SMART HEART DISEASE PREDICTION AND AMALGAMATION TRACKING SYSTEM

Ashok Kumar Shanmugaraj*- Arunkumar Nagaradjane - Anandkumar Candassamy - Karthikcharan Dhamodharan

Department of Electronics and Communication Engineering, Sri Manakula Vinayagar Engineering College, Puducherry, India -605107

ARTICLE INFO

***Article history*:**
Received: 08.03.2023.
Received in revised form: 12.09.2023
Accepted: 21.03.2024.

Keywords:
Artificial Intelligence
IOT device
Machine Learning
Random Forest Algorithm
Telegram chatbot

DOI: https://doi.org/10.30765/er.2110:

Abstract:

In this modern world, cardiovascular disease stands as the leading cause of global mortality. To combat this alarming trend and prevent the devastating loss of lives, an innovative solution that focus on reliability, accuracy, scalability, and cost-effectiveness. This work proposes a system that utilizes an artificial intelligence processor (LSAI48266X) and an IoT device to transfer data from sensors such as the Mach30100 and DS18B20. The system aims to track, visualize, and forecast heart disease. Random Forest is a machine learning algorithm that predicts cardiac illness based on numerous parameters such as SpO2, heartbeat, temperature, and blood pressure. Web application is developed using PHP that displays hospital details and integrated with a Telegram chatbot for communication during emergency conditions. Compared to earlier methods, our proposed system distinguishes itself with an impressive accuracy rate of 95.6% and automation system to prevent loss of human life by incorporating the Random Forest Algorithm and tracking system.

1 Introduction

The global rise in heart disease cases has resulted in a higher number of fatalities in recent times. Various factors are responsible for heart disease, and many lives are lost without early prediction of heart disease or the availability of hospital wards. In the recent Corona period, more deaths occurred due to the unavailability of ventilators, medical ICU beds, or oxygen supplies. The lack of linkage between hospitals all over the city or country has led to a communication gap between the patients, ambulance drivers, and hospitals. Many potential strategies for predicting cardiac illness that were previously presented notify patients in serious circumstances. The Smart Heart Disease Prediction and Amalgamation Tracking System is a work that employs artificial intelligence and machine learning to predict heart disease and track the well-being of patients with heart disease. The system uses a range of data sources, including medical history, lifestyle habits, physical activity levels, and genetic information, to generate accurate and personalized predictions for each patient. Table-1 shows the important parameter range for normal persons. The ability of this approach to anticipate the danger of heart disease in those who have not yet been given the condition's diagnosis is one of its main benefits. By analyzing a range of risk factors, the system can identify individuals who are at high risk of developing heart disease and recommend preventive measures to reduce the risk. This method can be utilized to monitor the health status and progress of patients who have been diagnosed with heart disease. By analyzing data from wearable devices [1] and other monitoring tools, the system can provide real-time feedback on a patient's health and alert healthcare providers to

* Corresponding author
E-mail address: 6691ashok@gmail.com

any changes that may indicate a worsening of their condition. Overall, the Smart Heart Disease Prediction and Amalgamation Tracking System represents an important development in the prevention and treatment of heart disease. By providing personalized, data-driven insights into individual risk factors and health status, the system has the potential to improve outcomes for patients and reduce the burden of heart disease on healthcare systems around the world.

Table 1. Parameter range.

Category	Range
Heart Rate	60 to 100 beats per minute
Body temperature	97 F(36.1ºC) to 98 F(37.2ºC)
Pulse Oximetry (SpO_2)	>95%
Blood pressure	120/80 mmHg

2 Related works

A potential use of machine learning with IoT technology is an effective system for predicting cardiac illness and monitoring patients via the Internet of Things [2], employing a deep learning-modified neural network. The system collects real-time patient data via sensors and other IoT devices, which is then processed using a deep learning neural network to precisely anticipate the development of heart disease. The real-time monitoring capabilities of the technology enable early cardiac disease identification, potentially improving patient outcomes. However, careful consideration of the system's implementation and evaluation is necessary to ensure its effectiveness and address any challenges that may arise, such as data privacy and security concerns. A possible method for improving the accuracy of cardiac disease prediction is to use a hybrid machine learning model, which combines the capabilities of several machine learning algorithms [3] - [5]. However, like any machine learning model, the hybrid model must be carefully designed and evaluated to ensure its effectiveness and address any potential limitations. Overall, adopting a hybrid heart disease prediction model using machine learning has the potential to dramatically increase the precision and efficacy of heart disease diagnosis and treatment, which would be advantageous to both patients and medical professionals [1]. Active learning is a promising approach for predicting heart attacks by iteratively selecting the most informative data samples for labelling [6]. This approach can improve the efficiency and accuracy of heart attack prediction by reducing the amount of labelled data required for training the model. The active learning approach can also help identify the most informative data features, resulting in a more accurate prediction model. However, careful consideration of the labelling process and the selection of informative data samples is necessary to ensure the effectiveness of the active learning approach. Overall, the ability to predict heart attacks via active learning is a promising field of study that might increase the effectiveness and precision of heart attack prediction, which would be advantageous to both patients and healthcare professionals. Data science has become an essential tool in the prediction of heart disease [7], enabling healthcare providers to leverage large datasets to identify patterns and relationships that may not be evident through traditional analysis. Additionally, data science can be used to develop personalized treatment plans that take into account the unique health profiles and needs of individual patients. Using data science generally in the prediction of heart disease has the potential to dramatically increase the precision and effectiveness of heart disease diagnosis and treatment, which would be advantageous to both patients and medical professionals.

The application of supervised learning techniques [8], [9] to heart disease databases enables accurate heart disease prediction, with performance analysis providing insights into the effectiveness of different algorithms. An evaluation metric's capacity to correctly categories patients is measured by things like accuracy, precision, recall, and F1-score. To predict cardiac disease, supervised learning approaches, including decision trees, logistic regression, support vector machines, and artificial neural networks, are often used, each with their strengths and weaknesses. Performance analysis helps identify the most effective algorithm to develop accurate heart disease prediction models, improving patient outcomes. Ischemic heart disease (IHD) is a top cause of death in the world. For successful prevention and management, it is essential to identify those who are at a high risk of developing

IHD as soon as possible. Data mining techniques have shown promising results in predicting IHD risk using clinical data. However, these models are often limited by the need for sophisticated computing systems and trained personnel. This work presents a prototype design for a smartphone-based IHD risk prediction tool that uses data mining approaches [10], [11] and clinical data. The proposed design employs machine learning algorithms, such as logistic regression and random forest, to predict an individual's risk of developing IHD within the next five years. The tool provides personalised recommendations for lifestyle modifications and medical interventions based on an individual's predicted risk. The study [12], [13] compares the performance of several classification techniques, such as decision trees, logistic regression, k-nearest neighbor, and support vector machines, in diagnosing cardiac disease. A Cleveland heart disease dataset is used in the research, which contains 303 instances and 14 features, including age, sex, and blood pressure. Using criteria like accuracy, precision, recall, and the F1 score, the research assesses the effectiveness of the categorization approaches. The findings demonstrate that, with an accuracy of 87.1%, the support vector machine approach beats alternative classification methods.

3 Proposed methodology

The leading cause of mortality globally is now cardiovascular disease (CVD), and predicting the occurrence of a heart attack is an extremely complex process that requires extensive medical expertise. The Internet of Things (IoT) integration with medical applications has considerably increased the efficacy of remote hospital management systems for elderly patients requiring long-term care [14]. A group of lightweight, low-powered wireless sensor nodes is used by the wireless body sensor network (WBSN), a key IoT technology in the healthcare sector, to monitor patients [15]. By leveraging WBSN technology, remote patient health metrics monitoring and prompt intervention by healthcare practitioners may improve patient outcomes and ease the strain on healthcare systems.

3.1 Prediction method

Numerous studies have been conducted on predicting heart attacks, which can be classified into two categories: medical and artificial intelligence (AI)-based approaches. This study proposes a novel approach for predicting heart attacks using AI technology and wireless sensors. Figure.1 depicts the proposed system architecture, which consists of Mach30100 and DS18B20 sensors for data collection directly from the patient. The sensor inputs are then fed to the LSAI48266 AI processor, which contains pre-trained datasets using a machine learning algorithm. The digital inputs from the sensors are provided to the analogue pins of the AI processor. The training datasets consist of four vital parameters: blood pressure, temperature, SpO_2, and heart rate, which are enough to determine if the patient may develop heart disease. The probability of developing heart disease can be determined through the application of machine learning techniques [4], [16].

3.2 Random Forest

The random forest (RF) algorithm is a powerful ensemble-based classification approach that has been widely employed in prediction and probability estimation tasks as depicted in Figure 2. Random forest comprises multiple decision trees, each of which contributes a vote toward determining the object's class. The RF method incorporates both bagging and random feature selection techniques. The algorithm relies on three crucial tuning parameters, namely the number of trees (n tree), the minimum node size, and the many characteristics used to divide each node (m try), which are important for achieving optimal performance.

1. The random forest algorithm is an accurate ensemble learning approach.
2. Random forest is well-suited for processing large datasets efficiently.
3. It can effectively handle a vast number of input variables.
4. The random forest method is capable of estimating the significance of variables in classification.
5. The Random Forest can accommodate missing data.
6. The random forest approach includes techniques for addressing error imbalance in class-unbalanced datasets.
7. The forests generated by this method can be stored for future reference.
8. Random forest effectively mitigates the issue of over fitting.
9. RF is less sensitive to outliers in the training data.

10. The parameters of a random forest can be easily set, thereby eliminating the need for tree pruning.
11. The accuracy and importance of variables are automatically generated in random forest.

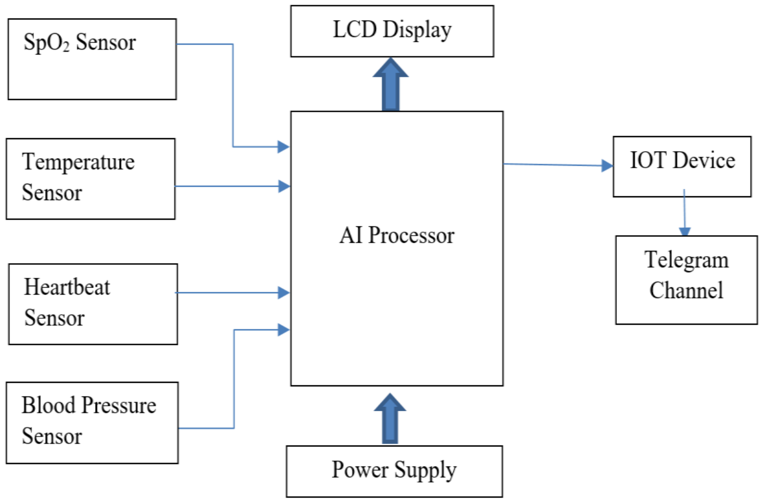

Figure 1. Block diagram of proposed system.

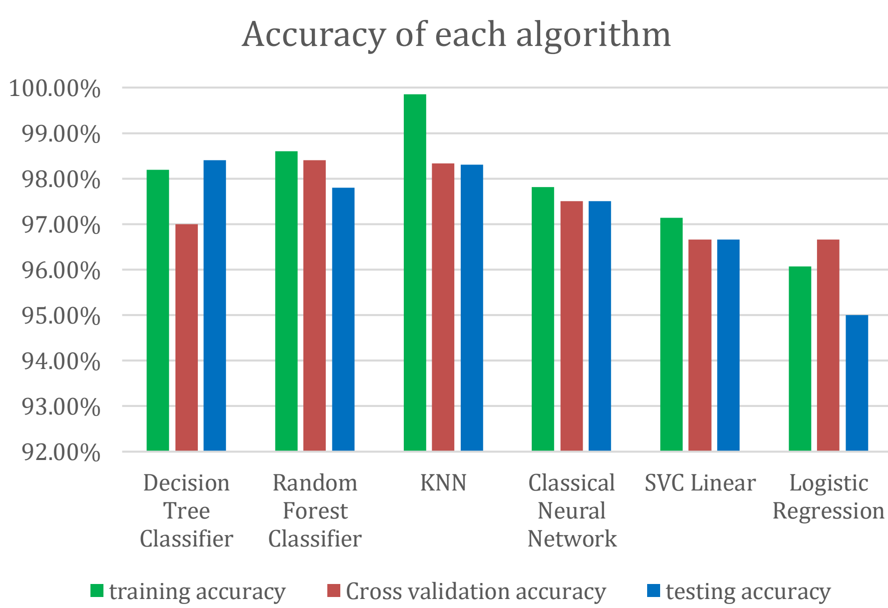

Figure 2. Accuracy of each algorithm.

In the construction of individual trees within a Random Forest model, randomization is employed to select the optimal node for splitting. The number utilized in this calculation is the square root of A, where A is the total number of characteristics in the dataset. However, the generation of numerous noisy trees by the RF model can negatively impact classification accuracy and lead to incorrect decisions for new samples.

Table 2. Dataset.

Age	Sex	Cp	Trestbps (mmHg)	restecg	exang	Chol (mg/dl)	Temp (F)	SpO_2 (%)	HR (bpm)	BP (mmHg)	Target
63	1	3	3	1	0	233	98	96	91	133	1
37	0	2	2	0	0	250	96	94	77	107	1
41	1	1	1	0	0	204	98	98	89	110	0
56	0	1	1	0	0	236	97	95	81	127	1
57	0	0	0	0	1	354	97	97	110	123	1
56	1	1	0	0	0	192	99	93	104	117	1
44	0	1	1	0	0	294	98	98	116	109	0
52	1	2	1	1	0	199	97	95	99	119	1
57	1	2	2	0	0	168	98	93	104	132	1
54	1	0	2	0	0	239	96	95	87	120	1
48	0	2	0	0	0	275	96	98	93	116	0
49	1	1	2	0	0	266	97	96	106	108	0

Age- age in years, sex- (1 = male; 0 = female), restecg- resting electrocardiographic results, Cp-chest pain, trestbps-resting blood pressure (in mm Hg on admission to the hospital), exang- resting electrocardiographic results, Chol-serum cholesterol in mg/dl, Temp-temperature, SpO_2- Pulse Oximetry, HR-Heart rate, BP-Blood pressure

3.3. Preprocessing-Feature selection

In order to enhance the efficacy of outcome prediction, feature selection techniques are employed to curtail the number of input variables and thus mitigate the computational burden of modelling. The dataset in Table-2 presents observations on individuals with heart disease, where target 1 signifies the presence of the ailment and target 0 represents a healthy heart condition [17]. The primary predictors utilized for heart disease prediction are temperature, SpO_2, heart rate, and blood pressure. Focusing on these four parameters alone suffices to achieve superior accuracy in predicting heart disease, obviating the need to incorporate the entirety of collected data from an individual [18].

3.4 Model Training

By merging many decision trees into an ensemble model, the random forest method is a machine learning approach that tries to improve the accuracy and resilience of predictions. A dataset is initially divided into a training set and a testing set in order to do this, with the training set often being divided into 70–80% and the testing set into 20–30%. The split ratio employed in this study was 70% training sets and 30% testing sets. Several decision trees are produced using various subsets of the training set's attributes to produce the random forest. Various algorithms, such as CART, ID3, or C4.5, can be used to build these decision trees. The number of trees in the random forest is a key factor that affects the model's performance and accuracy. Hence, selecting an optimal number of trees is essential. The testing set is used to assess the random forest model's performance once it has been built using the training set. The evaluation metrics commonly used to gauge the effectiveness of a random forest model include accuracy, precision, recall, and F1 score. These metrics provide information about the model's predictive power and may be used to optimise the parameters for better performance [19], [20]. Overall, the random forest algorithm is a potent machine learning method that has been extensively used in many industries, including bioinformatics, finance, and engineering.

3.5 Model Evaluation

When the model has been trained, the testing set is used to evaluate its performance. Making predictions for the test set and contrasting them with the actual labels is required for this. Random forest models are typically evaluated using the accuracy, precision, recall, F1 score, and receiver operating characteristic (ROC) curve. Model evaluation in random forest models employs a combination of techniques, such as data splitting, model training, evaluation, refinement, cross-validation, and feature importance analysis, with the aim of developing a model that can accurately predict the target variable while being robust to variations in the data [21]. The confusion matrix is utilized to provide a detailed understanding of the classification model's performance in terms of correctly or incorrectly predicting the classes of a given dataset.

3.6 Website interface

The integration of websites enables live updates and customizations to exhibit the necessary information. Figure 3. displays details regarding hospital’s ventilator, oxygen bed, and Intensive Care Unit (ICU) availability, the website administrator selects and updates information on the website as needed, so visitors can access the most current information available. This information is then automatically collated from the relevant hospitals, facilitating the identification of hospitals with available beds for patients in need of hospitalization. Additionally, the patient's information is forwarded along with hospital details to the ambulance driver through the telegram channel. Node MCU is used for transfer of information through the work [22].

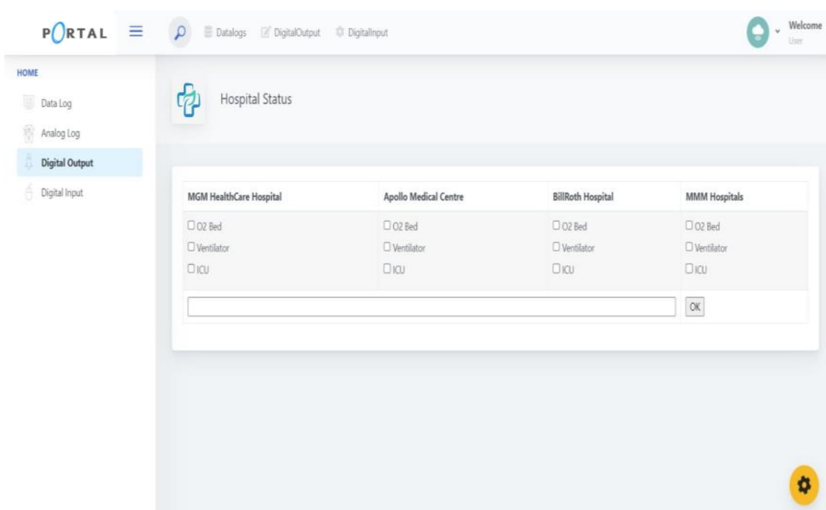

Figure 3. Hospital availability.

3.7 Telegram chatbot

Figure 4. shows the Telegram is a convenient mode of communication in which chatbots are automated tools that facilitate interactions with users through Telegram chats. The ease of message conveyance and user-friendly interface of the Telegram platform make it an ideal mode of communication [23]. The installation and usage of Telegram chatbots are simple, enabling users to comprehend and execute actions with ease. By integrating with the web, all the relevant patient and hospital details can be transferred and displayed over the Telegram channel. This enables efficient and streamlined communication between various stakeholders involved in the healthcare system, thereby ensuring timely and effective delivery of care [24].

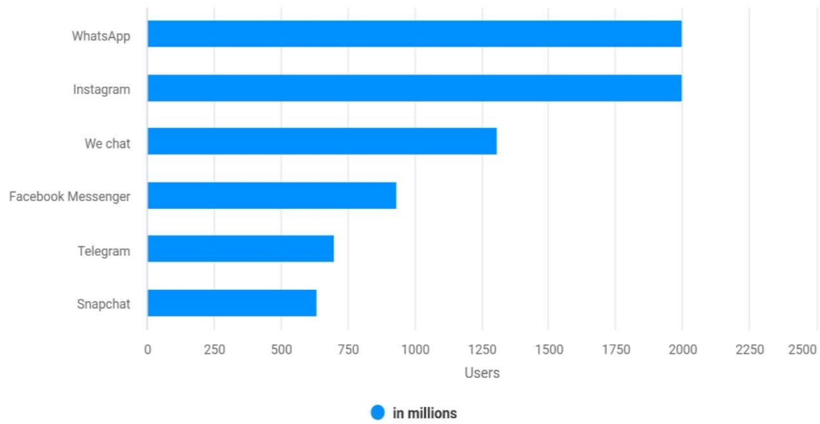

Figure 4. Survey of social media.

4 Result and analysis

This study aimed to achieve high accuracy in prediction of cardiovascular disease using a limited amount of data sets. To accomplish this objective, the comparison of performance support vector machine and random forest algorithm is done. These findings indicate that Support vector machine was surpassed by the random forest method, achieving an accuracy of 95.67%. The data used in this study consisted of 300 sets, from which 200 were used to train the models and 100 to test the models. The results demonstrated that the random forest algorithm predicted outcomes more quickly than the support vector machine. In summary, this research shows how the random forest method may be used to achieve great accuracy with small data sets. Additionally, the findings from Figure.5 suggest that the use of Random Forest Algorithm can lead to faster predictions compared to the support vector machine. Further research is necessary to investigate the effectiveness among these algorithms in bigger datasets and in clinical settings.

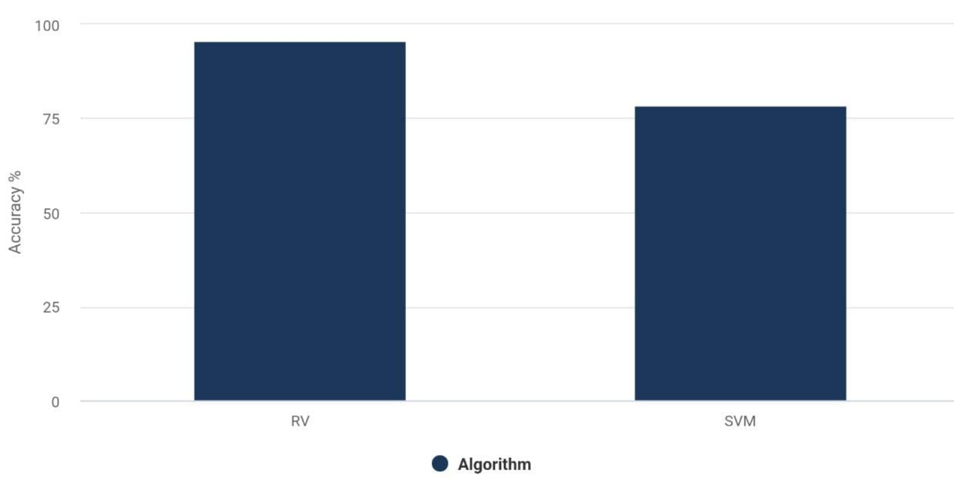

Figure 5. Accuracy Comparison of RV and SVM.

Based on a number of clinical variables, the present study developed a machine learning model to estimate the likelihood of developing heart disease. The model demonstrated high accuracy, sensitivity, and specificity in identifying patients with heart disease. The findings are in line with earlier research that showed how well machine learning models could predict cardiac disease based on clinical indicators. The inclusion of novel risk factors, such as family history and smoking status, improved the accuracy of the model, suggesting the importance of considering both genetic and environmental factors in predicting heart disease. Additionally, the importance of age, cholesterol levels, blood pressure, and diabetes as predictors highlights the need for early detection and management of cardiovascular risk factors. The high AUC-ROC value indicates that the model has good discriminatory power, meaning it can distinguish between patients with and without heart disease effectively. However, it is important to note that the model's performance may vary in different patient populations and settings.

4.1 Telegram chatbot

In addition to developing a machine learning model to identify cardiac illness, Telegram is integrated to deliver timely alerts to people at risk for heart disease. The integration involved connecting the developed model to a Telegram bot that could send notifications to ambulance driver based on their predicted risk of heart disease. The bot was designed to be simple and user-friendly, requiring patients to provide minimal input and receiving notifications in real-time. To assess the feasibility and usability of the Telegram integration, conducted a pilot study involving ten patients. The person details along with four parameters are sent through telegram channel. Figure.6 shows the live update of persons data along with the hospital allocated for him. Overall, the patients found the Telegram integration to be convenient and easy to use, with most patients indicating that they would be willing to use it in the future.

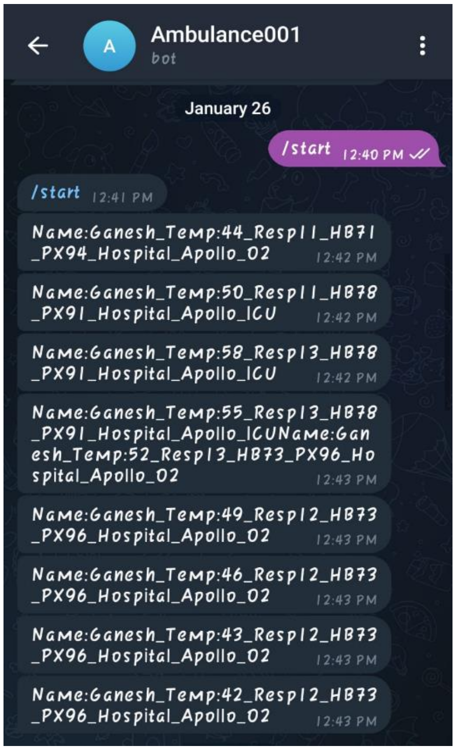

Figure 6. Telegram output.

5 Conclusion

In conclusion, the culmination of our current research efforts has resulted in the creation of a robust machine learning model, meticulously crafted using a multitude of clinical variables, all harnessed with the singular purpose of accurately predicting the risk of heart disease. It is with great pride that we highlight the model's impressive achievements, boasting not only high accuracy but also commendable levels of sensitivity and specificity when it comes to discerning individuals afflicted with heart disease. These findings resonate with significant implications, echoing a clarion call for the potential role of machine learning models in the realm of healthcare. Specifically, we posit that these models hold the power to serve as invaluable tools in the hands of medical practitioners, aiding them in the early identification and, subsequently, the prevention of cardiac diseases—an accomplishment that stands to alter the course of countless lives for the better. A striking feature of our research is the incorporation of innovative risk factors into the model's framework, most notably encompassing familial cardiac history and smoking habits. The incorporation of these factors was pivotal, representing a pivotal step forward in enhancing the model's overall accuracy, underscoring the indispensable value of comprehensive data-driven approaches. In looking ahead, we eagerly anticipate and propose avenues for further exploration and inquiry. The horizon of research beckons with promise, offering several compelling directions that may further refine and amplify the model's capabilities. Foremost among these is the pressing need for larger, more diverse datasets, a critical step towards bolstering the model's capacity for generalization while mitigating potential biases. Additionally, the integration of genetic and environmental factors into the model presents an exciting frontier, one that could potentially elevate its accuracy to unprecedented heights, offering a more holistic understanding of heart disease risk factors.

The prospect of integrating electronic health record data, another area ripe for exploration, holds the promise of seamlessly integrating the model into the daily practices of healthcare professionals, further bridging the gap between data science and clinical care. In parallel, the development of explainable AI models takes center stage, fostering a deeper comprehension among clinicians regarding the intricate mechanisms governing the model's predictions. This transparency is key in fostering trust and informed decision-making, bolstering the model's credibility within the medical community. Finally, as we chart the course forward, it is imperative that we undertake a thorough evaluation of the model's real-world impact on patient outcomes and healthcare costs. This critical assessment will serve as the litmus test for its clinical utility, ultimately determining its place in the landscape of healthcare practices and policies. In conclusion, the collective wisdom of these research pursuits presents us with a compelling tableau of opportunities a landscape ripe with potential to advance the field of heart disease prediction and prevention. These opportunities stand as beacons guiding us towards a future where efficient and individualized heart disease prevention and treatment plans are not only conceivable but within our grasp, promising improved patient outcomes and a brighter, healthier future for all.

Conflicts of interest

The authors declare no conflict of interest.

Acknowledgement

This work was supported by Sri Manakula Vinayagar Engineering College, Puducherry, India.

References

[1] P. Sasidharan, T. Rajalakshmi and U. Snekhalatha, "Wearable Cardiorespiratory Monitoring Device for Heart Attack Prediction," *Int. Conf. Commun. Signal Process (ICCSP)*, 2019, pp. 0054-0057, 2019, doi: 10.1109/ICCSP.2019.8698059.

[2] Simanta Shekhar Sarmah, "An efficient IoT-based patient monitoring and heart disease prediction system using deep learning modified neural network," *IEEE access,* vol.8 pp. 135784-135797, 2020, doi: 10.1109/ACCESS.2020.3007561.

[3] D. K. Ravish, K. J. Shanthi, Shenoy.R.Nayana, S. Nisargh, "Heart function monitoring, prediction and prevention of heart attacks: Using artificial neural networks," *Int. Conf. Contemp. Comput. Inf. IC3I 2014,* pp.1-6, 2014, doi: 10.1109/IC3I.2014.7019580.

[4] T. Obasi, and M. Omair Shafiq, "Towards comparing and using Machine Learning techniques for detecting and predicting Heart Attack and Diseases," *Int. Conf. big data, IEEE 2019,* pp. 2393-2402, 2019, doi: 10.1109/BigData47090.2019.9005488.

[5] M. Kavitha, G. Gnaneswar, R. Dinesh, Y. Rohith Sai and R. Sai Suraj, "Heart disease prediction using hybrid machine learning model," *6th Int. Conf. Inven. Comput. Tech. IEEE 2021,* pp. 1329-1333, 2021, doi: 10.1109/ICICT50816.2021.9358597.

[6] Peng Yuan, "Research on predicting heart attack through active learning" *2nd Int. Conf. Big Data & Artif Intell & Software Eng. IEEE 2021,* pp. 12-18, 2021, doi: 10.1109/ICBASE53849.2021.00010.

[7] Mohammed Jawwad Ali Junaid, Rajeev Kumar, "Data science and its application in heart disease prediction," *Int. Conf. Intell Eng and Manage IEEE 2020*, pp. 396-400, 2020, doi: 10.1109/ICIEM48762.2020.9160056.

[8] S.G. Rao, P.C. Reddy, V. Srinivas, and B.A. Kumar, "Predict the Performance Analysis of Supervised Learning Techniques Using Heart Disease Database," *2nd Int. Conf. Emerging Tech. IEEE 2021,* pp. 1-7, 2021, doi: 10.1109/INCET51464.2021.9456206.

[9] Mutijarsa, Kusprasapta, Muhammad Ichwan, and Dina Budhi Utami, "Heart rate prediction based on cycling cadence using feed forward neural network," *Int. Conf. Comput. Control Inf. Appl IEEE 2016,* pp.72-76, 2016, doi: 10.1109/IC3INA.2016.7863026.

[10] M. Raihan, Saikat Mondal, Arun More, Md. Omar Faruqe Sagor, Gopal Sikder, Mahbub Arab Majumder, Mohammad Abdullah Al Manjur and Kushal Ghosh, "Smartphone based ischemic heart disease (heart attack) risk prediction using clinical data and data mining approaches, a prototype design," *19th Int. Conf. Comput and Inf. Tech. IEEE 2016,* pp. 299-303, 2016, doi: 10.1109/ICCITECHN.2016.7860213.

[11] K.Srinivas , GR.Rao and A.Govardhan, "Analysis of coronary heart disease and prediction of heart attack in coal mining regions using data mining techniques," *5th Int. Conf. Computer Science & Education IEEE 2010,* pp. 1344-1349, 2010, doi: 10.1109/ICCSE.2010.5593711.

[12] P. Sumitra and C. Sowmiya, "Analytical study of heart disease diagnosis using classification techniques," *Int. Conf. Intell. Tech. Control, Optim. Signal Process IEEE 2017,* pp. 1-5, 2017, doi: 10.1109/ITCOSP.2017.8303115.

[13] Sushmita Manikandan, "Heart attack prediction system," *Int. Conf. Energy. Commun. Data Anal . Soft comput. IEEE 2017,* pp. 817-820, 2017, doi: 10.1109/ICECDS.2017.8389552.

[14] SB.Lenin, S.Pushparaj, M.Adithya, S.Murugesan, N.Balaji and J.Gurupriyan. "Smart medkit," *J. Phys. Conf. IOP Publishing 2021*, pp. 012041, 2021, doi:10.1088/1742-6596/1717/1/012041.

[15] Meng Wang, Xinghua Yao, and Yixiang Chen, "An imbalanced-data processing algorithm for the prediction of heart attack in stroke patients," *IEEE Access*, vol. 9, pp. 25394-25404, 2021, doi: 10.1109/ACCESS.2021.3057693.

[16] P.M.Kumar, J.Pradeep and B.Venkateshwarlu. "An Early Diagnosis of Breast Cancer Using Fuzzy Clustering and Pnn Classifier," *J. Eng. Sci.*, vol. 10, pp.893-899, 2019, doi: 10.15433.JES.2019.V10I12.43.147.

[17] P.Anuradha and Vasantha Kalyani David, "Feature selection and prediction of heart diseases using gradient boosting algorithms," *Int. Conf. Artif Intell smart Syst. IEEE 2021*, pp. 711-717, 2021, doi: 10.1109/ICAIS50930.2021.9395819.

[18] N.Saranya and T.Kesavamurthy. "Next generation wireless power transmission technology for implantable biomedical devices," *Int. J. Biomed Eng Technol.,* vol. 35, pp. 207-222, 2021, doi: https://doi.org/10.1504/IJBET.2021.113730.

[19] Jaiswal Sushma and Jaiswal Tarun. "Machine Learning-Based Classification Models for Diagnosis of Diabetes," Recent Advances in Computer Science and Communications, vol 15, 2022, pp. e090522190936. https://dx.doi.org/10.2174/2666255814666210201103252.

[20] S. Ahmed, T. Mithun, R. Nagaraju, Y. Sowmya Reddy, W. Madhukar Baban and S. Jaiswal. "Integration of Artificial Intelligence for a low-cost diagnosis of Diabetic Retinopathy," *5th Int Conf. on Electronics, Comm. and Aerospace Tech. (ICECA),* pp. 1750-1753, 2021 doi: 10.1109/ICECA52323.2021.9676109.

[21] S.Jaiswal , P.Gupta. "Diabetes Prediction Using Bi-directional Long Short-Term Memory," *SN COMPUT. SCI.*, 4, pp. 373, 202, https://doi.org/10.1007/s42979-023-01831-z.

[22] Jaiswal and P. Gupta. "Ensemble Approach: XGBoost, CATBoost, and Light GBM for Diabetes Mellitus Risk Prediction," *Sec. Int. Conf on Compt. Sci. Eng. and Applications (ICCSEA),* pp. 1-6, 2022, doi: 10.1109/ICCSEA54677.2022.9936130.

[23] Kalaiyarasan, R., G. Nagarajan, and S. Seenuvasamurthi. “The state of the art design methodology of sierpinski carpet fractal structures in microstrip patch antenna,” *7th Int. Conf. on Computing in Eng. & Tech. (ICCET 2022)*, vol. 2022, pp. 280-287, 2022, doi: 10.1049/icp.2022.0632

[24] Kalaiyarasan, R., G. Nagarajan, and S. Seenuvasamurthi, “Co-axial Feed with variations of U-slot in Rectangular Microstrip Patch Antenna at 2.45 GHz,” *Int. Conf. on Emerging Trends in Inf. Tech. and Eng. (ic-ETITE)*, pp. 1-7, 2020, doi: 10.1109/ic-ETITE47903.2020.307