed that does not require any physical input from the patient. Fig. 7. displays the full-scale prototype, which relates the voice controlled mechanism, which depends on the realtime clock operation.

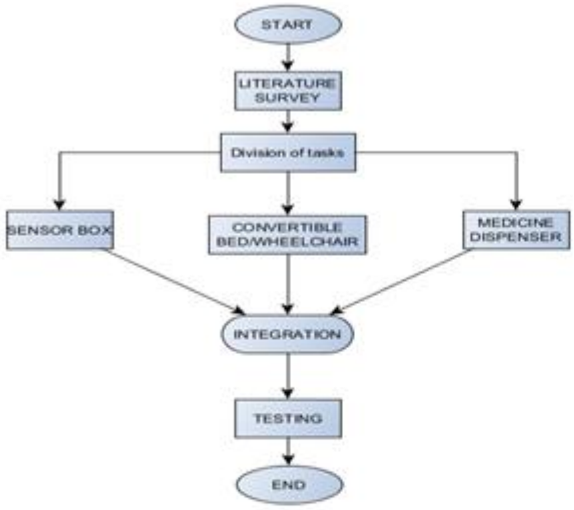

Fig.6. Work Flow of the proposed work

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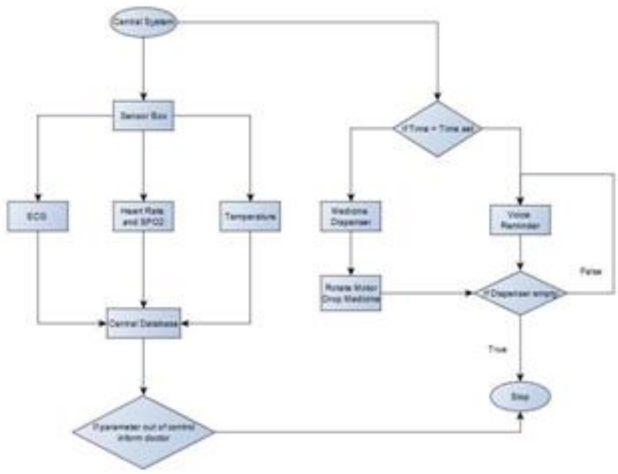

Fig.7. The final product of the proposed work

A. Sensor Box

The sensor box consists of an ECG sensor, an Oximeter, temperature sensor, and general condition using image processing to detect pupil dilation, tongue, and eye dis colouration, skin colour detection etc. All four are integrated to make a fully functioning detection system, as shown in Fig. 1.

B. Medical Dispenser

The medical dispenser consists of a Real Time Clock (RTC) that intimates the patient as to when they need to take their medicines [15].

Fig. 7. displays the full-scale prototype which relates the voice controlled mechanism and the medical dispenser unit. The mechanism is such that it drops the required quantity of capsules/tablets based on the information given to the system by the attending doctor whose design is inspired by Antoun, Abdo et. al [16]. The RTC acts like a clock to the Arduino, which is connected to a stepper motor. As the RTC starts, the stepper motor rotates, thereby dispensing the medicine at the stated time. The slots are such that only the required number of medicines fall, as shown in Fig. 2.

C. Convertible Bed/Wheelchair

Fig.8 reveals the working procedure of a convertible bed/wheelchair. The bed/wheelchair is to be made transformable using servo motors and includes voice control for the patient to be itinerant, as shown in Fig 3. The process shows the sensors are to be integrated for calibration, and the mechanical design of the convertible was first worked out in SolidWorks and then made into a working model.

D. Voice Control and Feedback Subsystem

For improving the patient interface with the automated system, some user-friendly interaction system is needed that does not require any physical input from the patient. Most voice interaction systems need to have a way to speak to the user in a human-like voice, which is understandable and friendly and also be able to understand what the human (patient in our case) is saying. So that would involve two subsystems, i.e., speech to text audio signal processing and text to speech audio voice synthesizer.

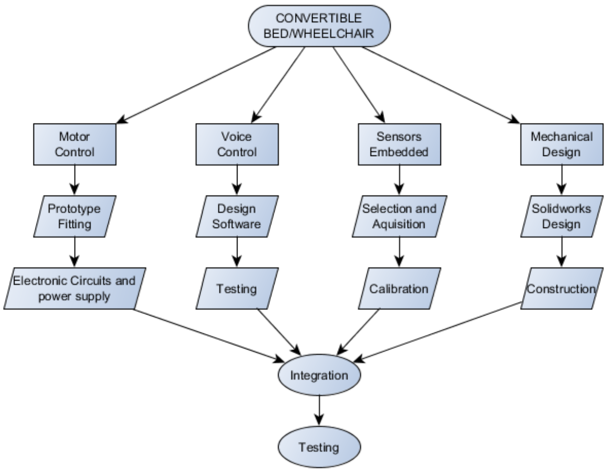

Fig.8. Working procedure for Convertible Bed/Wheelchair

Speech recognition is the inter-disciplinary sub-field of computational linguistics that develops methodologies and technologies that enable the recognition and translation of spoken language into text by computers [17]. Voice recognition earlier used to be done by the dynamic time warping, and now it is replaced by the widespread technique called Hidden Markov models or HMM-based approach. Also, another algorithm prevalent in this regard is through deep learning neural networks. But for this system HMM-based approach is used.

In most voice recognition systems, the processing takes place on the cloud over the Internet because a large amount of processing is needed, and then the text is relayed back to the user system. Since this patient assistance and monitoring system should be able to function in all sorts of remote places with or without internet connectivity and at the same time independent of the cloud.

CMU sphinx based voice recognition engine is used in this system, which is based on the Hidden Markov models based approach [18]. In this work, a statistical Markov model based system is exhibited by predicting the Markov process with unknown (i.e., hidden) states using Hidden Markov Model (HMM). HMM is a finite model that describes a probability distribution over an infinite number of possible sequences [19]. This approach to voice recognition is highly accurate. It needs an acoustic language model to train the HMM model, which is done by the CMU sphinx engine. The acoustic model is created and the HMM model is trained to translate specific words only thus eliminating the redundancy in the HMM and making it simple enough for the required embedded application [20].

It is crucial to consider the fact that the accuracy of voice recognition is more important than latency incurred by the system. Since the voice recognition system would look for keywords and sounds like screaming, asking for help, and others that require immediate medical attention.

The voice synthesizer system converts the text, which is generated by the system that it wants to communicate to the patient into a voice signal, then routed to a speaker. The voice synthesizer is implemented using the Espeak platform. Espeak platform works by text to phoneme translation, where the input text is translated into pronunciation phonemes. Next, these pronunciation phonemes are synthesized into sound by looking into a phoneme voice conversion database [21]. The voice synthesizer is used for communication as well as reminding the patient various activities they have to stay in the best of their health.

The system relies on a hybrid of speech and non-speech communication with the patient, which is accepted to be better than a single mode of communication in similar cases [22]. This subsystem is used for mobility assistance and hence navigation. Navigation is based on vision SLAM and localization using computer vision [23].

E. Learning Process for Heart Disease Prediction

In this era comprising of various diseases and ailments in humans, heart disease is one of the most common ones. Diagnosing patients accurately and repetitively on a timely basis is the most challenging task. Diagnosis is often made based on experience and knowledge of medical practitioners who have been seasoned for 2 years and beyond. Due to this, there are chances of unwanted biases, errors, and it also takes a longer time in the accurate and precise diagnosis of the disease. Medical diagnostic systems play a fundamental role in medical practice and are used exhaustively [15].

The proposed system uses a multilayered feed forward neural network model to predict whether the patient has a heart problem or not by training the dataset and then using the test case of the patients to arrive at an accurate prediction [25]. The University of California provides the dataset, Irvine [UCI] machine learning repository is used for training and testing. This model is also called a multilayered perceptron backpropagation algorithm [26].

Table 1. Statistical Summary of Dataset

	age	sex	chest_pain	blood pressure	serum_cholestoral	fasting_blood_sugar	electrocardiographic	max_heart_rate	induced_angina
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.438944	0.679868	3.158416	131.689769	246.693069	0.148515	0.990099	149.607261	0.326733
std	9.038662	0.467299	0.960126	17.599748	51.776918	0.356198	0.994971	22.875003	0.469794
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000
25%	48.000000	0.000000	3.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000
50%	56.000000	1.000000	3.000000	130.000000	241.000000	0.000000	1.000000	153.000000	0.000000
75%	61.000000	1.000000	4.000000	140.000000	275.000000	0.000000	2.000000	166.000000	1.000000
max	77.000000	1.000000	4.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000

A layer is formed by taking a processing element called a neuron using the primary feed-Forward neural network. The model contains an input layer, a hidden layer, and an output layer. The input layer accepts 19 different features as input from the dataset, the hidden layer consists of 25 units, and the output is just 1 neuron with a binary answer of 1 or 0 to denote whether heart disease is present or not.

Table 2. Correlation Table of the Dataset

	age	sex	chest_pain	blood pressure	serum_cholestoral	fasting_blood_sugar	electrocardiographic	max_heart_rate
age	1.000000	-0.097542	0.104139	0.284946	0.208950	0.118530	0.148868	-0.393806
sex	-0.097542	1.000000	0.010084	-0.064456	-0.199915	0.047862	0.021647	-0.048663
chest_pain	0.104139	0.010084	1.000000	-0.036077	0.072319	-0.039975	0.067505	-0.334422
blood pressure	0.284946	-0.064456	-0.036077	1.000000	0.130120	0.175340	0.146560	-0.045351
serum_cholestoral	0.208950	-0.199915	0.072319	0.130120	1.000000	0.009841	0.171043	-0.003432
fasting_blood_sugar	0.118530	0.047862	-0.039975	0.175340	0.009841	1.000000	0.069564	-0.007854
electrocardiographic	0.148868	0.021647	0.067505	0.146560	0.171043	0.069564	1.000000	-0.083389
max_heart_rate	-0.393806	-0.048663	-0.334422	-0.045351	-0.003432	-0.007854	-0.083389	1.000000
induced_angina	0.091661	0.146201	0.384060	0.064762	0.061310	0.025665	0.084867	-0.378103
ST_depression	0.203805	0.102173	0.202277	0.189171	0.046564	0.005747	0.114133	-0.343085
slope	0.161770	0.037533	0.152050	0.117382	-0.004062	0.059894	0.133946	-0.385601
vessels	0.359489	0.092891	0.232332	0.098707	0.118525	0.143967	0.127487	-0.263408
thal	0.127368	0.379300	0.264895	0.133534	0.014190	0.070658	0.024449	-0.278530
diagnosis	0.222853	0.224469	0.407075	0.157754	0.070909	0.059186	0.183696	-0.415040
diag_int	0.223120	0.276816	0.414446	0.150825	0.085164	0.025264	0.169202	-0.417167

The algorithm is as follows:

1. The CSV file containing the dataset of the heart patients is imported to the program.
2. The dataset is preprocessed to remove unwanted data
3. From the given data, the test data and the training data set are separated using cross-validation.
4. The parameters of the different layers are set with input layer size, hidden layer size, and the output size.
5. Forward propagation of the Neural Network is performed without regularization, which means the lambda value or the weight decay parameter, which tends to decrease the magnitude of the weights and helps prevent over-fitting. The cost function of the Neural network is n calculated.
6. Forward propagation using regularization is performed by setting the lambda factor to a non-zero value, preferably 0.000001. The cost function of the Neural network is calculated again.
7. The neural network is trained. The iteration value is set as a precursor, the results are more accurate when a larger number of iterations are performed. The cost function, Theta1 and Theta2 are calculated. Their layer sizes are updated based on the cost calculation and the neural network parameters.
8. The accuracy of the training set is computed. The Z values are the inputs to the activation function and calculated as Z1, Z2, Z3. Three different values for Z because there are only 3 layers in total. A sigmoid function is used as the activation function and is applied to all the three different Z values, and the activation function applied on Z3 is the final output, which is stored in ZTheta.
9. The error percentage of the code is calculated by comparing the values between the output we get from the output layer during the feed-forward algorithm process and the test set output.

The accuracy of the model is around 95.2 percent according to the error rate when the test case is applied to the trained model.

This neural network so trained use the data collected by the various sensors of the system to predict heart disease in a patient. Hence it provides valuable insights to doctors in their diagnosis.

IV. RESULTS AND DISCUSSIONS

The full prototype is implemented in the academic environment. Rahman et.al., [27] reported a wheelchair that is controlled by eye blink, and extra features like speed control and obstacle detection are added with the wheelchair reported in [28]-[30]. Ordinary people accommodate the proposed work at a low cost. The evaluation is conducted in a step by step manner with different sensors like heart rate, temperature, electro cardio Graph, and the results are displayed in this section. Furthermore, this research concentrates on building an intelligent wheelchair that operates based on the English command. The aforementioned multifunctional prototype is tested in the laboratory.

A. Sensor Results

Fig. 9 shows the Oximeter data in two different colours. Raw, unprocessed pulse oximeter data (purple) and heart rate sensor data (green) coming from the MAX30100 is the raw IR data, containing both DC and AC components. With a DC offset, it becomes tough to analyze the data, and hence the signal is passed through a DC removal filter. The output of this is allowed through a mean differentiator filter to clean up the waveform and detect the pulse easier.

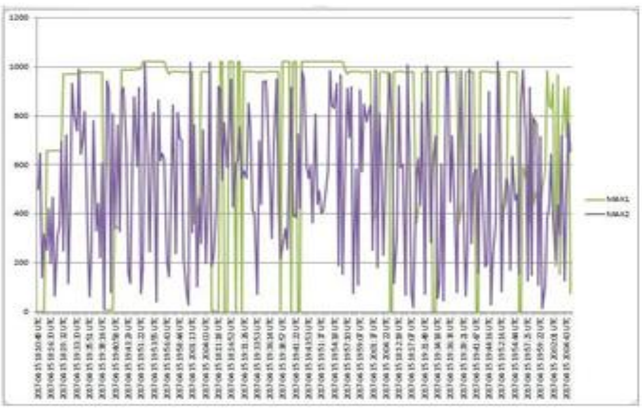

Fig.9. Oximeter Data

The temperature of the patient is to be monitored and plotted online, as shown in Fig.10. The sensor takes the data periodically, and the graph is plotted, which are adhered to the same. A range of values is chosen to make sure the patient's temperature is not too high or too low. If the value goes beyond the range, an alert is to be triggered, and the attending doctors must be informed of the patient's instability.

Electrocardiography (ECG or EKG) is the process of recording the electrical activity of the heart over a period of time. Electrodes are placed on the skin, and it is very commonly performed in the cardiology test. The ECG signal has 3 peaks called P, R, T points. The ECG signal has 2 minima points called Q and S, as seen in Fig.11.

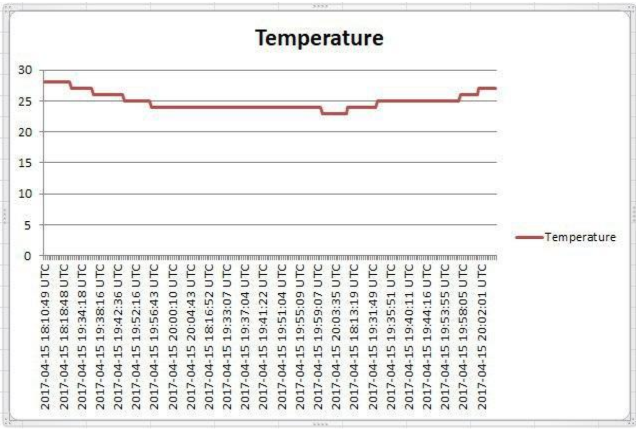

Fig.10. Temperature of Patient

These points signify the different pumping mechanism of the heart. Commonly, some issues arise in this process, and they are identified as noise from the device. So this process generally requires one to preprocess the signal before the actual processing of it.

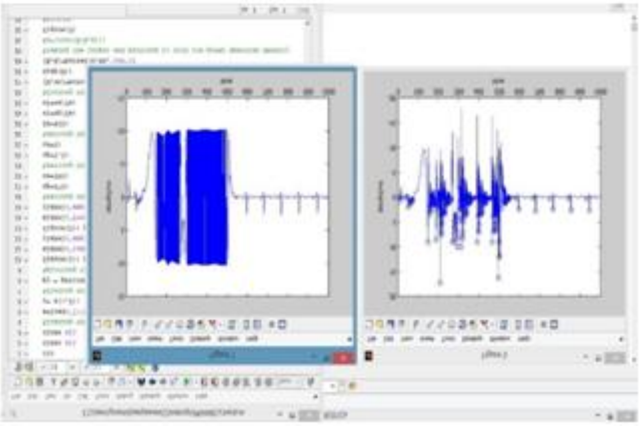

Fig.11. ECG of a heart in normal sinus rhythm

B.Voice Controlled Output

Language model used: The (fixed) discount mass is 0.5. The backoffs are computed using the ratio method. This model based on a corpus of 10 sentences and 22 words. [29] –[30]. When the microphone heard a speech signal, it used the trained HMM to determine the phrase Input Audio Phrase: "Move Backward". The voice controlled output is shown in Fig.12.

Output: DETECTED: ['<s>', 'MOVE', '<sil>', 'BACKWARD', '[SPEECH]', '</s>']

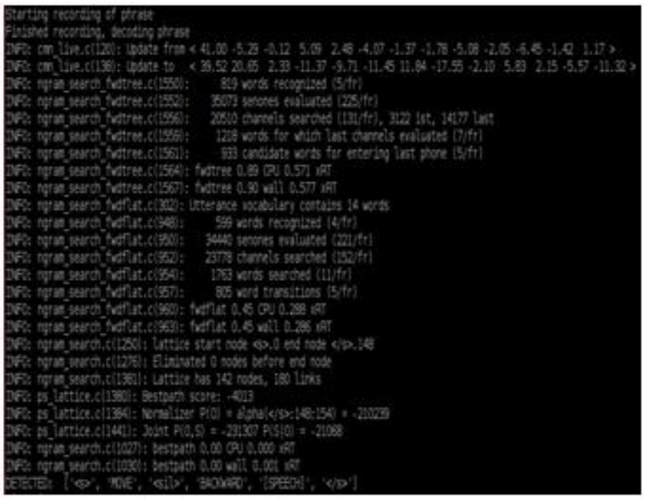

Fig.12. Voice Controlled Output

V. CONCLUSION

The multifaceted working of the proposed model ensures the process is not cumbersome and does not require extensive human intervention. Autonomy is a crucial factor that decides the worth of this product. With the learning processes involved, the machine takes care of everything that initially required a human to get involved. The sensors are used to monitor the patient's vitals at regular intervals without being reminded at intervals of time. With safe zones marked out, the attending medics needn't continuously keep checking in on the patient as they are alerted in case of an anomaly. This helps scatter the medics and prioritizing patients, finding the ones who need to be attended to earlier and who can wait. The unique feature of our proposed work is the medicine dispenser system that makes sure that the process of reloading medicines in a hassle-free affair. Where other products have a technique in which the user must manually reload each medicine in small containers, this product makes sure that all the users need to do empty the medicine package into a container. The system takes care of the rest, and it has the potential to be an efficient system to take care of the sick, helping us direct our human resources to areas that require them, as well as eliminating erroneous tendencies.

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