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A Novel IoT-Enabled Device for Early Prediction and Detection of Chronic Disease

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Abstract: - Chronic diseases is increasing day-by-day according to world health organization (WHO), and now its health challenge worldwide that requires early prediction and detection of accurate diagnosis of a chronic diseases. In this paper is to design a device to get the reading from medical sensor calculate the early warning score (EWS) by using machine learning algorithms. The main target of this paper is to offer actual readings of medical sensor which gives blood pressure (BP) and pulse rate (PR) readings as per the prescribe time interval suggest by the medical professionals. EWS calculated by using machine learning (ML) algorithms, this paper includes K-NN, Naïve Bayes, support vector machine, and random forest for early prediction of chronic diseases. In this Naïve Bayes, gives 99.44% accuracy result which is a crucial aspect of in case of ICU admission due to chronic diseases. The paper target to decrease healthcare expenses and identify wrongdoings in the chronic diseases.

Keywords: world health organization (WHO); early warning score (EWS); Machine learning (ML); internet of things (IoT).

I.   INTRODUCTION

Anxiety, a prevalent condition affecting 1130 million people worldwide, predominantly in developing countries, has been identified as a significant factor contributing to accelerated aging and the onset of cardiovascular illnesses such as heart attacks, hypertension, and elevated blood pressure. Statistics from 2015 reveal that one in every four men and one in every five women were afflicted with hypertension, a trend that has likely persisted and even worsened by 2022 [1]. In summary, integrating regular monitoring facilitated by IoT-enabled device into healthcare protocols represents a proactive and effective approach to combating the detrimental effects of anxiety-driven hypertension [2]. By leveraging this technology, healthcare professionals can identify early warning signs, intervene promptly, and ultimately reduce the burden of cardiovascular diseases on global health [3]. As per the guidelines set forth by the American Heart Association and the American College of Cardiology, hypertension is classified into four distinct stages for diagnostic purposes: elevated, hypertension stage 1, hypertension stage 2, and hypertensive crisis. In the elevated stage, the upper blood pressure reading falls between 120 and 129 mmHg, while the lower reading remains under 80 mmHg. Progressing to hypertension stage 1, the lower number ranges from 80 to 89 mmHg, with the upper number elevated to between 130 and 139 mmHg [4]. Advancing further to hypertension stage 2, the upper number reaches 90 mmHg or above, accompanied by a lower number of 140-149 mmHg or higher. Finally, in a hypertensive crisis, the upper number surges beyond 180 mmHg, and the lower number rises above 120 mmHg, signifying a critical medical emergency [5]. Innovative technology, such as IoT enabled device, plays a pivotal role in continuously monitoring a patient's blood pressure [6]. This system operates by continually checking the patient's blood pressure and securely transmitting the data to the cloud for accessibility and analysis. By leveraging the power of IoT, healthcare providers can access real-time blood pressure readings remotely, enabling timely interventions and personalized patient care [7].

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TABLE 1: Hypertension stages collection by American College of Cardiology hypertension

Type of Blood Pressure	Systolic (Upper No.)	Diastolic (Lower No.)
Normal	Less than 120mmHg	Less than 80 mmHg
Elevated	120-129mmHg	Less than 80 mmHg
Hypertension stage 1	130-139mmHg	80-89mmHg
Hypertension stage 2	140-149mmHg	90mmHg or higher
Crisis of hypertension Consult your physician right away.	Higher than 180 mmHg	Higher than 120mmHg

As per the guidelines established by the American Heart Association and the American College of Cardiology, hypertension is classified into four stages: elevated, hypertension stage 1, hypertension stage 2, and hypertensive crisis. Each stage is characterized by specific ranges of systolic and diastolic blood pressure readings. The IoT-enabled device continuously monitors a patient's blood pressure and securely transmits the data to the cloud for accessibility and analysis. In this study, a wrist-cuff digital blood pressure measurement device is employed to conduct one-day monitoring, facilitated by the Things Board, an open-source IoT platform [8]. This platform efficiently stores data on the cloud and provides a user-friendly interface for streamlined analysis. By customizing measurement intervals based on healthcare provider instructions, the system aims to enable early detection of chronic heart diseases [9]. The primary objective of the research is to implement an Early Warning Score (EWS) prediction system utilizing machine learning algorithms such as K-Nearest Neighbors (K-NN), Naïve Bayes, Support Vector Machine, and Random Forest. These algorithms are leveraged to forecast early warning scores, serving as vital indicators for preemptive intervention

II. RELATED WORKS

Table 2 presents a comparative analysis of previous research efforts in the field. It is evident that the integration of Internet of Things (IoT) technology has garnered significant attention in the realm of medical science, with notable contributions such as the IoT-based health monitoring system developed by Tamilselvan et al.. This system incorporates an array of sensors, including an eye blink sensor, oxygen saturation sensor, and thermometer, integrated into an Arduino-board. These sensors facilitate the monitoring of vital signs such as oxygen saturation percentage, heart rate, eye movement, and body temperature. However, several challenges and limitations have been identified in prior research [10]. Issues pertaining to data visualization, continuous monitoring without impeding patient mobility, and constraints in data availability, timer functionality, and power consumption have been highlighted [8]. These challenges underscore the need for further innovation and refinement in IoT-based healthcare monitoring systems. Despite these challenges, IoT holds immense potential to revolutionize healthcare monitoring practices. Through ongoing research and development efforts, addressing these limitations can pave the way for more efficient and patient-centric healthcare solutions [9]-[10].

TABLE 2: Comparative analysis of previous work

Sr. No	Reference No.	Algo-rithm/Method Used	Accu-racy/AUC (area under the receiver operating characteris-tic curve)	Limitation
1	V. Tam-ilselvi et. Al [10]	Arduino-Uno Board	>70%	No exact performance trials exist for any of the patients

2	Acharya and. Patil et al [11]	Raspberry processor3	>65%	Insufficient interfaces for data visualization are the system's most serious problem
3	Gregoski et al. [12]	A mobile brightness and camera	< 95%	If you need to continuously monitor your heartbeat throughout the day without disturbing the patient's mobility, this proposed technology doesn't work
4	Oresko et. al. [13]	A mobile brightness and camera	< 98%	Only coronary rhythm was observed in real-time by the proposed prototype, not HR (bpm) over time and hence it's difficult to detect cardiovascular disease
5	Trivedi, and Cheeran et al. [14]	A smartphone and Arduino-based system	<98%	Using this technology medical professionals can monitor and analyses clinical data remotely and prescribe things remotely

Albur et al. introduced a dynamic marker for assessing severity and prognosis in patients with Gram-negative bacteremia and sepsis, while Ng et al. [11] validated sex-specific prognostic models, demonstrating robust predictive performance. Siddiqui et al.'s research showcased the high sensitivity and specificity of EWS for detecting sepsis, severe sepsis, and septic shock, indicating its potential utility in early diagnosis and effective management [12]. Additionally, Khekare, Ganesh, et al. delved into the features, capabilities, and challenges of the Internet of Things (IoT) and its profound impact on global quality of life [13]. Through these studies, the collective efforts contribute to advancing medical diagnostics, prognostics, and healthcare management, while also highlighting the transformative potential of IoT technology in enhancing quality of life worldwide [14]-[16].

III.   3. PROPOSED METHODOLOGY

Figure 1 shows the flow diagram of IoT enabled device, the patient starts the IoT enabled device manually and sets the time interval using the Blynk mobile application. The BP sensor measures systolic, diastolic, and pulse rate readings, which are checked by the system. If the readings are correct, immediately sent to a Things Board an open-source IoT platform. If an error message is displayed, the system restarts and repeats the process until the reading is displayed [17]. The proprietary circuit diagram of the IoT enabled device is shown in Figure 2.
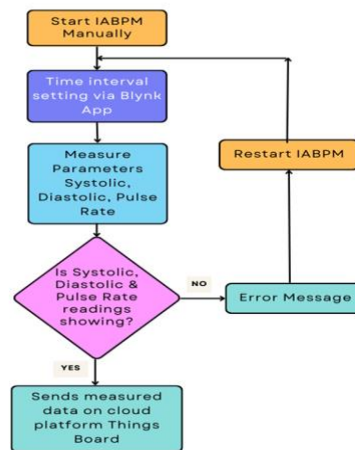

Figure 1. Flow Diagram of IoT enabled device

The IoT-enabled system, illustrated in Figure 2, comprises essential components including a D1 mini controller, a transistor-based switching circuit, and a blood pressure (BP) sensor. Serving as the central component, the D1-mini controller features an integrated Wi-Fi module and microcontroller capabilities, forming the backbone of the system's functionality [18]. Interaction with the BP sensor is facilitated through the D1-mini controller, which receives commands from a mobile application. The Blynk mobile application offers convenient ON/OFF control of the BP sensor, coupled with a timer function for precise measurement intervals. Moreover, the D1-mini controller retrieves clinical data from the BP-02 sensor, seamlessly integrating this information into the cloud platform Things Board for further analysis and accessibility. The circuitry encompasses various components, including a driver IC, 330-ohm resistors, LED and buzzer are used for indication purpose, and a 2N-2222 N-P-N transistor utilized for switching [19]-[22] the BP medical sensor ON and OFF. This comprehensive system architecture underscores the fusion of IoT technology and medical instrumentation, facilitating remote monitoring and data-driven healthcare solutions.
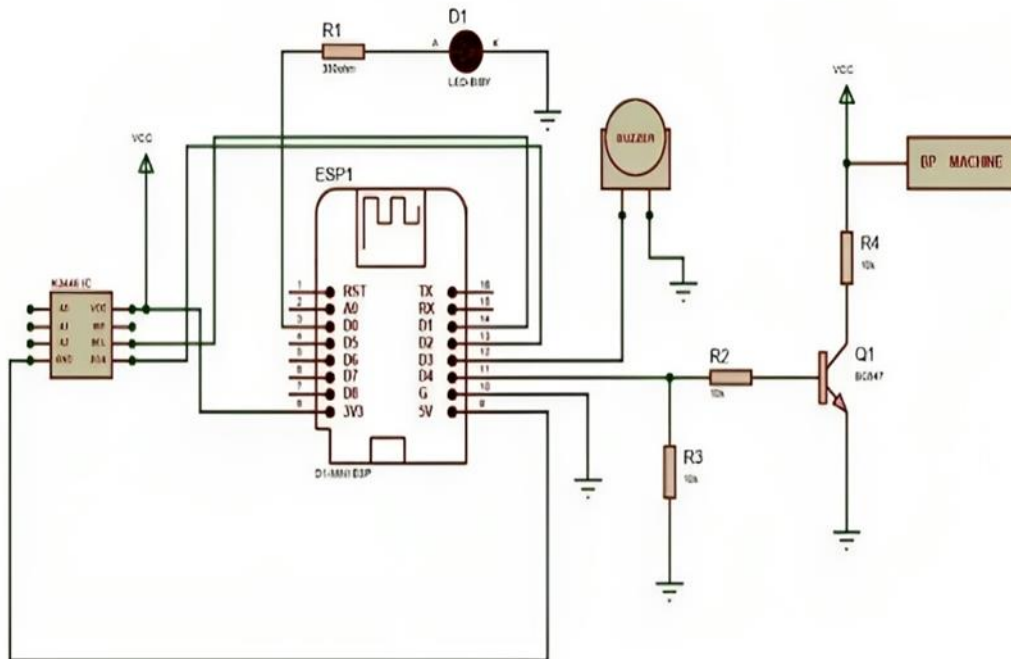

Figure 2. Circuit Diagram of an IoT enabled system

3.1   Finding the best suitable machine learning algorithm

TABLE 3. Samples of clinical data From SMHRCE Hospital

Entry id	Age	Systolic Upper No.	Diastolic Lower No.	PR	Gender M=1 F=0	Level	Target
1	45	128	85	80	0	1	0
2	46	129	94	79	0	1	0
3	46	127	89	89	0	1	0

4	45	125	88	84	0	1	0
5	48	126	76	75	0	1	0
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
495	46	156	92	82	1	3	1
496	48	144	78	76	1	3	1
497	46	210	100	99	1	1	1
498	62	165	70	98	1	1	1
499	41	168	69	102	1	2	1
500	42	199	99	83	1	4	1

Table 3 presents clinical data collected from SMHRCE hospital, comprising a dataset of 500 samples encompassing eight attributes. This dataset originates from the IoT enabled device, and is instrumental in conducting result analysis and guiding future research directions. The attributes included in the dataset are: entry ID, patient age, systolic upper no. BP, diastolic lower no. BP, PR, patient gender, level of chronic heart diseases, target attribute. This comprehensive dataset facilitates in-depth analysis of patient health parameters and serves as a foundation for investigating abnormalities and predicting outcomes [23]. To examine abnormalities within the dataset, a Naïve Bayes classifier function (equation (1)) is employed. The Naïve Bayes model, a common tool utilized in IoT enabled device, calculates probabilities p(Ck|x1, x2, ..., xn) for each of the K potential outcomes or classes Ck, given a problem instance encoded by a vector x=(x1, x2, ..., xn) comprising n independent variables or features. This statistical approach aids in identifying patterns and predicting potential health issues based on the available clinical data [24].

$$p(Ck \mid x) = \frac{p(Ck)\, p(x \mid Ck)}{p(x)} \tag{1}$$

Equation (2) may thus be written as follows using the chain rule for ABPM of conditional probability:

$$p(C_k, x_{1,\dots} x_n) = p(x_{1,\dots} x_n, C_k)$$

$$= p(x_1 \mid x_{2,\dots} x_n, C_k) \quad p(x_{2,\dots} x_n, C_k)$$

$$= p(x_1 \mid x_{2,\dots} x_n, C_k)\, p(x_2 \mid x_{3,\dots,} x_n, C_k)\, p(x_{3,\dots} x_n, C_k)$$

$$\dots\dots\dots$$

$$= p(x_1 \mid x_{2,\dots} x_n, C_k)\, p(x_2 \mid x_{3,\dots,} x_n, C_k) \dots p(x_{n-1} \mid x_n, C_k)\, p(x_n \mid C_k)\, p(C_k) \tag{2}$$

Assuming a conditional category, x is employed as a mutual independent variable. (Equ. (3))

$$p(xi|xi + 1, \ldots \ldots, xn, Ck = p(xi|Ck) \tag{3}$$

The joint model may thus be written as follows (equation (4)):

$$\begin{aligned} p(C_k \mid x_1, \ldots, x_n) &= \propto p(C_k, x_1, \ldots, x_n) \\ &\propto p(C_k)p(x_1 \mid C_k)p(x_2 \mid C_k)p(x_3 \mid C_k)\cdots \\ &\propto p(C_k)\prod_{i=1}^{n} p(x_i \mid C_k) \end{aligned} \tag{4}$$

In the context of the stated independence assumptions, the proportionality symbol ($\propto$) signifies proportionality [25]. Equation (5) illustrates the conditional distribution concerning the class variable C. This distribution is influenced by the independence assumptions mentioned earlier [26].

$$p(C_k \mid x_1, \ldots, x_n) = \frac{1}{Z}p(C_k)\prod_{i=1}^{n}p(x_i \mid C_k) \tag{5}$$

To enhance classification accuracy and minimize misclassification, the model integrates a decision rule known as the maximal a posteriori decision rule, alongside the naive Bayes classifier. This decision rule advises selecting the hypothesis with the highest likelihood to minimize errors. Utilizing equation (6), the Bayes classifier categorizes k based on the probability distribution [27].

$$\hat{y} = \underset{k\in\{1,\ldots,K\}}{\operatorname{argmax}} p(C_k)\prod_{i=1}^{n} p(x_i \mid C_k) \tag{6}$$

3.2   Processed data

Figure 3 illustrates the cross-correlation matrix of the database provided by SMHRCE. The matrix reveals a significant correlation of 89% between the Medical Sensor (SYS) and level attributes [28]. To ensure the robustness of the machine learning model, the dataset is divided into training data (80%) and testing data (20%). This approach, detailed in references [29], enhances the accuracy and reliability of the machine learning model, ultimately contributing to the reduction of patients affected by level-3 and level-4 conditions.
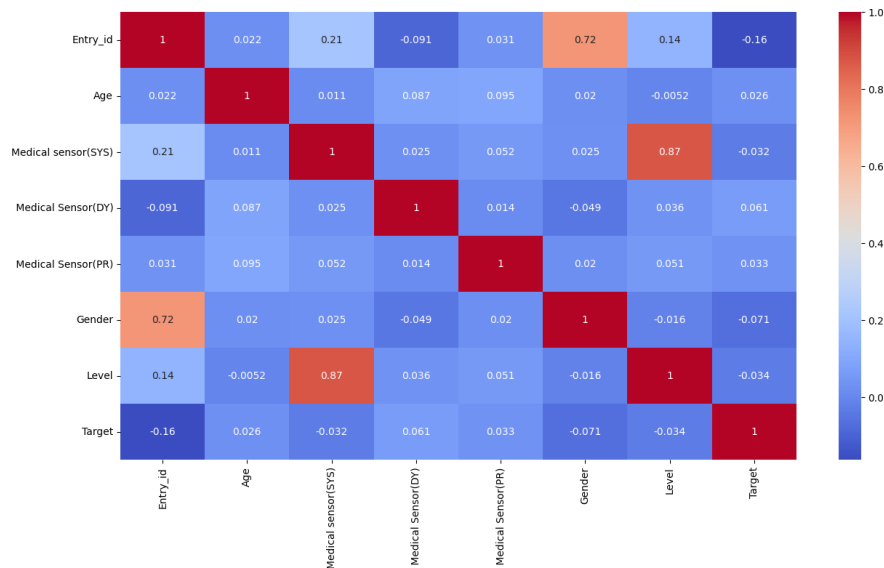

Figure 3. **Correlation matrix using process database.**

Figure 4 depicts the Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) curve for a multiclass dataset [20]. This curve serves as a critical evaluation tool for machine learning models employed in multiclass classification scenarios, where the target variable can be assigned to multiple classes [21]. Its significance is particularly pronounced in binary classification problems, aiding in assessing the model's efficacy in predicting chronic heart diseases [22]. Equation (7) elucidates the calculation of True Positive Rate (TPR), also known as Recall or Sensitivity, which serves as a key metric for evaluating the model's performance [23]. TPR is calculated as the ratio of True Positives (TP) to the sum of True Positives (TP) and False Negatives (FN). True Positives represent the instances correctly predicted as positive by the model, while False Negatives denote positive instances incorrectly classified as negative by the model [24]-[25]. This equation offers insights into the model's ability to accurately identify positive instances, thereby aiding in gauging its overall performance [26].

$$\text{TPR/Recall/Sensitivity} = \frac{TP}{TP+FN} \qquad (7)$$

Specificity of ROC curve

$$\text{Specificity} = \frac{TN}{TN+FP} \qquad (8)$$

False Positive Rate

$$\text{FPR} = 1 - \text{Specificity} = \frac{FP}{TN+FP} \qquad (9)$$

Equation (8) computes Specificity, a critical metric utilized in binary classification models. The Area Under the Receiver Operating Characteristic curve (AUC-ROC) provides a comprehensive assessment of a classification model's performance. It quantifies the area under the ROC curve, with values ranging from 0 to 1. An AUC value of 0.5 indicates the model possesses no discrimination capability, whereas an AUC value of 1 signifies perfect classification ability. In conclusion, a higher AUC range signifies superior performance, indicating the model's efficacy in distinguishing between positive and negative classes [20][23]. Figure 4 illustrates the ROC-AUC curve for a multiclass dataset, showcasing exceptional results. This indicates that the model under consideration exhibits impeccable classification ability.
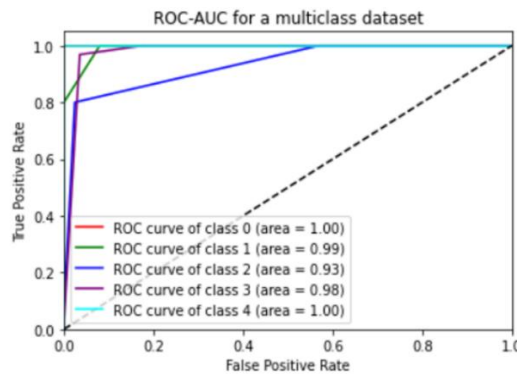
Figure 4. ROC-AUC curve for a multiclass process dataset

3.3   Model Deployment

In Table 4, various machine learning classifiers, including SVM, Random Forest, K-Nearest Neighbors (KNN), and Naïve Bayes, are listed along with their respective characteristics and applications. SVM is employed for classifying unseen data, random forest is adept at handling both classification and regression tasks, whereas KNN stores existing data and organizes new data points based on similarity. Naïve Bayes, commonly utilized in data analysis, spam filtering, and recommendation systems, is noted for its excellent performance, although it may require independent predictors for optimal results. Upon analysis, it is evident from Table 4 that the Naïve Bayes algorithm exhibits superior performance in terms of F1-score, accuracy, precision, and recall metrics, thereby emerging as the preferred choice among the listed classifiers.

TABLE 4.   Different Machine Learning Algorithm Implementation

Classifier	F1-Score	Accuracy	Recall	Precision
Random Forest	0.9480	0.9778	0.9312	0.9692
K-NN	0.9642	0.9889	0.9579	0.9765
SVM	0.7378	0.9200	0.7467	0.7294
Naïve Bayes (Proposed System)	0.9713	0.9944	0.9600	0.9875

3.4   Testing and Prediction

Machine learning techniques are meticulously selected based on their performance metrics in specific tasks, with a primary focus on achieving optimal balance across accuracy, F1-score, precision, and recall [24]. In clinical settings, where precision and timely decision-making are paramount, the Naïve Bayes ML algorithm emerges as a suitable choice, meeting the requirements of healthcare professionals. Testing of this algorithm is conducted with new data, ensuring alignment with the training set. The results, as depicted in TABLE 5, effectively identify emergencies necessitating immediate medical consultation [25]. These findings have been rigorously validated by the Shalini Tai Meghe Hospital Research Center Education (SMHRC) in India, as attested by the attached validation report, available for review. Ultimately, the selection of the most appropriate machine learning technique is guided by the specific problem at hand and the resources available for implementation [26].

TABLE 5.   Naïve Bayes result

Entry ID	Age	Upper No.	Lower No.	PR	Male/Female
1	44	120	82	85	0
Result				You are Elevated	

3.5   Discussion

This paper aims to provide an early warning score for the detection of chronic heart disease (CHD) by leveraging the best machine learning algorithm based on the available dataset, meeting the requirements of medical personnel. It represents a synergy between hardware and software components, where the hardware aspect involves gathering blood pressure (BP) data from patients and making this data available on the cloud for medical professionals to analyze and prescribe appropriate treatment.

IV.   FUTURE SCOPE AND CONCLUSION

This research paper adopts an approach that deviates from starting with a clean slate and creating something entirely novel. Instead, it signifies a deliberate decision by the creator or team not to embark on a completely original design process. IoT enable device system introduced in the paper serves as a healthcare solution offering real-time monitoring and early warning scores for patients with medical conditions. It seamlessly integrates with other medical devices, facilitating patient care in a home setting.

Credit Authors statement: Yogesh Kale: conception (leader); technique; software; data curation; and first draft authoring. Project management, conception, methodology, Validation, software, and project administration are all supported, and initial draft writing (assisting); validation (assisting); review and editing (leading). Validation, software, and project administration are all led by **Shubhangi Rathkanthiwar.**

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Declarations:

Competing interests No authors have disclosed any **conflicts of interest**.

The SMHRC Hospital granted **ethical approval.**

Acceptance of participation the relevant writers have all consented to take part in the paper that has been submitted.

Permission to publish the authors of this work have all given their complete approval for the article to be published.

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