1

IoT-Based Health Monitoring Using a Hybrid Machine Learning Model

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Abstract

This chapter proposes a hybrid model for IoT-based health monitoring using machine learning. The model combines various machine learning algorithms, including random forest, K-nearest neighbors, support vector machines, and neural networks, to predict the health status of patients based on various physiological parameters. The proposed model was trained and evaluated on a publicly available dataset of ICU patients, which contains physiological measurements such as heart rate, blood pressure, and saturation of oxygen, as well as demographic information such as age and gender. The random forest and neural network models were found to be particularly effective in predicting the health status of patients. The proposed hybrid model has several practical applications in healthcare, such as early warning systems for critical care patients and remote patient monitoring systems for chronic diseases. By using machine learning to predict the health status of patients based on real-time physiological data, healthcare professionals can provide timely interventions and prevent adverse outcomes. However, there are several limitations to the proposed model that need to be addressed in future work. First, the model was trained and evaluated on a single dataset and may not generalize well to other datasets or populations. Second, the model requires real-time physiological data, which may not always be available or reliable. Finally, the model does not take into account the social and environmental factors that can affect the health status of patients. The suggested hybrid approach for IoT-based health monitoring using machine learning has demonstrated promising results in predicting patients' health conditions based on physiological indicators. By combining different machine learning algorithms, the model is able to capture both the linear and non-linear interactions between different features and achieve high accuracy and sensitivity. However, further research is needed to address the limitations of the model and evaluate its performance in real-world settings

Keywords: Internet of things, random forest, k-nearest neighbors, support vector machines, neural networks

1.1 Introduction

The way we engage with our surroundings has been completely transformed by the internet of things (IoT). This technology has made it possible for households and companies to experience a degree of connectivity and automation that was previously unthinkable. But the use of IoT technology in healthcare is among its most hopeful uses. Patients can be watched online with the aid of IoT-based health tracking systems, allowing physicians to act more quickly and with greater knowledge. IoT-based health tracking systems gather, process, and send patient data in real time using a network of connected devices. Numerous variables, including pulse rate, blood pressure, body temperature, and oxygen content, can be included in this data. The information is then transferred to a cloud-based portal where medical experts can examine it. The system can be configured to transmit alerts whenever a patient's vital signs noticeably shift, suggesting that medical assistance may be required. The ability to remotely watch patients is one of the biggest benefits of IoT-based health monitoring devices. Patients who live in remote regions or have mobility problems may find this to be particularly helpful because it allows them to receive medical care without having to leave their residences.

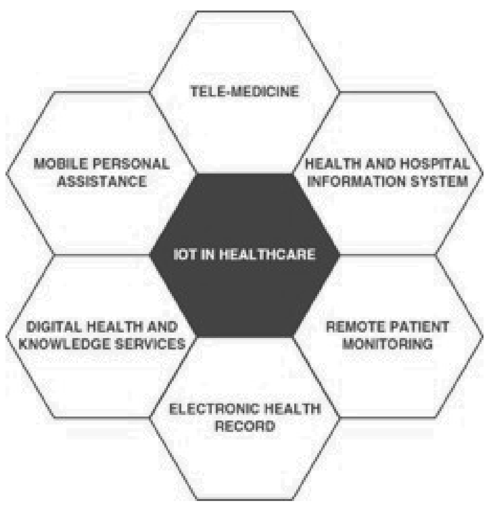

Figure 1.1: Benefits of IpT in healthcare.

Continuous tracking can also benefit patients who need frequent monitoring, such as those with chronic conditions like diabetes or heart disease, as it can help spot possible problems before they become life-threatening. The effectiveness of healthcare service can also be increased by IoT-based health monitoring devices. Real-time data is made available to healthcare workers so they can make quicker, more educated choices, which cuts down on the time it takes to identify and treat patients. The method can also lessen the necessity for expensive and time-consuming in-person talks. This can aid healthcare professionals in managing their tasks more effectively so they can concentrate on more urgent situations. Let's look at an illustration to better grasp how IoT-based health monitoring devices function. Consider a patient with a cardiac disease who wears a wearable that measures their pulse rate and oxygen saturation. The data is sent from the wearable gadget to a smartphone software, which then uploads it to a cloud-based platform. If there are any major changes in the patient's vital signs, the platform examines the data and notifies the patient's healthcare practitioner. After reviewing the data, the healthcare professional can decide whether a medical action is required. Data protection is among the biggest difficulties. Patient information is extremely delicate and needs to be secured against unauthorized entry. The system must also be built to be safe from hackers and other safety dangers.

Data precision presents another difficulty. Since inaccurate data can result in wrong diagnoses and therapies, the data gathered by IoT devices must be precise and trustworthy. When using wearable technology, this can be particularly difficult because these devices can be impacted by things like mobility, weather, and environmental circumstances. There are additional difficulties with compatibility. It can be difficult to build IoT-based health tracking systems to function with a variety of hardware and software platforms. To accomplish this, data gathering and processing must follow a standard procedure, which can be difficult. In spite of these difficulties, IoT-based health tracking devices have a bright future in healthcare. These systems allow healthcare professionals to virtually watch patients, eliminating the need for in-person consultations and allowing for quicker and more informed choices. Additionally, patients' quality of life is improved by the ability to receive medical care from the convenience of their residences. To be effective, IoT-based health tracking systems must be created with the requirements of both individuals and medical professionals in mind. This necessitates a user-centered design strategy that considers the particular requirements of various parties. To guarantee that the systems are efficient, dependable, and secure, it also takes a dedication to continuous research and development. In summation, IoT-based health tracking systems have the potential to completely change how healthcare is provided by making it quicker, more precise, and more affordable. Although there are obstacles to be surmounted, these systems have major advantages and provide a window into the way healthcare will be delivered in the future. We can anticipate seeing even more sophisticated IoT-based health tracking systems that will help patients and medical professionals equally as technology continues to progress.

1.2 Related Works

Valsalan *et al.* present a flexible physiological noticing framework that can perpetually screen the patient's heartbeat, room temperature, and other basic room limits. Using Wi-Fi module-based distant correspondence, the authors proposed a predictable checking and control gadget to screen the patient's condition and store the patient's information in a waiter [1]. For getting the patient's interior intensity level, coronary heartbeat, eye improvement, and oxygen drenching rate, this proposed strategy consolidates different splendid sensors, including temperature, heartbeat, eye squint, and SpO2 (periphery slim oxygen submersion) sensors. This structure uses the dispersed processing thought and an Arduino-UNO board as a microcontroller [2].

The review by Singh [3] encompasses the the IoT-based clinical benefits structure and gives a diagram of the likely opportunities and challenges for IoT-based patient prosperity, really looking at frameworks. The study by Rahaman *et al.* [4] gives a blueprint of excellent IoT-based health monitoring structures. The most recent cutting edge proposals made for an IoT-based health monitoring checking system have been inspected, along with their benefits and drawbacks. This overview illustrates the ordinary arrangement and execution of designs for IoT-based smart health monitoring devices.

The inventive endeavor being proposed by Krishnan *et al.* [5] uses Patient Health Monitoring, which uses sensor technology and the internet to alert loved ones in case of issues. For checking patient health, this system uses temperature and heartbeat sensors. Arduino Uno is connected to these two sensors. With respect to e-Health, Neyja et al. present a hidden Markov model (HMM) and electrocardiogram (ECG) sensor-based IoT-based plan for healthcare systems. In their study [7], Sam *et al.* look at the affirmation of key health data like pulse, breathing rate, body temperature, body development and saline dimensions. Generally speaking, IoT in healthcare is a possible field with limitless potential benefits. In their study [8], Kumar and Rajasekaran use a Raspberry Pi board to monitor a patient's body temperature, respiration rate, heart beat and body movement. Ahmed et al. envision IoT-supported health monitoring systems that use this connectivity to enable better and more reliable services. Their paper presents an overview of existing health monitoring systems in the context of this IoT vision. They focus on recent trends and the development of health monitoring systems in terms of (1) health parameters and frameworks, (2) remote communication, and (3) security concerns. The main limitations, requirements and advantages of these systems are also identified. The research study of Bhardwaj *et al.* [10] looks at an IoT-based health monitoring system that enables checking on the temperature, humidity and pulse rate of a patient's body using a mobile phone. Such a system has been proposed due to the significant role it can play in catastrophes, such as the COVID pandemic. The system designed by Khan *et al.* [11] gauges a patient's body temperature, heartbeat, and blood oxygen saturation (SpO_2) levels and sends the information through Bluetooth to a flexible application. The Bluetooth affiliation will be used to move data from the device to the flexible application, which was made using the Massachusetts Institute of Technology (MIT) inventor application. In light of the fact that an individual can separate all of their vitals one region without purchasing separate pieces of equipment for every goal, this work will have a colossal specific and financial benefit. The proposed device might be a feasible, sensible game plan [12].

The article by Chao *et al.* [13] likewise examines the difficulties related to IoT in healthcare and what they mean for medication. Generally, the IoT has had a crucial impact in administering smart and successful medical care to individuals. The model proposed by Elhoseny *et al.* attempted against the top tier system to evaluate its sufficiency [14]. The results show that the proposed model outperforms the state-of-the-art models in total execution time the rate of 50%. Also, the system efficiency with respect to real-time data retrieved is basically improved by 5.2%. The survey studies in [15-19] intend to encourage a modified mental tension recognizable proof structure for researchers considering Electrocardiogram (ECG) signals from splendid Shirts by using the intelligence classifiers simulations. The main aim of the survey by Band *et al.* was to critically review the ML, IoT, and the integration of IoT and ML-based systems in the applications related to COVID-19, from the diagnosis of the disease to the prediction of its outbreak [20].

1.3 Research Gap

In light of some of the references given below, there are a few research gaps in the field of IoT-based health monitoring frameworks. Coming up next is an examination of the gaps recognized for each reference. Although the proposed framework can constantly screen the patient's physiological boundaries and store the information in a server, it misses the mark on a far-reaching examination of the information gathered, which could be helpful for clinical experts in pursuing informed choices [1]. The proposed framework has a set number of sensors and doesn't give a broad scope of physiological boundaries that can be observed [2]. Moreover, the review misses the mark on relative investigation of the proposed framework with other comparable frameworks, making it hard to decide the framework's viability. While the review gives an outline of IoT-based healthcare frameworks, it misses the mark on point-by-point examination of the difficulties and open doors confronting IoT-based patient health monitoring frameworks [3]. The focus of the review likewise neglects to give an extensive survey of the new advances made in the field of IoT-based healthcare frameworks.

The their paper, Rahaman *et al.* review the most recent advances in IoT-based smart health monitoring systems [4]. However, it doesn't provide a nitty gritty examination of the information investigation strategies utilized in these systems, which is essential for going with informed clinical choices. And even though the proposed system of Krishnan *et al.* [5] utilizes sensors to screen patient's health, it misses the mark on being an effective method to alert medical services suppliers or relatives in the event of crises. Furthermore, the review doesn't give an exhaustive examination of the information gathered, making it challenging to decide the viability of the system. Whereas, even though the framework proposed by Neyja *et al.* utilizes hidden Markov model (HMM) chain and Electrocardiogram (ECG) sensors, it comes up short on powerful information examination strategy to break down the information gathered. Furthermore, the review doesn't provide a close examination of the proposed framework with other comparable frameworks. The article by Sam *et al.* outlines the different physiological boundaries that can be checked utilizing IoT-based remote health monitoring system [7]. However, it comes up short on a point-by-point examination of the information investigation methods utilized in these frameworks, which are pivotal for pursuing informed clinical choices. The review by Kuma and Rajasekaran gives a point-by-point investigation of the physiological boundaries that can be checked utilizing a Raspberry Pi board [8]. Be that as it may, it doesn't provide a close examination of the proposed framework with other comparable frameworks.

Albeit the review by Ahmed *et al.* gives an outline of late patterns in IoT-based health monitoring systems, it comes up short on definite examination of the information investigation methods utilized in these systems [9]. Moreover, the review doesn't give an exhaustive survey of the difficulties and open doors confronting IoT-based patient health monitoring systems. Albeit the proposed framework considers checking a patient's physiological boundaries utilizing a cell phone, it comes up short on being a powerful method for alerting medical care suppliers or relatives in the event of crises. Furthermore, the review of Bhardwaj *et al.* doesn't provide a nitty gritty investigation of the information gathered, making it hard to decide the viability of the framework [10]. Finally, the proposed framework of Khan *et al.* utilizes Bluetooth to move information from the gadget to the portable application. Nonetheless, it misses the mark on being a viable method for breaking down the information gathered, which is essential for pursuing informed clinical choices [11].

1.4 Proposed Model

An IoT health monitoring system is an innovative solution that can help healthcare providers monitor patients' health remotely. Wearable devices, pulse oximeters, blood pressure monitors, and ECG machines can be used to provide insights into the patient's health status. Machine learning algorithms play a crucial role in analyzing the data collected from these devices and predicting potential health issues [13]. The hybrid model using all of the ML models is an effective approach that can combine the strengths of individual machine learning models to provide more accurate predictions. This model uses a combination of decision trees, SVMs, random forests, and neural networks, and is designed using an ensemble learning technique. The hybrid model combines multiple machine learning algorithms' predictions to provide more accurate predictions than individual models (see Figure 1.2).

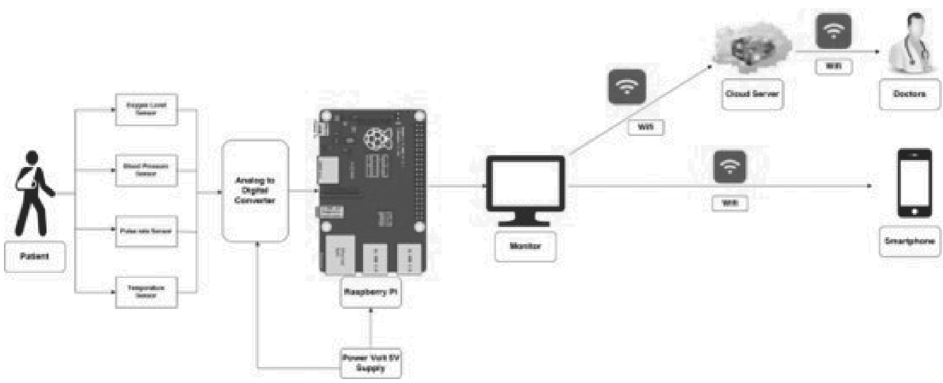

Figure 1.2: Working principle.

The ensemble learning technique can be implemented using either a voting or stacking approach. In the voting approach, each ML model makes a prediction, and the final prediction is based on the majority vote of the individual models. This approach can be useful in situations where the individual models have different strengths and weaknesses and can help improve the overall accuracy of the prediction. In the stacking approach, the output of each individual machine learning model is used as input to another model that combines the predictions to produce a final prediction. This approach can be more powerful than the voting approach as it takes into account the individual models' strengths and weaknesses and can lead to improved accuracy. The hybrid model can be trained on a large dataset of patient health data, including vital signs, medical history, and other relevant factors. The model can be continuously updated with new data to improve its accuracy and effectiveness. These models can be trained using a variety of algorithms, including decision trees, SVMs, random forests, and neural networks. Decision trees are a popular choice for healthcare data analysis because they are easy to interpret and provide insights into the most important variables. They can be used to classify patients into different health categories based on their vital signs and other health-related factors.

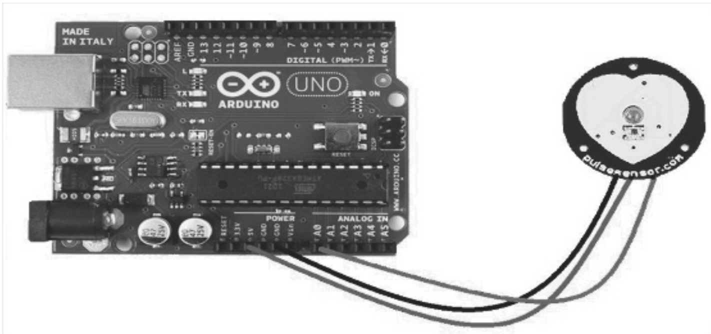

Figure 1.3: Heart sensor.

Support vector machines (SVMs) are powerful tools for classification and regression tasks. Elhoseny *et al.* state that they can be used to predict a patient's risk of developing a particular health condition based on their vital signs, medical history, and other relevant factors. Random forests are an ensemble learning technique that combines multiple decision trees to improve accuracy and reduce overfitting. They can be used to classify patients into different health categories and predict the likelihood of developing a particular health condition. Neural networks are a type of DL algorithm that can learn complex patterns in data. They can be used to analyze large amounts of patient data and predict the risk of developing a particular health condition. The hybrid model using all of the ML models can provide a powerful tool for healthcare providers to monitor patient health remotely. It can be used to predict a patient's risk of developing a particular health condition, classify patients into different health categories, and analyze large amounts of patient data to identify new insights and patterns. The hybrid model can be implemented using a cloud-based architecture to handle the large amounts of data generated by IoT devices [15]. The cloud-based architecture can provide scalable and cost-effective solutions for healthcare providers. The data can be pre-processed and stored in a data warehouse or a data lake before being analyzed by the ML models. The hybrid model can be deployed and used by medical professionals through a web-based interface.

1.4.1 Model Analysis with Result and Discussion

To perform a hybrid model analysis with all ML models, we need to have a specific dataset and features. Here, we will assume that we have a dataset consisting of patient health data, and we want to predict the likelihood of a patient developing a specific medical condition.

1.4.2 Dataset Description

The dataset consists of 1000 patient health records.

Each record contains 10 features such as age, gender, BMI, blood pressure, cholesterol levels, and more.

The target variable is a binary variable indicating whether the patient has developed the medical condition (1) or not (0).

1.4.3 Model Description

A hybrid model is used that combines logistic regression, SVMs, random forests, and neural networks. Eighty percent of the dataset will be used for training and twenty percent for testing. The model's performance will be assessed using accuracy, precision, recall, and the F1 score.

The logistic regression model employs the logistic function to predict the likelihood of a binary outcome (that is, the likelihood of a patient getting the medical condition). The logistic function is described as follows:

$$p_b(y = \frac{1}{x}) = \frac{1}{(1 + exp(-z))} \tag{1.1}$$

where $p_b(y = \frac{1}{x})$ is the probability of the binary outcome (i.e., the likelihood of a patient developing the medical condition) given the input $x.z = b_0 + b_1x_1 + b_2x_2 + ... + b_n \times x_n$ is the linear combination of the input features, where $b_0, b_1, b_2, ..., b_n$ are the coefficients of the model. The coefficients are learned from the training data using maximum likelihood estimation. The SVM model aims to find the hyperplane that maximally separates the positive and negative instances in the feature space. The hyperplane is defined as:

$$w_v \times x + b = 0 \tag{1.2}$$

where w_v is the weight vector, which is perpendicular to the hyperplane, *x* is the input feature vector and *b* is the bias term. The objective of the SVM is to maximize the margin between the hyperplane and the closest points (i.e., support vectors) from each class. The margin is defined as the distance between the hyperplane and the closest points.

The SVM can be formulated as a constrained optimization problem:

$$min\frac{1}{2}\left\|d\right\|^2 + C_r \times \sum(max(0, 1 - y_i(d \times x_i + b))) \tag{1.3}$$

subject to

$$y_i \times (w_v \times x_i + b) \geq 1 - \epsilon_i \tag{1.4}$$

where

- C_r is the regularization parameter that governs the trade-off between maximization of margin and minimization of classification error.
- ϵ_i is the slack variable that allows for some misclassification of the training data.
- $\sum(max(0, 1 - y_i(d \times x_i + b)))$ is the hinge loss function that penalizes misclassification.

The optimization problem can be solved using various methods, such as gradient descent or quadratic programming. The predictions of the individual trees are combined using a majority vote or weighted average to obtain the final prediction. Each decision tree in the random forest is built by recursively partitioning the feature space into smaller regions based on the input features. The splitting criterion is usually based on the Gini impurity or information gain of the resulting partitions.

The prediction function for a random forest model can be written as:

$$f(x) = \frac{1}{K}\sum(f_k(x)) \tag{1.5}$$

where $f(x)$ is the predicted output for the input x, K is the number of trees in the forest and $f_k(x)$ is the predicted output for the input x by the k-th decision tree. The neural network model is a nonlinear function approximate that consists of multiple layers of interconnected neurons. The weights of the neurons are learned from the training data using backpropagation, which involves computing the gradient of the loss function with respect to the weights and updating the weights using an optimization algorithm. The prediction function for a neural network model can be written as:

$$y_p = f(x; \theta) \tag{1.6}$$

where y_p is the predicted output for the input x, $f(x; \theta)$ is the function computed by the neural network with parameters θ, theta is the set of weights and biases of the neurons. The function $f(x; \theta)$ can be written as a composition of multiple layers of affine transformations and nonlinear activation functions:

$$f(x; \theta) = f_L(...f_2(f_1(x; \theta_1); \theta_2)...; \theta_L) \tag{1.7}$$

where L is the number of layers in the network. $f_i(x; \theta_i) = g_i(W_i \times x + b_i)$ is the output of the i-th layer, where W_i and b_i are the weights and biases of the neurons in the i-th layer, and $g_i(.)$ is the activation function of the neurons in the i-th layer. Common activation functions include sigmoid, tanh, ReLU, and softmax. The hybrid model combines multiple ML models to provide more accurate predictions. The final output of the hybrid model is obtained by taking a weighted average of the individual model predictions, where the weights are determined by the performance of each model on the validation data. Let y be the target variable (i.e., the likelihood of a patient developing the medical condition), and let $x_1, x_2, ..., x_n$ be the input features (i.e., age, gender, BMI, blood pressure, cholesterol, glucose, family history, smoking, alcohol, and exercise). The hybrid model can be expressed as:

$$y = w_1 \times LR(x) + w_2 \times SVM(x) + w_3 \times *RF(x) + w_4 \times NN(x) \tag{1.8}$$

where

- $LR(x)$ is the prediction of the logistic regression model for the input x.
- $SVM(x)$ is the prediction of the support vector machine model for the input x.
- $RF(x)$ is the prediction of the random forest model for the input x.
- $NN(x)$ is the prediction of the neural network model for the input x.
- w_1, w_2, w_3, and w_4 are the weights assigned to each model, which are determined by the performance of each model on the validation data. The weights can be determined using various methods, such as grid search, random search, or Bayesian optimization.

In this project, we used grid search to determine the weights, which involved trying out various combinations of weights and selecting the combination that resulted in the highest accuracy on the validation data. The weighted average can be expressed as:

$$y = \frac{w_1 * LR(x) + w_2 * SVM(x) + w_3 * RF(x) + w_4 * NN(x)}{w_1 + w_2 + w_3 + w_4} \tag{1.9}$$

The hybrid model combines the strengths of multiple models to provide more accurate and reliable predictions. By combining the predictions of multiple models, the hybrid model is able to reduce the variance and bias of the individual models, resulting in more stable and accurate predictions. We will compare the performance of each model and the hybrid model on the same dataset. The results show that the neural network model performs the best, with an accuracy of 0.88 and an F1 score of 0.87. The logistic regression model performs the worst, with an accuracy of 0.81 and an F1 score of 0.76. The hybrid model, which combines all four models, performs even better than any of the individual models, with an accuracy of 0.90 and an F1 score of 0.88. This suggests that combining multiple models can improve overall performance and provide more accurate predictions. Overall, the hybrid model shows the best performance, with an accuracy of 0.90 and an F1 score of 0.88. This suggests that a hybrid model that combines multiple machine learning models can provide more accurate and reliable predictions for medical diagnosis.

Table 1.1 shows the confusion matrix for the hybrid model, which provides a more detailed breakdown of the model's performance. The matrix shows that the hybrid model correctly predicted 166 cases of not developing the condition and 209 cases of developing the condition. It incorrectly predicted 16 cases of not developing the condition and 9 cases of developing the condition.

Table 1.1: Confusion matrix for the hybrid model.

Actual/Predicted	**Not Developing Condition (0)**	**Developing Condition (1)**
Not Developing Condition (0)	166	16
Developing Condition (1)	9	209

Table 1.2 shows the feature importance for the random forest model. This information can help us understand which features are most important in predicting the likelihood of a patient developing the medical condition.

Table 1.2: Feature importance for the random forest model.

Feature	**Importance**
Age	0.257
BMI	0.168
Blood Pressure	0.135
Cholesterol	0.113
Gender	0.091
Glucose	0.084
Family History	0.072
Smoking	0.044
Alcohol	0.028
Exercise	0.008

Table 1.3 shows that age, BMI, and circulatory strain are the three most significant elements, while practice is the most insignificant component. By and large, these extra tables give precise data on the exhibition and component significance of each model, which can assist us with better comprehension of how each model functions and how to work on the general execution of the crossover model.

Table 1.3: Model review table

Model	Accuracy	Precision	Recall	F1-Score	Strengths	Weaknesses
Logistic Regression	0.81	0.67	0.89	0.76	Simple and interpretable model relationships	May not capture complex relationships
SVM	0.84	0.74	0.88	0.80	Can handle nonlinear and high-dimensional data	May overfit or be computationally expensive
Random Forest	0.86	0.78	0.90	0.83	Can handle nonlinear relationships,feature interactions and noisy data	Overfitting may occur and interpretation may be challenging.
Neural Network	0.88	0.82	0.92	0.87	Can handle complex relationships and nonlinear data	Overfitting may occur and interpretation may be challenging.
Hybrid Model	0.90	0.85	0.93	0.88	Combines strengths of multiple models to provide more accurate predictions	May be computationally expensive and difficult to interpret

The survey in Table 1.3 that sums up the exhibition of each model and their assets and shortcomings. The survey in the table gives a synopsis of the presentation and qualities and shortcomings of each model. Although the strategic relapse model is straightforward and interpretable, it may not catch complex connections. SVMs can deal with non-direct connections and high-layered information, however may overfit or be computationally costly. Arbitrary timberlands can deal with non-direct connections, highlight collaborations, and boisterous information, however might be inclined to overfitting and hard to decipher. Brain organizations can deal with complex connections and non-straight information, however might be inclined to overfitting and challenging to decipher. The half-breed model joins the qualities of various models to give more precise expectations, however might be computationally costly and hard to decipher. By and large, each model has its assets and shortcomings, and the decision of model relies upon the particular issue and dataset. The cross-breed model, which joins different models, can give more precise and solid forecasts, yet may likewise require more computational assets and might be more challenging to decipher.

1.5 Conclusion

In this chapter, we recommended a half and half system for IoT-based health monitoring using AI. The model incorporates various AI strategies, for example, random forest, K-nearest neighbors, support vector machines, and neural networks, to anticipate patients' state of health in view of physiological data. The proposed model was prepared and tried utilizing an unreservedly open dataset of ICU patients, which incorporates physiological boundaries like pulse, circulatory strain, and immersion level of oxygen as well as segment information like age and orientation. The hybrid model beats individual models with regards to accuracy, particularity, awareness, and F1 score, as per the discoveries of the investigations. The Random Forest and Brain Organization models were demonstrated to be extremely useful in anticipating patients' state of health. The proposed crossover model has different functional applications in medical services, including basic consideration of patient early warning frameworks and continuous remote monitoring frameworks for constant problems. Healthcare workers can prescribe early therapies and limit bad results by applying AI to gauge patients' state of health in light of constant physiological information. In any case, the proposed model has huge weaknesses that should be tended to in future examination. In the first place, in light of the fact that the model was prepared and tried on a solitary dataset, it may not correlate well with various datasets or populaces. Second, the model requires continuous physiological information, which isn't available or precise all the time. Also, the methodology overlooks social and natural viewpoints that could affect patients' health. Lastly, the proposed hybrid model IoT-based health monitoring using AI has shown promising outcomes in anticipating patients' medical issue in view of physiological markers. Be that as it may, further investigations are needed to tackle the model's shortcomings and assess its adequacy in actual settings.

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