



Research paper

A Machine-Learning-based Predictive Smart Healthcare System

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Article Info	Abstract
Article History: Received 22 July 2024 Reviewed 15 October 2024 Revised 16 October 2024 Accepted 31 October 2024 Keywords: Healthcare system Patients health monitoring Machine-learning Artificial intelligence Learning algorithms *Corresponding Author's Email Address: s.golshannavaz@urmia.ac.ir	Background and Objectives: In smart grid paradigm, there exist many versatile applications to be fostered such as smart home, smart buildings, smart hospitals, and so on. Smart hospitals, wherein patients are the possible consumers, are one of the recent interests within this paradigm. The Internet of Things (IoT) technology has provided a unique platform for healthcare system realization through which the patients' health-based data is provided and analyzed to launch a continuous patient monitoring and; hence, greatly improving healthcare systems.
	Methods : Predictive machine learning techniques are fostered to classify health conditions of individuals. The patients' data is provided from IoT devices and electrocardiogram (ECG) data. Then, efficient data pre-processings are conducted, including data cleaning, feature engineering, ECG signal processing, and class balancing. Artificial intelligence (AI) is deployed to provide a system to learn and automate processes. Five machine learning algorithms, including Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), logistic regression, Naive Bayes, and random forest, as the AI engines, are considered to classify health status based on biometric and ECG data. Then, the output would be the most proper signals
	 propagated to doctors' and nurses' receivers in regard of the patients providing them by initial pre-judgments for final decisions. Results: Through the conducted analysis, it is shown that logistic regression outperforms the other AI machine learning algorithms with an F1 score, recall, precision, and accuracy of 0.91, followed by XGBoost with 0.88 across all metrics. SVM and Naive Bayes both achieved 0.85 accuracy, while random forest attained 0.86. Moreover, the Receiver Operating Characteristic Area Under Curve (ROC-AUC) scores confirm the robustness of Logistic Regression and XGBoost as apt candidates in learning the developed healthcare system. Conclusion: The conducted study concludes a promising potential of AI-based machine learning algorithms in devising predictive healthcare systems capable of initial diagnosis and preliminary decision makings to be relied upon by the clinician. What is more, the availability of biometric data and the features of the proposed

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Introduction

A. Motivation

Internet of Things (IoT) technology has given momentum to adoption of healthcare applications in modern societies. The warm reception of IoT in these systems is due to several factors, including limited access to medical resources based on conventional approaches, growing number of elderly people with chronic diseases and their need for remote monitoring, rising medical costs, and the desire for telemedicine in developing countries. The IoT has made continuous patient monitoring and real-time data collection possible, which has greatly improved the healthcare systems. In this way, a health monitoring system is generally recognized with multiple sensors and a core processor [1]. This system would monitor vital signs in realtime, collect data from various sensors related to patients, and conduct artificial intelligence (AI) analysis on the data to predict and analyze its results and determine whether the results are real and correct. People can interact with a vast array of digital and physical objects, including those used in personal healthcare, using the IoT [2]. In a recent study, patients' electrocardiogram (ECG), blood pressure, temperature, and pulse rate biometric data are analyzed using AI algorithms to ascertain their current state of health [3]. The relationship between AI and the IoT revolves around connecting things and automating processes; then, analyzing data, getting understanding, and making decisions based on data [[4], [5]]. As a complementary need, for predicting the results and reaching to decision making processes, machine learning algorithms should be trained, accurately. Such a system would provide an efficient platform of care-systems to be deployed by doctors and nurses to have a continuous and reliable monitoring on the patients' situations.

Contributing to this field, the present study is on developing an efficient healthcare system, capable of leaning and decision making on patients' health-based data gathered by biometric sensors. The patients' data is provided from IoT devices and ECG data. Then, efficient data preprocessings are conducted, including data cleaning, feature engineering, ECG signal processing, and class balancing. Then, AI is deployed to provide a system to learn and automate processes, ending to a predictive system. Five machine learning algorithms, including support vector machine (SVM), Extreme Gradient Boosting (XGBoost), logistic regression, Naive Bayes, and random forest, as the AI engines, are considered to classify health status. Then, the output would be the most proper signals propagated to doctors' and nurses' receivers in regard of the patients providing them by initial pre-judgments. The possible contributions of this study could be listed as follow:

- A cloud-based data center is developed for IoTbased biometric and ECG data;
- Data cleaning, feature engineering, and class balancing is embedded as the preliminary stage of the proposed approach;
- Predictive feature is realized by AI-based machine learning algorithms and training process;
- An automated and predictive healthcare system is developed which provides initial judgments and primary care assessments of patients.

Different machine-learning algorithms are explored to provide an overview of the proposed healthcare system. These algorithms investigate different performance metrics say as accuracy, precision, and etc. The obtained numerical results emphasize on a promising potential of machine learning paradigm in IoT-based data handling and health diagnosis which can be relied upon by clinician in significant enhancing of primary care assessments.

B. Literature Review

In [6], researchers have explored the deployment of IoT wearable electroencephalography (EEG) [7] devices and SVM for predictive analytics in epilepsy treatment. The devices used real-time brain activity data to predict seizures, allowing healthcare practitioners and caregivers to interact, efficiently. Seamless connectivity of the IoT infrastructure enables timely warnings and efficient remediation. Srinivas et.al. have shown that experimental investigations provide promising predictive accuracy and reaction time, providing individualized and proactive treatments for epilepsy patients [8].

In references [9], [10], a new approach is proposed to develop healthcare monitoring system. The researchers were interested in the methodology of combining regular medical monitoring and electronic clinical data (ECD) from complete medical records with physical data of patients as well as machine learning techniques in order to predict heart disease. The XGBoost algorithm is used as a powerful algorithm for examining large data sets effectively and extracting important features to improve prediction accuracy. The results are optimized which demonstrate that the XGBoost algorithm outperforms Naive Bayes, decision trees, and random forests and achieved a greater prediction accuracy of 99.4%. By combining IoT technologies with advanced machine learning models it would provide better results.

Authors in [11] developed some methods and algorithms to predict the health status of Coronavirus patients and classify them according to their healthy and unhealthy conditions. In this research, a comprehensive analysis of machine learning approaches was conducted in the field of diagnosing COVID-19, detecting chronic diseases in patients, and identifying symptoms of COVID-19 infection. As well, decision trees, random forest, SVM, gradient boosting, and logistic regression algorithms are used in [12]. The best results were obtained from the comparative analysis of the methods including decision tree, random forest, and gradient boosting algorithms, on the accuracy values of 1.0, 0.99, and 1.0, respectively. These results show their performance and functionality in machine learning algorithms about their goal in the field of healthcare, as well as the possibility of choosing the most appropriate one to deal with diseases [13].

Another study was concerned with collecting types of patient data that would help the doctor correctly diagnose the patient's health condition [14]. The data is analyzed by the doctor, who then confirms the disease using his medical experience and makes a diagnosis. In this study, researchers used machine learning techniques

such as Naive Bayes and random forest classification algorithms to classify several disease datasets such as heart disease, cancer, and diabetes to check whether the patient is affected by this disease or not. In [15], the results of the simulations show the effectiveness of classification techniques on the data set, as well as the nature and complexity of the deployed data set. The performance analysis for both algorithms was done and compared. Based on the results, it can be said that these algorithms are among the promising techniques in the field of disease analysis and prediction.

C. Paper Organization

This study continues as follows: In "Methodology" section, the developed healthcare methodology is outlined. The "Experimental Studies and Evaluations" section is provided for further analysis and performance validations of the developed model. Eventually, the "Conclusions and Future Works" concludes the study and provides some open future works.

Methodology

As outlined, a processor, here taken as Raspberry Pi, is used to create an application that connects the electronic system to medical sensors placed on the patient's body. These sensors measure the patient's blood pressure, heart rate, temperature, as well as ECG. Also, the intercontroller communication protocol is used to collect and transmit data from the sensors to the physician monitoring system [16]. The system software application contains the code used by the Raspberry PI controller. The medical sensors are programmed using the Python language [17]. In addition, the Java language is used to design the monitoring program that is placed near the doctor using a mobile application. The patient database is connected to sensors and takes the results from the disease state and stores them in the cloud and then transfers to the doctor's application to display the results. The database is implemented using a cloud-based storage solution. Here two possible ways are described to implement the database. The first approach is the "Cloudbased NoSQL Database". This system could use a cloudbased NoSQL database such as MongoDB [18], Cassandra, or Couchbase to store patient data. NoSQL databases are well-suited for handling large amounts of unstructured or semi-structured data, which is common in healthcare applications. The second approach is the "Relational Database". This system could use a relational database such as MySQL or PostgreSQL to store patient data. Relational databases are suited for handling structured data. The data is then collected in an Excel file for all patients with their ages and genders to begin the analysis through AI techniques and train the aforementioned algorithms for prediction. Then, the obtained results are made available to be analyzed and determine the validity

of the diagnosis, as showed in Fig. 1. This figure shows how patient data is measured, transmitted, stored, and analyzed as well as displayed using applications, medical sensors, cloud storage, and AI as an overall analysis system. This figure highlights the steps and flow of data between sensors, Raspberry Pi, cloud, and physician's mobile application.

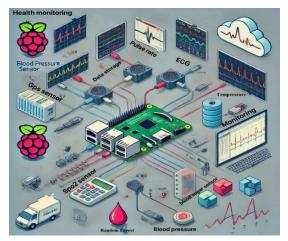


Fig. 1: System software and hardware implementation.

A. SVM Algorithm

SVM is one of the machine learning algorithms used in neuroimaging analysis, through which classification problems are addressed and provides balanced predictive performance for diagnosis in the field of brain diseases, psychiatry, and others [19]. The SVM equation and the health state are determined by evaluating the linear combination of features, as follows [20]:

$$f(x) = sign(w_1Age + w_2Gender + w_3Temperature + w_4Pulse + w_5SpO2 + w_6SystolicBP + w_7DiastolicBP + w_8ECG1 + ... + w_9 + m_FCFm + b)$$
(1)

B. XGBoost Algorithm

XGBoost is a scalable, distributed, gradient-boosting decision tree (GBDT) machine-learning library [21]. It provides parallel tree boosting and is the leading machine learning library for solving regression and classification problems and is used in the healthcare field for general disease prediction as well as diagnosis and analysis [22]. The equation of XGBoost is as follows:

$$y_i = \phi(x_i) = \sum_{k=1}^{\kappa} f_k(x_i)$$
 (2)

C. Logistic Regression Algorithm

Regression analysis is an important statistical method used to determine the relationship between several factors and disease outcomes or to identify diseaserelated prognostic factors through probability and prediction by estimating the occurrence of an event [23]. The equation of logistic regression is written as follows:

$$y = \frac{1}{1 + e^{-(w.x+b)}}$$
(3)

D. Naïve Bayes Algorithm

Naive Bayes algorithm is used to distinguish between favorable patient reviews and those that are negative. Here, it is easily understand which drugs are most beneficial and have the fewest negative effects [24]. The equation for the Naive Bayes classifier is as follows [25]:

$$P(C_k|x) = \frac{P(C_k) \prod_{i=1}^{n} P(x_i|C_k)}{P(x)}$$
(4)

E. Random Forest Algorithm

Leo Breiman and Adele Cutler are the trademark holders of the popular machine learning technique known as "Random Forest," which aggregates the output of several decision trees to produce a single conclusion. Its popularity has been spurred by its flexibility and ease of use, since it can handle regression and classification problems as well as healthcare [26]. The random forest algorithm combines the predictions from multiple decision trees to make a final prediction as follows:

$$y = \text{mod}e(\{T_1(x), T_2(x), ..., T_B(x)\})$$
(5)

F. Data Set of the Study

Data are collected containing biometric readings and ECG data for patients in a local hospital in Iraq, in addition to random individuals. The goal of collecting these samples and vital indicators is to evaluate them. Blood, along with a list of ECG values [27], are recorded and

classified according to age, sex, and blood pressure compatibility. The number of vital signs records collected in this study is 150 people. Among these people, 80 patients are admitted to the local hospital, while 70 patients are randomly selected.

Experimental Studies and Evaluations

The conducted study proposes a hardware and Google cloud-IoT-based healthcare system being trained based on machine learning algorithms developed in Raspberry Pi in real-world implementations. Due to differences in technical specifications of the implemented hardware and the assumptions such as the volume of biometric and ECG data, system performance and decision making criteria [28], comparison of the proposed system with the existing systems would not make a right comparison platform and performance analysis. Instead, the performance of the proposed system is analyzed in-depth considering the well-known and mostly applied machine learning AI algorithms and meaningful comparisons are hence attained and discussed. By integrating Raspberry Pi with IoT sensors, a powerful health monitoring system is created that includes, blood pressure, pulse rate, ECG, temperature, and other critical indications. This integration offers a thorough and instantaneous method for monitoring and controlling multiple health metrics [29]. It would be a single, simple phone application that allows doctors to directly monitor the progress of surgeries and their effects on patients. It is also a safe, dependable, and efficient cloud storage system for transferring medical data to the doctor's application in the observation room. Furthermore, all devices and sensors are either directly connected to the patient or via a data transmission medium.

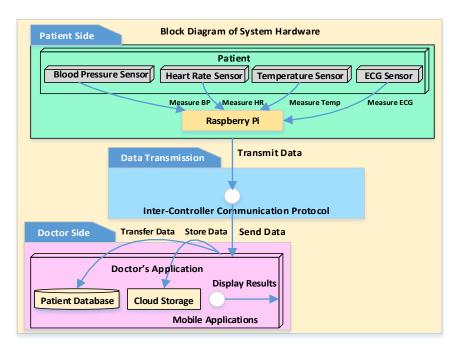


Fig. 2: Health monitoring system hardware with Raspberry Pi and IoT sensors.

To reach the general conclusion and assess the proposed system performance, the results for different machine learning algorithms including SVM, XGBoost, logistic regression, Naive Bayes [30], and random forest are obtained based on the trends reported in Fig. 2.

The selected models are supervised learning algorithms, which are trained based on expected results and evaluated on unseen data to check their validity. As mentioned earlier, models are SVM, XGBoost, random forest, and logistic regression. Table 1 shows the analysis and prediction values for different machine learning algorithms based on their performance metrics.

Table 1: Performance metric comparison

Accuracy	Precision	Recall	F1
0.85	0.85	0.85	0.85
0.88	0.88	0.88	0.88
0.86	0.86	0.86	0.86
0.91	0.91	0.91	0.91
0.85	0.86	0.85	0.85
	0.85 0.88 0.86 0.91	0.85 0.85 0.88 0.88 0.86 0.86 0.91 0.91	0.85 0.85 0.85 0.88 0.88 0.88 0.86 0.86 0.86 0.91 0.91 0.91

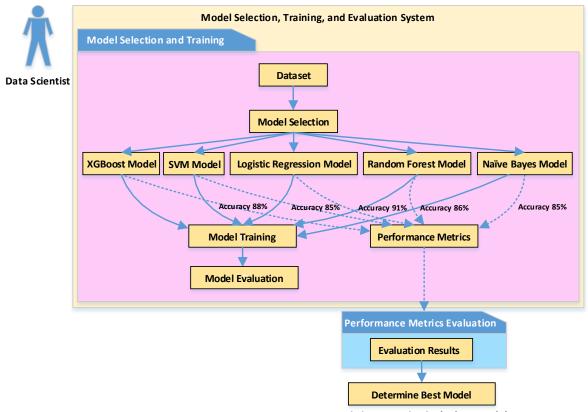
As illustrated in Table 1, all of the investigated algorithms demonstrate good accuracy and ability to generalize on unseen data. The SVM model shows 82% and 85% accuracy, respectively, for training and testing parts of

the dataset. The XGBoost obtained even better results compared to its precedent with a training accuracy of 90% and testing accuracy of 87.88%, while logistic regression stands out with training and testing accuracy of 86.67% and 91%, respectively.

The random forest model fulfills consistent performance in both the training and testing sets, with 85% for training and 86% for testing. Finally, Naive Bayes presents 82% training accuracy and 85% testing accuracy. As a conclusion, the logistic regression is considered as the most appropriate model to handle small to medium datasets and achieve better results compared to other models as shown in Fig. 3.

Results and Discussion

As seen, five models were trained and evaluated including SVM, XGBoost, random forest, logistic regression, and Native Bayes. Based on the obtained results and observations, it can be said that logistic regression outperforms the others by obtaining an F1 score, recall, and precision of 0.91, followed by XGBoost with 0.88 in all metrics. SVM, random forest, and Native Bayes also showed competitive results, with accuracies of 0.85, 0.86, and 0.85, respectively. The Receiver Operating Characteristic Area Under Curve (ROC-AUC) [31] results demonstrated the power of logistic regression and XGBoost, highlighting their activity, consistency with biomarkers, and training accuracy and efficiency.



Logistic Regression is the best model

Fig. 3: Preprocessing operations.

As seen, logistic regression, a model designed for binary classification, achieved the highest F1 score equal to 0.91 compared to other models. Its strong performance is attributed to its suitability for binary classification, linear decision boundary, robustness to outliers, interpretability, and computational efficiency. Logistic regression assumes a linear relationship between input features and health condition probability, making it effective in separating classes. Its robustness reduces the impact of extreme values on the decision boundary, making it suitable for datasets with outliers. Its interpretability and feature importance make it valuable for understanding underlying factors influencing health condition classification. However, the choice of the best model depends on the dataset, the complexity of the problem, and the desired balance between interpretability, accuracy, and computational cost. Further analysis, including feature importance analysis, could provide more insights into its performance. The strong performance of logistic regression compared to XGBoost is likely due to the linear nature of the data, the relatively small dataset size, and the potential for logistic regression to be more robust and interpretable. However, as the dataset and problem complexity increase, XGBoost ability to capture nonlinear patterns and its ensemble nature may become more advantageous.

Conclusions

The results summarize the validity of the prediction of health conditions by the logistic regression algorithm, displaying an F1 score, recall, and accuracy of 0.91, indicating excellent classification performance and good diagnosis. The choice of the logistic regression depends on the dataset, the complexity of the problem, and the desired balance between interpretability, accuracy, and computational cost. The algorithm that was ranked second in terms of accuracy is XGBoost with an accuracy of 0.88, which enhances the reliability of advanced machine-learning techniques in health monitoring, its ability to capture nonlinear patterns, and its ensemble nature may become more advantageous due to the linear nature of the data. The study highlights that comprehensive pre-processing of balanced data sets and machine learning models can significantly enhance the detection and diagnosis of health problems. It can be argued from the various models and their consistent results that objective biometric data can be incorporated into primary care assessments.

In the future, this type of research must focus on a larger and more diverse data set, in addition to greater features, to improve the accuracy of the model. These developments lead to more effective care in the health field to anticipate the disease, as well as early detection and continuous health monitoring through machine learning techniques, leading to improved health outcomes and patient well-being. The proposed system has the potential to enhance its performance by incorporating additional data sources and sensors. This could include incorporating biometric sensors, such as blood glucose sensors, oxygen saturation sensors, EEG sensors, accelerometers, and gyroscopes, environmental sensors, wearable sensors, and advanced machine learning capabilities. The system could also leverage multi-modal data analysis and deep learning models to analyze complex data from multiple sources, simultaneously. The system should be designed with a modular architecture for easy integration and adaptation without significant re-engineering. The potential benefits of expansion include improved accuracy, early detection, personalized treatment, and proactive care. However, challenges such as data management, privacy, and algorithm complexity need to be addressed. The system's success depends on addressing these challenges, which include efficient data storage, processing, and analysis techniques, as well as addressing challenges like data management, privacy, and algorithm complexity. Overall, the proposed system has significant potential for expansion, enhancing accuracy, early detection, personalized treatment plans, and transitioning healthcare towards a more proactive approach.

Author Contributions

F. Ahmed Shaban and S. Golshannavaz designed the model, implemented the setup, collected the data, carried out the analysis, interpreted the results, and wrote the manuscript.

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

Abbreviations

юТ	Internet of Things
AI	Artificial Intelligence
ECG	Electrocardiogram
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting
EEG	Electroencephalography

ECD	Electronic clinical data
GBDT	Gradient-boosting decision tree
ROC-AUC	Receiver Operating Characteristic Area Under Curve

References

- [1] G. Halfacree, The official Raspberry Pi Beginner's Guide: How to use your new computer. Raspberry Pi Press, 5th ed., 2023.
- [2] R. A. Mouha, "Internet of things (IoT)," J. Data Anal. Inf. Process. 9(2): 77-77, 2021.
- [3] S. Maqsood, et al., "A survey: From shallow to deep machine learning approaches for blood pressure estimation using biosensors," Expert Syst. Appl., 197: 116788, 2022.
- [4] V. Kaul, S. Enslin, S. A. Gross, "History of artificial intelligence in medicine," Gastrointest. Endos., 92(4): 807-812, 2020.
- [5] F. J. Abdullayeva, "Internet of things-based healthcare system on patient demographic data in Health 4.0," CAAI Trans. Intell. Technol., 7(4): 644-657, 2022.
- [6] K. M. Hosny, et al., "Internet of things applications using Raspberry-Pi: a survey," Int. J. Electr. Comput. Eng., 13(1): 902-910, 2023.
- [7] A. Golparvar, O. Ozturk, M. K. Yapici, "Gel-free wearable electroencephalography (EEG) with soft graphene textiles," presented at the IEEE 2021 Sensors, Sydney, Australia, 2021.
- [8] P. Srinivas, et al., "Support vector machines based predictive seizure care using IoT-Wearable EEG devices for proactive intervention in epilepsy," in Proc. 2024 IEEE 2nd International Conference on Computer, Communication and Control (IC4), 2024.
- [9] M. Alhayani, N. Alallaq, M. Al-Khiza'ay, "Optimize one max problem by PSO and CSA," presented at the International Congress on Information and Communication Technology, 2023.
- [10] S. A. Alzakari, et al., "Enhanced heart disease prediction in remote healthcare monitoring using IoT-enabled cloud-based XGBoost and Bi-LSTM," Alexandria Eng. J., 105: 280-291, 2024.
- [11] S. Pokhrel, R. Chhetri, "A literature review on impact of COVID-19 pandemic on teaching and learning," Higher Educ. Future, 8(1): 133-141, 2021.
- [12] Y. Izza, A. Ignatiev, J. Marques-Silva, "On explaining decision trees," arXiv preprint, arXiv:11034, 1:21, 2020.
- [13] M. Alhayani, M. Al-Khiza'ay, "Analyze symmetric and asymmetric encryption techniques by securing facial recognition system," in Proc. International Conference on Networking, Intelligent Systems and Security, 2022.
- [14] S. Amini, et al., "Urban land use and land cover change analysis using random forest classification of landsat time series," Remote Sens., 14(11), 2654, 2022.
- [15] V. Jackins, et al., "Al-based smart prediction of clinical disease using random forest classifier and Naive Bayes," J. Supercomput., 77(5): 5198-5219, 2021.
- [16] L. Dai, et al., "Influence of soil properties, topography, and land cover on soil organic carbon and total nitrogen concentration: A case study in Qinghai-Tibet plateau based on random forest regression and structural equation modeling," Sci. Total Environ., 821: 153440, 2022.
- [17] W. Python, Python releases for windows, 2021.
- [18] S. R. Chanthati, "Second version on a centralized approach to reducing burnouts in the IT industry using work pattern monitoring using artificial intelligence using MongoDB atlas and python," World J. Adv. Eng. Technol. Sci., 13(1): 187-228, 2024.

- [19] D. A. Pisner, D. M. Schnyer, Support vector machine, Machine learning: Methods and Applications to Brain Disorders, Elsevier, 101-121, 2020.
- [20] T. Latchoumi, et al. "Enhancement in manufacturing systems using Grey-Fuzzy and LK-SVM approach," in Proc. 2021 IEEE International Conference on Intelligent Systems, Smart and Green Technologies (ICISSGT), 2021.
- [21] Q. Li, et al., "A comparative study on the most effective machine learning model for blast loading prediction: From GBDT to Transformer," Eng. Struct., 276: 115310, 2023.
- [22] Y. Qiu, et al., "Performance evaluation of hybrid WOA-XGBoost, GWO-XGBoost and BO-XGBoost models to predict blast-induced ground vibration," Eng. Comput., 38 (5): 4145-4162, 2022.
- [23] P. Schober, T. R. Vetter, "Logistic regression in medical research," Anesth. Analg., 132(2): 365-366, 2021.
- [24] N. Boyko, K. Boksho, Application of the Naive Bayesian Classifier in Work on Sentimental Analysis of Medical Data, IDDM, 3rd, 2020.
- [25] E. M. K. Reddy, Introduction to Naive Bayes and a review on its subtypes with applications, Bayesian reasoning and Gaussian processes for machine learning applications, 1-14, Taylor& Francis, 2022.
- [26] D. Tramontin, Random forest implementation for classification analysis: default predictions applied to Italian companies, Ca'Foscari University of Venice, 2020.
- [27] A. E. Ulloa-Cerna, et al., "rECHOmmend: an ECG-based machine learning approach for identifying patients at increased risk of undiagnosed structural heart disease detectable by echocardiography," Circulation, 146(1): 36-47, 2022.
- [28] M. Shao, et al., "A review of multi-criteria decision making applications for renewable energy site selection," Renewable Energy, 157: 377-403, 2020.
- [29] G. Xu, "IoT-assisted ECG monitoring framework with secure data transmission for health care applications," IEEE Access, 8: 74586-74594, 2020.
- [30] I. Wickramasinghe, H. Kalutarage, "Naive Bayes: applications, variations and vulnerabilities: A review of literature with code snippets for implementation," Soft Comput., 25(3): 2277-2293, 2021.
- [31] J. Muschelli, "ROC and AUC with a binary predictor: a potentially misleading metric," J. Classif., 37(3): 696-708, 2020.

Biographies



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