An IoT-based blood pressure monitoring system using Support Vector Machine

Patience U. Usip[1,*,†], Ekrika Kenewenemor[2,†] and Francis B. Osang[2,†]

[1]*Department of Computer Science, University of Uyo, Uyo, Nigeria*
[2]*National Open University of Nigeria, Abuja, Nigeria*

Abstract
The introduction and integration of IoT in daily lives and the general community can be seen in many different astonishing scenarios such as health care. Several medical conditions predominant in patients are often related to high blood pressure. Hence, the need for blood pressure to be closely monitored and the blood pressure made available for IoT devices. Due to the confidentiality and security issues required, machine learning approaches are seen as most suitable. Four machine learning approaches including the support vector machines were used for training the dataset with its discovering patterns and predicting when the patient is in danger. A machine learning-based system for monitoring blood pressure in patients was modeled to provide a reliable blood pressure (systolic and diastolic) prediction and classification to patients. The performance of these models was evaluated using mean square error, mean absolute error, root mean square error, and coefficient of determination (R2). The models were ranked, and the best model selected. This system can accurately predict blood pressure with R2 performance of 0.995551 for SVR, 0.993488 for KNN, 0.993935 for RF, and 0.989557 for CART. This adoption of IoT based blood-pressure monitoring model is encouraged for predicting blood pressure of patients.

Keywords
Machine learning, medical conditions, Health data,, Data confidentiality and security,

1. Introduction

The introduction of IoT medical devices has tremendously transformed the healthcare continuum on an unprecedented scale with many noticeable benefits. The IoT is one of many technologies that has gradually stepped into the health care domain and has provided renewed and improved delivery of healthcare services. With these IoT healthcare monitoring devices, patients may no longer require making regular visits to the hospital as the devices are designed to monitor vital signs of patients anywhere, they are in the universe and data collected are uploaded to a cloud repository, where a remote doctor or nurse can examine for further analysis. The IoT's real-time monitoring empowers doctors to make actionable insight on data on a continuous basis. This facilitates early detection of disease before it aggravates. These devices are easy

AISD-2024: Second International Workshop on Artificial Intelligence: Empowering Sustainable Development, October 2, 2024, co-located with the Second International Conference on Artificial Intelligence: Towards Sustainable Intelligence (AI4S-2024), Virtual Event, Lucknow, India. Year: 2024.
[*]Corresponding author.
[†]These authors contributed equally.
patienceusip@uniuyo.edu.ng (P. U. Usip); ekrikakenny@gmail.com (E. Kenewenemor); fosang@noun.edu.ng (F. B. Osang)
0000-0002-6516-5194 (P. U. Usip); 0000-0002-2111-5785 (E. Kenewenemor); 0009-0000-7301-4866 (F. B. Osang)

to use and are available in many different forms: smart watches, eyeglasses, belts etc. they are easy to use and are capable of tracking on real-time data generated from the body such as temperature, sleep, EEG, blood sugar, heart rate, pulse rate, BP levels although the list is not exhaustive. The incidence of cardiovascular disease is commonplace in our local community. For this reason, this has perhaps led to early deaths in recent times. Therefore, the use of these wearable medical devices can provide a medical support system for patients managing heart disease. More so, the use of these collaborative smart medical devices and Machine learning techniques can provide health status forecasts and give doctors insight to prevent heart attack, stroke or worse case death in patients.[1]

2. Recent Related Works

Khan et al. [2] proposed an IoT algorithm for forecasting whether the patient under close observation is in undergoing stress or not by monitoring his/her heartbeats. The system is designed to detect the pulse signals and waveform using a specifically dedicated Wi-Fi equipment board that sends data to a server repository. Next, the raw data garnered at different intervals are assembled and stress prediction is evaluated by applying ML techniques as seen in [3] and others such as Support Vector Machine (SVM) and Logistic regression is applied. Results from the simulation tests showed that the precision of the proposed framework can reach up to 68Verma P and Sook [4] proposed an approach for active monitoring of various diseases. It predicts the level of severity of these diseases from normal to severe in a sample data using students. The concept of computational science on the data was garnered from the student using low power sensors. The data is collected and stored in the repository for analysis to predict the severity of the disease. Additionally, the approach used various ML algorithms for classification to forecast the occurrence of such diseases. Although other intelligent approaches have been adopted in Health other than machine learning [5]. The result was evaluated using various metrics such as T-measuring, specifications, and sensitivity. Consequently, the simulation result shows that in terms of correction and precision, the purported methodology surpassed the orthodox approach. The authors Kumer and Gandhi [6] developed a framework of three-layered architecture to deposit or cache enormous sensory data for fast prediction of heart diseases. In the proposed framework, the foremost layer is the data collection layer. The second layer is the repository layer where data is stored in the cloud. The final layer is the third layer, a forecast model is designed to predict the likelihood of heart diseases. Also, at this layer, analysis is performed to spot potential symptoms of heart disease before they occur. On any wearable device, the data collected is transmitted to an edge computing network as the wearable device is not able to hold an enormous amount of data. Geloyo et al. [7] presented a novel framework of a machine learning-based model for disease classification used in the health monitoring of patients. The simulation is done using this methodology produced accurate results in detecting diseases. Verma et al. [8] proposed a smart student m-healthcare monitoring framework based on cloud-centric IoT is suggested. This framework calculates the severity of a student's ailment by temporally mining the health metrics obtained from medical and other IoT devices to anticipate the probable disease and its level. An architectural model for a smart student health care system has been built to properly evaluate student healthcare data. In this case study, we used a health dataset of 182 suspected students to construct instances of waterborne diseases. Using the k-cross-validation technique, this data is further evaluated to validate the model. Various classification algorithms are used to apply a pattern-based diagnosis scheme, and the results are then computed based on accuracy, sensitivity, specificity, and reaction time. In terms of the above-mentioned parameters, experimental findings reveal that decision tree and k-nearest neighbor algorithms outperform other classifiers. Furthermore, the suggested technique aids decision-making by providing time-sensitive information to the caretaker or doctor at a given moment. Finally, the suggested system's temporal granule pattern-based presentation yields good diagnosis findings. Based on Internet-of-Things (IoT) technology, Zhe Yang1 et al. [9] presented a novel approach for ECG monitoring. ECG data is collected via a wearable monitoring node and wirelessly transferred to the IoT cloud. The Hypertext Transfer Protocol (HTTP) and MQ Telemetry Transport (MQTT) protocols are used in the IoT cloud to offer users visible and fast ECG data. The cross-platform difficulty has been significantly reduced because nearly all smart terminals with a web browser can easily obtain ECG data. Experiments on healthy volunteers are carried out to ensure that the entire system is reliable. The suggested system is reliable in collecting and presenting real-time ECG data, which can help in the primary diagnosis of some cardiac conditions, according to experimental results.

3. Methodology

The research methodology focuses on the use of blood pressure datasets obtained from an online repository of patient's vital signs, the approach will employ SVR and CART for data classifications and relations. Afterwards, train a model leveraging ML algorithm and the dataset obtained as describe above. The overall result of this methodology is to design a system that can correctly predict spikes in blood pressure levels and inform the relevant healthcare providers or givers on real time. Lastly, the system will be evaluated to measure correctness and accuracy of the system

3.1. Proposed System Framework

This work proposes a machine learning-based system for monitoring blood pressure in patients. The work employs a mix of machine learning models namely support vector regression (SVR), random forest (RF), k-nearest neighbor (KNN), and classification and regression tree (CART) to predict patient blood pressure level. Machine learning algorithms learn from datasets to predict patient's blood pressure employing the blood pressure dataset obtained from kaggle.com. The blood pressure dataset is partitioned into training set and testing set. The training set is made up of 70To select the best machine learning model, model evaluation is carried out using standard regression-based machine learning model evaluation techniques such as MSE (Mean Square Error), MAE (Mean Absolute Error), and RMSE (Root Mean Square Error). The proposed framework of machine learning-based system for monitoring blood pressure in patients is presented in Figure 1. The system framework depicts the structure, components and the relationship among the various components making up this research work.

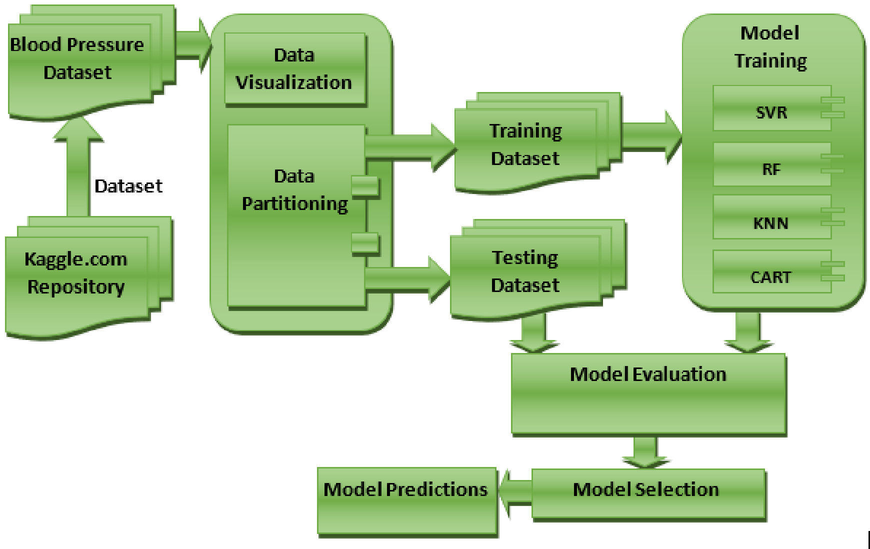

Figure 1: System Framework

4. Model Performance Result and Discussions

The ability of each machine learning model to accurately predict the blood pressure given a new dataset is evaluated using Mean Square Error, Root Mean Square Error, Mean Absolute Error, and Coefficient of Determinant (R2). The performance of these models is presented in Table 2.

From Table 2, it is observed that SVR has the best performance/accuracy in predicting the blood pressure by RF, KNN then CART. The performances of these models are presented graphically in Figure 2. From Figure 2, it is observed that SVR outperforms all other models in terms of MSE, RMSE, MAE, and R2. Hence Support Vector Regression is recommended for effective prediction of blood pressure in patients.

Model Selection The best model is a model with the highest coefficient of determination. The graph in Figure 3, ranks our machine learning model in order of its performance.

From Figure 3, SVR is the best model with R2 of 0.995551. The interpretation of the SVR model result is presented in Table 3 It shows the predicted severity of blood pressure.

5. Conclusion

A machine learning-based system for monitoring blood pressure in patients was modeled to provide a reliable blood pressure (systolic and diastolic) prediction and classification to patients. After an in-depth review of the study area, machine learning models – support vector machine, random forest, k-nearest neighbor, and classification and regression tree models where developed. These models where trained and tested using the blood pressure dataset. The performance of these models was evaluated using mean square error, mean absolute error, root

Table 1
Model Predictions: SVR

Temp	rr %	Hr %	diastolic %	systolic %	SVR diastolic	SVR systolic
29.98063	2	30	57	16	61.32608	11.09031
39.97486	2	59	16	115	15.51658	119.2956
29.51347	33	103	63	16	59.47146	11.0465
20.32661	24	73	7	3	10.16969	7.594763
28.08248	43	107	63	168	65.39091	166.0555
29.91006	21	34	59	75	61.40598	74.60439
23.43972	16	27	106	148	105.4465	147.3131
20.519	38	146	144	178	140.5831	176.1364
32.98457	11	133	133	144	128.8536	146.0056
28.74359	23	98	6	87	6.253409	84.05716
34.378	50	162	118	43	118.6306	43.42842
25.48815	1	64	26	92	26.46416	94.8899
38.93474	3	12	17	151	16.47869	152.0219
30.79187	7	148	106	101	108.2135	96.75982
34.46068	52	138	129	106	124.5589	102.0308
20.92426	21	88	139	49	140.9551	44.47636
25.31142	11	134	90	194	89.41622	194.3509
37.71674	42	185	118	65	121.199	63.0154
31.55399	53	35	91	32	91.75912	31.95917
32.42716	43	162	97	88	92.60312	83.23546
36.4954	26	3	80	81	78.78053	81.11791
37.86951	17	166	136	122	139.7972	124.0788
34.48373	0	26	118	67	118.0558	67.86683
22.25193	9	192	138	132	138.4186	127.6537

mean square error, and coefficient of determination (R2). The models were ranked, and the best model selected. This system can accurately predict blood pressure with R2 performance of 0.995551 for SVR, 0.993488 for KNN, 0.993935 for RF, and 0.989557 for CART.

References

[1] D. S. Rajput, R. Gour, An iot framework for healthcare monitoring systems, International Journal of Computer Science and Information Security 14 (2016).

[2] F. Khan, M. A. Jan, A. ur Rehman, S. Mastorakis, M. Alazab, P. Watters, A secured and intelligent communication scheme for iiot-enabled pervasive edge computing, IEEE Transactions on Industrial Informatics 17 (2020) 5128–5137.

[3] P. Naveen, M. Maragatharajan, R. Thangaraj, Contextual reinforcement learning for enhanced machine translation using transformers., in: SWIoT+ MSW@ KGSWC, 2023, pp. 39–50.

[4] P. Verma, S. K. Sood, A comprehensive framework for student stress monitoring in fog-cloud

Table 2
Model Performance on blood pressure dataset

	MSE	RMSE	MAE	R2
SVR	8.656671	2.942222	2.546986	0.995551
RF	11.80007	3.435124	2.972931	0.993935
CART	20.31929	4.507692	3.917981	0.989557
KNN	12.67081	3.559607	3.064961	0.993488

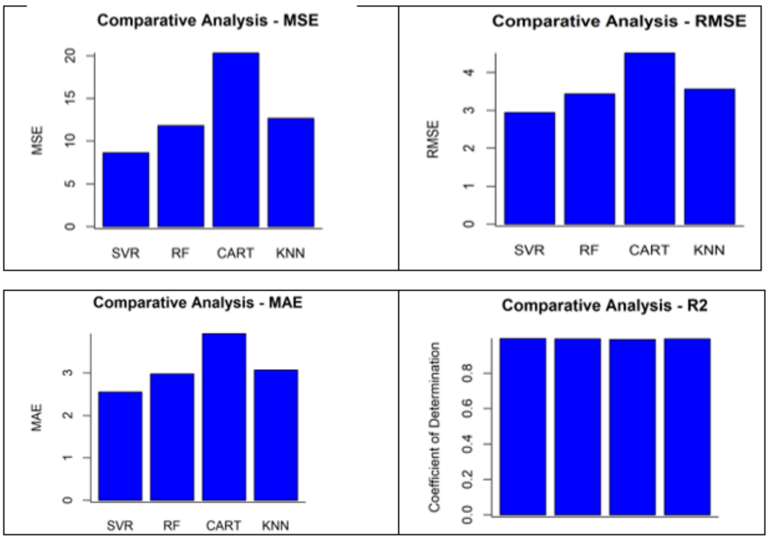

Figure 2: Model performance graphs

iot environment: m-health perspective, Medical & biological engineering & computing 57 (2019) 231–244.

[5] P. U. Usip, M. E. Ekpenyong, F. F. Ijebu, K. J. Usang, Integrated context-aware ontology for mnch decision support, in: Semantic Models in IoT and eHealth Applications, Elsevier, 2022, pp. 227–243.

[6] P. M. Kumar, U. D. Gandhi, A novel three-tier internet of things architecture with machine learning algorithm for early detection of heart diseases, Computers & Electrical Engineering 65 (2018) 222–235.

[7] Y. E. Gelogo, J.-W. Oh, J. W. Park, H.-K. Kim, Internet of things (iot) driven u-healthcare system architecture, in: 2015 8th International Conference on Bio-Science and Bio-Technology (BSBT), IEEE, 2015, pp. 24–26.

[8] P. Verma, S. K. Sood, S. Kalra, Smart computing based student performance evaluation

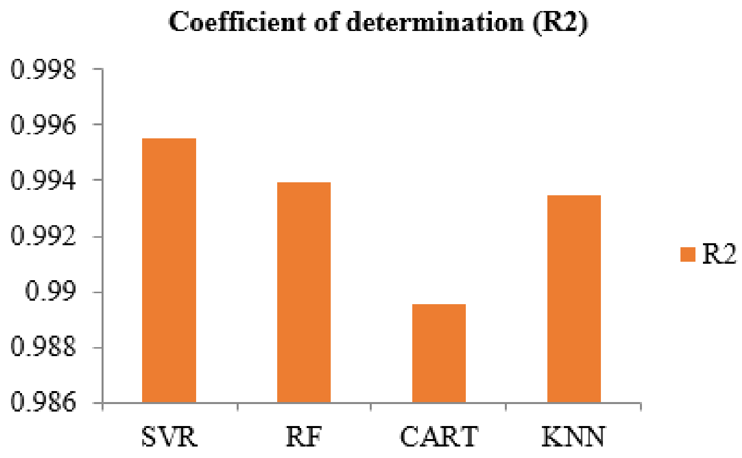

Figure 3: Model Ranking

framework for engineering education, Computer Applications in Engineering Education 25 (2017) 977–991.

[9] Z. Yang, Q. Zhou, L. Lei, K. Zheng, W. Xiang, An iot-cloud based wearable ecg monitoring system for smart healthcare, Journal of medical systems 40 (2016) 1–11.

Table 3
Interpretation of the SVR model result

Temp	rr	Hr	diastolic	systolic	SVR (diastolic)	SVR (systolic)	Severity
29.98063	2	30	57	16	61.32608	11.09031	Low
39.97486	2	59	16	115	15.51658	119.2956	Ideal
29.51347	33	103	63	16	59.47146	11.0465	Low
20.32661	24	73	7	3	10.16969	7.594763	Low
8.08248	43	107	63	168	65.39091	166.0555	High
29.91006	21	734	59	75	61.40598	74.60439	Low
23.43972	16	27	106	148	105.4465	147.3131	High
20.519	38	146	144	178	140.5831	176.1364	High
32.98457	11	133	133	144	128.8536	146.0056	High
28.74359	23	98	6	87	6.253409	84.05716	Low
34.378	50	162	118	43	118.6306	43.42842	High
25.48815	1	64	26	92	26.46416	94.8899	Ideal
38.93474	3	12	17	151	16.47869	152.0219	High
30.79187	7	148	106	101	108.2135	96.75982	High
34.46068	52	138	129	106	124.5589	102.0308	High
20.92426	21	88	139	49	140.9551	44.47636	High
25.31142	11	134	90	194	89.41622	194.3509	High
37.71674	42	185	118	65	121.199	63.0154	High
31.55399	53	35	91	32	91.75912	31.95917	High
32.42716	43	162	97	88	92.60312	83.23546	High
36.4954	26	3	80	81	78.78053	81.11791	Ideal
37.86951	17	166	136	122	139.7972	124.0788	High
34.48373	0	26	118	67	118.0558	67.86683	High
22.25193	9	192	138	132	138.4186	127.6537	High