International Journal of Computer Applications (0975 - 8887)
Volume 186 - No.24, June 2024

Ensemble based Machine Learning Approach for Patient Health Monitoring

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ABSTRACT

In the present era, healthcare analysis has been continuously evolving to serve the medical demands of the patients. Due to the advancement in the sensor technology, to be used in the wearable health devices for monitoring the health status of the people, enormous quantity of data is being produced progressively. Wearable healthcare equipment is essential for early detection and treatment of chronic diseases. An in-depth study is required to design a healthcare system that collects, records, analyses and share large data streams containing medical information of the users in real-time and efficiently to increase health risks and reduce health-related costs. Many machine learning based approaches have been prominent in the classification of sensors data from these healthcare devices. In this work, an ensemble based classifier has been designed based on majority voting consisting of five types of classifiers namely, logistic regression, XGB classifier, support vector machines, AdaBoost classifier and artificial neural networks from which the results of the physiological sensor data are predicted from the clinical environment. The models are evaluated using four evaluation metrics that are confusion matrix, accuracy, precision and recall.

General Terms

Machine Learning, Health monitoring

Keywords

Vital signs, sensor data, logistic regression, XGB classifier, support vector machines, AdaBoost classifier, artificial neural networks, ensemble learning

1. INTRODUCTION

Preventive medical care, thereby avoiding various modern diseases can be done by keeping track of the health of the person continuously. The various diseases that can be prevented are cancer, diabetes, chronic respiratory diseases [48]. Nowadays, wearable health devices are introduced that monitor the health status of the person. These devices are frequently used to check the risk parameters of the person [22, 42, 1, 44]. The continuous monitoring of a person's health is important for detecting and treating chronic diseases at an early stage. The health condition of the person can be monitored by tracking various vital signs that includes blood pressure, heart rate, respiration rate, blood oxygen levels (SpO2) and body temperature [38]. These vital signs can be continuously monitored to analyze the health condition of the human body and development of any diseases in the future.

Wearable health devices are an evolving technology for constant monitoring of the health of the person during daily life at home, work, during sports activities etc. [12]. It also monitors in a health care environment without any mental or physical uneasiness and involvement in normal daily activities [10]. Wearable health devices are crucial in observing and checking the progress and early detection of number of chronic disease [50]. It helps to monitor people their health status for self-health tracking and provides data to health care professional for earlier diagnostic and counseling of the treatment. It helps doctor to treat the patient efficiently by sending a notification to the doctor from the wearable health devices. Hence, the threat to patient's heath is reduced by these devices.

The world health organisation organised a study that explained that rise of heart related diseases [11]. The heart related diseases are caused by eating habits, obesity, smoking, chewing tobacco and lack of physical exercise[46]. The patients can suffer from secondary diseases after a surgical procedure. In some cases patients can also suffer from cardiac problems after getting back to normal routine. Because of this continuous monitoring of the ECG of these patients are required after a surgical procedure [40]. It provides prior medical care to the irregular working of the heart. It provides safety measures in the treatment of theses diseases. The life's of the patients can be saved by treating them earlier if any complication occurs. Hence, continuously keeping track of the physical condition of the subject is necessary to prevent various chronic diseases. The patients that are suffering from heart diseases are in constant need for monitoring the vital signs to get treatment quickly whenever necessary [33].

With the recent development in the field of artificial intelligence and its allied areas such as machine learning and deep learning, the huge quantity of data produced by the wearable equipments with the help of Internet-of-Things (IoT) are very important for researchers to utilize in the constantly expanding medical field [30, 34]. The IoT-based health monitoring framework is the continuation of the traditional medical practice with the help of remotely monitoring the vital body condition of a patient. The systems used for detection commonly available in health wards are distinguished by large and sophisticated connections. Now continuous progress within the semiconductor technology industry has led to smaller in size of sensors and micro-controllers, faster operating, lower consumption of power and cheaper cost. So it is suitable to be used in remote observation of the fundamental physical health indicators of the subjects, particularly the older people.

The inbuilt sensors in the wearable health devices uninterruptedly monitor the vital signs of the human body. It obtains the vital data during the various daily activities and this data can be directly obtained by the user through wearable health device console or smart phones. The wearable devices are also very useful in monitoring an athlete's performance or the health status of military personnel in various dangerous surroundings. There are many instances of positive outcomes in various streams of healthcare technology, viz., oncology [26], radiology [24], surgery [3], geriatrics [37], rheumatology [21], neurology [18], hematology [41] and cardiology [47]. Because of the utilization of these healthcare devices, it is changing the current face of the healthcare market.

In this paper, five types of classifiers have been used for the design of an ensemble based classifier based on majority voting, for the analysis of the vital signs data generated from sensor devices. The classifiers used are logistic regression (LR), XGB classifier (XGB), support vector machine (SVM) , Adaboost classifier (ADA), artificial neural network (ANN). This ensemble based approach has proven to be very impressive by improving the prediction performance. The dataset used for the purpose is the University of Queensland vital signs dataset [25] which includes the vital signs data of 32 patients.

The paper is formed as: Section 2 gives an overview of the previous efforts demonstrated in this domain in the last few years. Section 3 gives the information on the dataset used and the detailed framework of the idea considered here. Section 4 reveals the results obtained by the techniques performed on the vital signs dataset. In the last section 5 a summary of the paper is presented and highlight on the future perspectives of the research.

2. RELATED WORKS

Many researchers are actively conducting a huge number of studies in investigating different machine learning technologies and various techniques have already been proposed for the e-healthcare domain. Since there is no working model that can guarantee 100% prediction on the vitals signs of the human body, the problem still exists and requires further extensive research. In this section, a brief review of some of the relevant efforts are given which are worth mentioning in the use of machine learning approaches for the investigation of wearable sensor data.

In a work, a machine learning based model introduced by Thakur et al. [45] predicts the number of dialysis sessions required by patients with the help of data generated by a wearable health device. The accuracy of the proposed model is favourable and they conclude that the data generated by the sensor can be adopted to keep track of the vital parameters and early detection of any future diseases. The limitation of the approach is that it reveals the details of the patients in every part of the dialysis period. It also did not observe many other essential vital signs that are required for constant monitoring the health of the person.

In another work, Martinez et al. [19] proposed a technique for classification of the various motions of the body during sleep and extracting the features using feature learning. The model proposed predicts the various sleeping disorders and the diseases linked with sleeping disorders. The algorithm used in this work is bispectral entropy analysis. The performance parameter used is bispectral entropy histograms with 41.7% of the pairs are correlated. The performance of the model is not satisfactory and further research in this work has to be done.

A machine learning based prediction to identify and predict severe sepsis is introduced in the work of Le et al. [23]. The machine learning model is proposed using decision trees. The symptoms that was taken into account are blood pressure, peripheral oxygen saturation (SpO2), heart rate, temperature, and respiratory rate. The system used the following machine learning based classification algorithms: logistic regression and random forest. The performance parameter used is area under the receiver operating characteristic (AUROC) curve. At the time of onset and 4 hour prior to onset, it achieves an AUROC of 0.916 and 0.718 respectively. The study has good future prospects to accomplish good performance in prediction of pediatric severe sepsis.

In another work, a machine learning based prediction model is proposed for the prediction of the health status using vital signs in the human body by Vistisen et al. [48]. The machine learning model is designed using regularized lasso logistic regression and random forest regression. The system continuously keep track of the human vital parameters such as heart rate, mean arterial pressure, respiratory rate, and peripheral oxygen saturation (SpO2). The accuracy achieved from the system is 81% and area under the ROC curve of 87%. This allows earlier diagnostics or safeguard from hemodynamic fatal crisis.

Baker et al. [2] presented a machine learning approach to forecast the possibility of in-hospital death for a patient in intensive care units. A deep learning technique is proposed in which convolution neural network is augmented with long short-term memory (LSTM). The symptoms that he took into account are systolic and diastolic blood pressure, peripheral oxygen saturation (SpO2), heart rate, temperature, and respiratory rate. The system can be used in clinics to help the heath workers to classify the patients according to duration of possibility of in-hospital death. The main measuring standard used in the system is area under the receiver-operator curve (AUROC) and the highest-performing model achieve an AUROC of 0.884.

For early diagnosis of acute renal failure, Diego et al. [27] designed two machine learning models to predict acute renal failure. The prediction is done on acute renal injury stage 1 and stage 2. The main evaluation of the accuracy of the system was ROC curve. The highest accuracy for acute renal failure is 81% and lowest accuracy is 74% respectively. The major drawback in this system is that the predicted results were research oriented. It is difficult to classify which patients stick with acute or chronic renal failure.

3. MATERIALS AND METHODS

In this section, a reference to the dataset and the approaches used in this work is provided. The vital parameters dataset taken from the University of Queensland has been utilized [25]. It holds huge quantity of information documented while monitoring patients in 32 cases. This is expressed in detail in Sub-section 3.1. Five types of classification models have been used in this work to design the ensemble classifier based on majority voting, in order to predict the patient's health condition from the essential vital body signs. These models are namely, logistic regression, XGBoost classifier, support vector machines, AdaBoost classifier and artificial neural networks. Each of the model are expressed in detail in Sub-section 3.2. The ensemble-based classifier built based on majority voting approach by combining these five classification models for the same prediction purpose, is discussed in Sub-section 3.3.

Table 1. Structure of the vital signs dataset.

HR	ST-II	Pulse	SpO2	Perf	etCO2	imCO2	awRR	NBP (S)	NBP (D)	Alarms
55	0	55	100	0.4	0	0	0	113	60	1
55	0	53	100	0.8	0	0	0	113	60	1
59	0	58	100	1.2	0	0	0	113	60	2
62	0	58	100	1.2	0	0	0	113	60	2

3.1 Dataset

The vital signs dataset holds huge quantity of vital signs data documented from the clinical environment while monitoring patients in 32 cases [25]. Heart rate, pulse oximeter, systolic blood pressure, respiration rate and many other vital signs, consisting of a total of 47 vital signs, are documented as data in majority of the cases. Moreover, based on the subject's physical condition, the dataset also consists of 5 patient alarms (0 being the lowest level of risk and 4 being the highest). A small chunk from the dataset is shown in Table 1. The complete dataset can be obtained in the original file [25].
The dataset is partitioned down into train set and test set in a random order. Here, percentage of training data is taken as 80% and percentage of test data is taken as 20%.

—Train set: The train set constitute about 80% of the data from the entire dataset. This implies that almost 7297 samples are gathered from 26 patients. Thus the training set is set up by 26 patients x 7297 samples.

—Test set: The test set constitute about 20% of the data from the entire dataset. This implies that almost 7297 samples are gathered from 6 patients. Thus the test set is set up by 6 patients x 7297 samples.

3.2 Training and testing

The prediction of the health status of the subject and generating the specific alarm accordingly is a multi-class classification problem which rely on the formerly known samples. The model learns the relation between the vital signs and the health status of the patient. In other words, the model checks the patterns between the input data and the output when it is trained with samples. In this way, the model can suggest its own output based on the level of training whenever a new incoming data is received. In order to resolve this multi-class classification task, five different machine learning classification techniques have been used for creating our ensemble model. These techniques include logistic regression, XGBoost classifier, support vector machine, AdaBoost classifier and artificial neural network. Interpretable ability is taken into consideration while selecting the comparison techniques [43]. The ensemble model is constructed using the majority voting approach.

3.2.1 Logistic Regression. Logistic regression (LR) is one of the commonly applied models in the medical classifications tasks [8]. Logistic regression [29] uses the logistic function which performs the classification task used for prediction of a target variable [17]. The contribution of the Sigmoid function by the statisticians in machine learning helped to evolve the logistic function which maps any real number into another number in the range of 0 and 1. The function is used to map predicted values to probabilities.
The mathematical representation of LSTM cell is as follows:

$$y = e^{(b0+b1*x)}/(1 + e^{(b0+b1*x)}) \quad (1)$$

In Equation (1), y signifies the predicted output value, $b0$ signifies the bias part. $b1$ constitute for the coefficient for the single input value x. Generally, b is a coefficient (constant real value) which is linked to each column in the input data, that is learned using the training data.
By default, multi-class classification tasks, which have more than two class labels cannot be handled smoothly by the logistic regression model. So, in case of multi-class classification the model needs to use some meta strategies. In this case, one-vs-rest strategy (Figure 1) was used. In this approach, one binary classification problem per class is formed by breaking down a multi-class situation. Thus in this case, to solve the multi class situation, we have used the one-vs-rest technique [15].

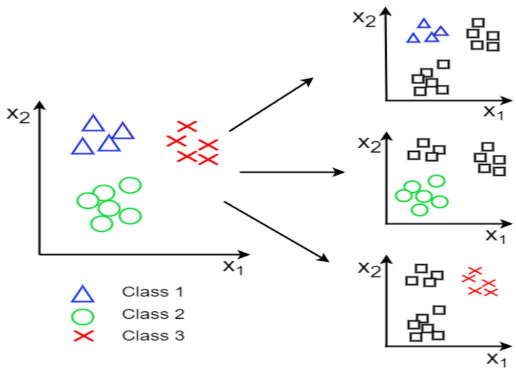

Fig. 1. One-vs-rest strategy for multi-class classification

3.2.2 XGB Classifier. XGB classifier is used for the classification tasks, which is basically an ensemble technique that uses the concept of decision trees. Gradient boosting structure is applied in XGBoost. Since XGBoost is known for its fast implementation speed and performance, therefore it is kept over other gradient boosting machines (GBMs) [6].
During the training period, the XGB classifier build trees by utilizing all the processors through parallel computation. It uses the 'max depth' parameter for the stopping criteria while modelling. This process is followed by the tree pruning method in the reverse direction. The former and the later process combine together to polish up the computational performance of the classifier remarkably over the rest GBM. Moreover, it is known for handling sparsity patterns effectively as it can grasp the absent value on its own counting on the training loss [28].
The function of XGB classifier is:

$$F_{Obj}(\theta) = L(\theta) + \Omega(\theta) \quad (2)$$

The objective function contains two component: $L(\theta)$ and $\Omega(\theta)$, where θ implies the variables in the dataset. $L(\theta)$ is called the loss function. This function calculates the divergence of the prediction $\hat{y}_i$ from the target y_i, given by:

$$L(\theta) = l(\hat{y}_i, y_i) \quad (3)$$

$\Omega(\theta)$ is the expression that castigates complex models.

$$\Omega(\theta) = \gamma T + 1/2\lambda||w||^2 \quad (4)$$

The tree contains leaves which is denoted by T, learning rate is denoted by γ. γ and T together helps to prevent the over-fitting problem. In the term $1/2\lambda||w||^2$, λ is a regularized parameter and w refers to the weight of the leaves.

The outcome of the objective function in Equation (2) is the non-success of conventional procedures to be improved. So, the final target y_i can be evaluated by:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}^{t-1} + S_t(T_i)) + \Omega(\theta) \quad (5)$$

The optimum objective is to build a tree pattern which reduces the target function in every repetition. $S_t(T_i)$ constitutes the tree created by the occurrence i at the t iteration. Although, the function in Equation (5) is the best procedure for resolving the square loss function, but this is complex for other loss functions. So, Equation (5) is converted to Equation (6) by the second order Taylor extension, that helps to calculate other loss functions as well.

$$L(\theta) = \sum_{i=1}^{n} [l(y_i, \hat{y}^{t-1}) + g_i S_t(T_i) + \frac{1}{2} h_i S_t^2(T_i)] + \Omega(\theta) \quad (6)$$

Here, $g_i = \partial_{\hat{y}^{t-1}} l(y_i, \hat{y}^{t-1})$ and $h_i = \partial^2_{\hat{y}^{t-1}} l(y_i, \hat{y}^{t-1})$. The final objective function count on the first and second derivatives of every sample point in the error function. This helps to speed up the optimization process [7].
One-vs-rest [15] (as shown in Figure 1) approach is used in this work to accomplish the multi-class classification problem. In this approach, one binary classification problem per class is formed by breaking down a multi-class classification problem. Interpretability is one of the advantage of this method other than its efficiency.

3.2.3 Support vector machines. Support vector machine (SVM) is a technique which predicts the output based on a collection of labelled dataset [49]. SVM models are mostly known for their classification tasks in the healthcare and medical domain [32].
In a SVM model, the input is supplied with the data points and it provides a hyper-plane of the type $w^T x + b = 0$ as the output. This hyper-plane is responsible for the partition between the classes and helps in separating the labels or tags. It is also referred as the decision boundary. Suppose the output consist of the class labels $y = \{-1, 1\}$, then the decision function for every sample x_i can be described as:

$$f(x_i) = sign(w^T x + b) \quad (7)$$

In the Equation (7), if the sample, x_i satisfies $w^T x + b > 0$, then it falls under the category of class 1 otherwise it belongs to the category of class 1, as shown in Figure 2.

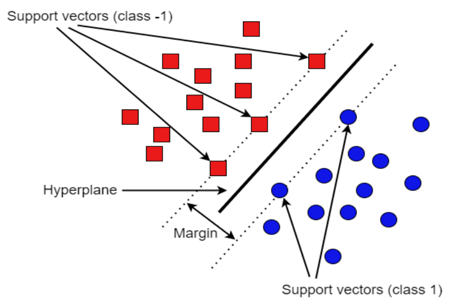

Fig. 2. A SVM with a hyper-plane

SVM is basically used for binary classification. Since a multi-class dataset is being used in this work, so to make the SVM work for multi-class problems, one strategy called one-vs-one (Figure 3) is used which works by dividing the multi-class problem into one binary problem for the individual pair of classes [31].

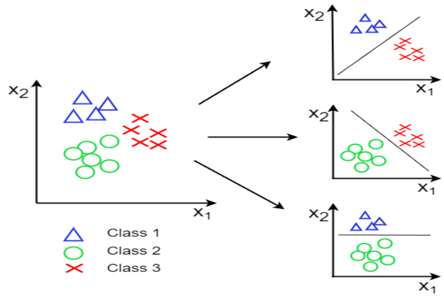

Fig. 3. One-vs-one strategy for multi-class classification

In this work, the partition among the classes is not a linear hyperplane. Thus to solve the issue nonlinear kernel functions are applied to convert the input samples into a attribute area which is of high dimension, where the data can be much more distinguishable. The hyper planes with the maximum-margin are created after the kernel functions are used. Here, the algorithm relies only on a batch of the trained samples rather than whole adjoining borders of the class. SVMs are said to belong to "kernel methods". Therefore, to handle the high-dimensional aspect of the dataset, a kernel function, namely, radial basis kernel, is used [5].

3.2.4 AdaBoost classifier. AdaBoost [14], short for adaptive boosting have been very successful in resolving classification tasks. In this method, various weak classifiers are merged to create one single strong classifier. The models reach accuracy just more than random possibility on a classification task.
Let $(x_1, c_1), ..., (x_n, c_n)$ be a collection of training data, where the prediction variable x_i, and the response variable c_i is qualitative and presumes that a finite set contains the values, for e.g. $\{1, 2, ..., K\}$. K implies the total count of classes. Generally, it is deduced that, from an untold probability distribution $Prob(X, C)$ the training data are separately allocated samples [14]. The objective is that a class label c from $\{1, ..., K\}$ can be assigned whenever any variable x is provided as the new input. The mis-classification error rate $C(x)$ is given by:

$$C^{(x) = arg\ max_k\ Prob(C=k|X=x)}(8)$$

The Equation 8 is the Bayes classifier, and Bayes error rate is the error rate of the technique. AdaBoost algorithm is a repetitive process that aims to resemble the Bayes classifier $C(x)$ by merging various below par classification approaches into a single powerful classification approach [16]. In this work, one against all approach is used to accomplish the multi class situation. It can be solved by using ensemble of classifiers that break down a multi-class issue into a number of binary classification issues and solved it one by one.

3.2.5 Artificial neural network. Artificial neural network (ANN) [4] are the models that are roughly inspired by the biological neural networks that set up the human or animal brains. Animal brain is extremely complex which is not linearly organised. It has the capability to arrange the structural element which are known as neurons. These neurons help to carry out the calculations which are required for existence such as the motor control. These operations performed by the human brain are faster than the high-speed computers available today. Similarly, an ANN is a machine that attempts to mimic the tasks and operations performed by the human brain [9]. In Figure 4, there are neurons which are attached to set of weights and they together create a network. A neuron, known as the processing node, computes the weighted average of its input and add a bias, and the sum is moved across an activation function which is a nonlinear function. One such function is the sigmoid function [20].

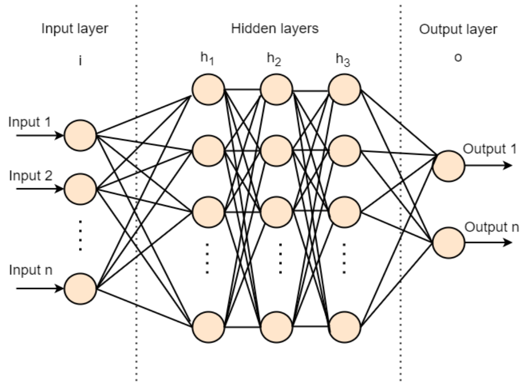

Fig. 4. Basic architecture of Artificial Neural Network

Numerically, an ANN can be described by the Equation (9):

$$y = (w1x1 + w2x2 + w3x3 + 1b) \tag{9}$$

where $w1$, $w2$ and $w3$ are the weights applied on the inputs $x1$, $x2$ and $x3$ respectively. b is the bias which helps the model in a way that it can fit best for the given data.
In this work, the architecture of the artificial neural network contain input layer which consists of 47 vital signs data known as the features. The health status of the patient is represented by 5 classes which acts as the output. To obtain best results, more than one hidden layer is used, in this technique.

3.3 Ensemble learning

An ensemble-based approach is used to construct one best predictive model by incorporating various similar or conceptually different models [13]. In this procedure numerous models, for instance are utilized in a well-planned manner and put together to compute a specific computational intelligent task [36]. Ensemble learning is majorly used for upgrading the performance of a model. This performance is basically measured in the domain of classification, prediction and the function approximation.
In order to achieve the ensemble learning approach, the meta-classifier known as the ensemble classifier has been used for blending various conceptually dissimilar classifiers used in machine learning for the classification tasks through the process of majority voting. As shown in Figure 5, the frequently predicted class label is set as the final class label by the model [39]. In this approach, the data is first split into training and testing sets. Then the five machine learning classification techniques are trained such as logistic regression, XGBoost classifier, support vector machine, AdaBoost classifier and artificial neural network to make predictions on the test set. Then predictions from the test set are used as features for a meta model. Then final predictions on the test set are made using the meta model through the process of majority voting.
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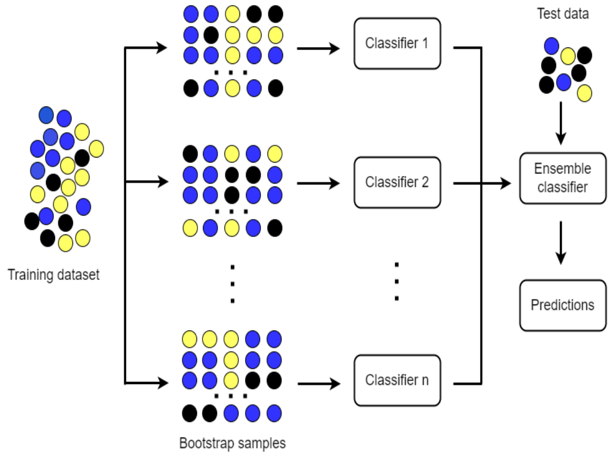

Fig. 5. Ensemble vote classifier

Table 2. Outline of a confusion matrix for binary classification.

	Target: True	Target: False
Actual: True	TP	FN
Actual: False	FP	TN

The class label computed is the output forecast by the model. For a specific occurrence x, the class label $\hat{y}$ is evaluated by the Equation (10):

$$\hat{y} = mode\{C_1(x), C_2(x), ..., C_m(x)\} \tag{10}$$

where $C_1(x)$, $C_2(x)$, ..., $C_m(x)$ are the outputs as predicted by the classifiers C_1, C_2, ..., C_m, sequentially. Through the process of majority voting, the ensemble model would compute the class label that obtain the maximum total vote.

3.4 Evaluation criteria

The classification of the machine learning models is evaluated with the help of confusion matrix. The matrix is computes the efficiency of a machine learning approach. It is divided into four parts that provides various mixtures of predicted and actual values. The table 2 gives the outline of the confusion matrix for a binary classification.
The four parts of the confusion matrix are represented as follows [35]:

—True negatives (TN) denotes that both the predicted and true target output are negative.
—True positives (TP) denotes that both the predicted and true target output are positive.
—False negatives (FN) denotes that true target output is positive but the approach predicted a negative value.
—False positives (FP) denotes that true target output is negative but the approach predicted a positive value.

Accuracy is the fundamental standard for measuring the performance of a classification approach. Accuracy is measure by Equation (11):

$$Accuracy = \frac{TN + TP}{TN + FN + TP + FP} \tag{11}$$

Table 3. Performance results of the classifiers.

	LR	XGB	SVM	Adaboost	ANN	Ensemble learning
Accuracy	0.884	0.929	0.922	0.829	0.955	0.961
Precision	0.866	0.926	0.918	0.810	0.953	0.962
Recall	0.884	0.929	0.922	0.829	0.955	0.961

Equations (12) to (13) are for calculating precision and recall:

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

4. RESULTS AND DISCUSSION

In this work, an effort have been made to predict the health status of a person using an ensemble classifier made up of five types of classification models, viz., logistic regression, XGB classifier, support vector machine, AdaBoost and artificial neural network. Also the ensemble model based on majority voting approach was compared with the individual classifiers for the same classification purpose. Furthermore, a prototype framework was developed to deploy the machine learning approach for monitoring the health status in the backend of the health monitoring system.

4.1 Experimental results

The machine learning models were build using a neural network API known as Keras. The computer language used in the proposed machine learning models is Python. It is run on Tensorflow, an open-source machine learning platform. Here, the Tensorflow library is used in these models. A PC of i5-7200U CPU with 2.50GHz, 8 GB RAM, and an NVIDIA GeForce 920MX with 2GB memory is used in the training of these models and the monitoring of the patient health. The operating system used is Windows with 64 bits.
The training set have been subjected to 5-fold cross validation with an objective to attain the optimum performance for each approach. The performance of each model which is its ability to correctly classify the health status have been interpreted using accuracy, precision and recall which is given in Table 3.

4.2 Performance analysis

The performance of ensemble classifier in comparison to the other machine learning approaches is very effective in classifying the health status of the individuals as seen in Table 3. This is due to the fact that ensemble classifiers combines the predictions of the multiple classifiers in contrast to the individual classifiers. It chooses the best performance for modelling the predictive learning of the health status from the physiological data of an individual.
The accurate predictions of the ensemble learning approach are very significant, especially in predicting the health risk status in the dynamic clinical environments. Timely alertness to the concerned authority about the health status of an individual can lead to prompt action on the prevalent condition.
The confusion matrices for each approach is shown in Figure 6 and 7. As seen from Figure 6 and 7, ensemble learning is very efficient in correctly predicting the true values corresponding to the health status of a patient as compared to the other machine learning approaches. That is, ensemble learning reduces the number of prediction errors which may be made by the individual classifiers.

The reason for the reduced number of mis-classifications in the ensemble classifier is that it grants trade-off between the learning processes of the various individual learners in the ensemble, which may not be possible from a single approach. Also the distinct learning methodologies of the individual learners ensures that the ensemble classifier does not overfit.

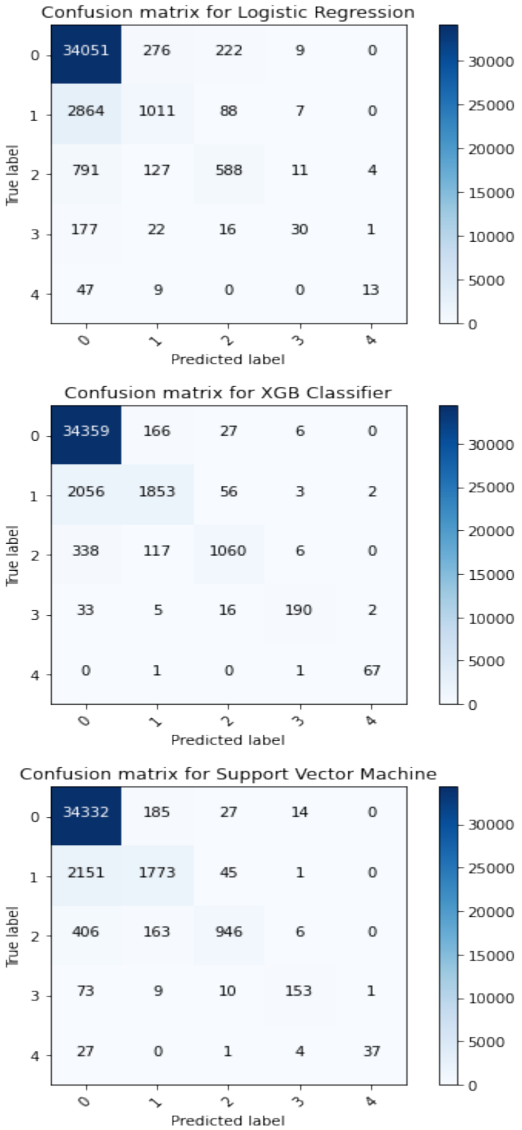

Fig. 6. Confusion matrices for Logistic regression, XGB classifier, Support vector machine

5. CONCLUSION

The aim of any machine learning problem is to obtain the best performance model for predicting the results. In this paper, it has been tried to anticipate the well-being by analysing the patient's vital sign and monitor their health status. Here, an ensemble-based approach is used to construct one best predictive model by incorporating various similar or conceptually different models and average

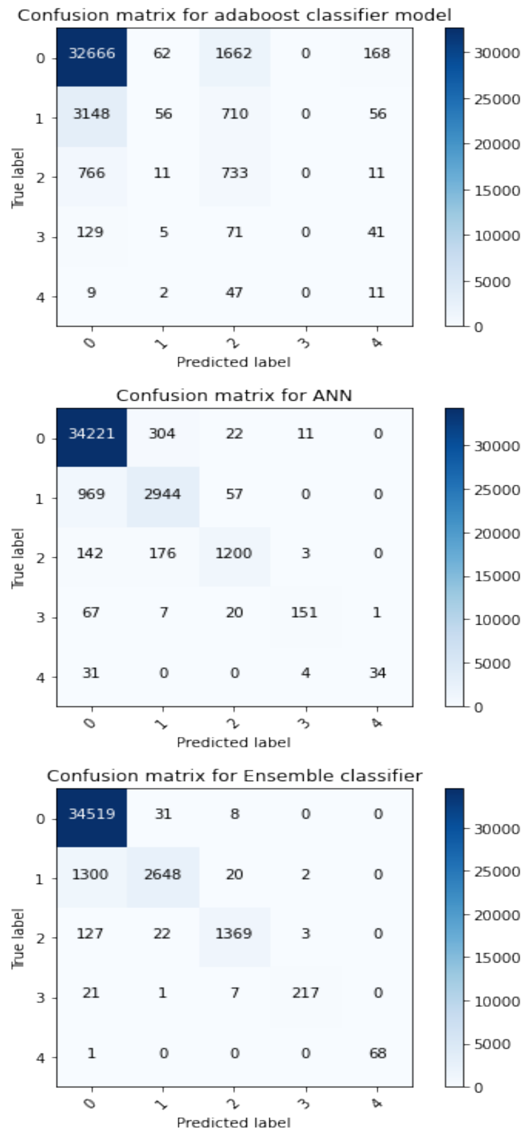

Fig. 7. Confusion matrices for AdaBoost, Artificial neural network and Ensemble classifier

those models to construct one final model rather than building one model and thinking this to be the best estimator. For this purpose, several types of classification approaches have been combined to form an ensemble classifier. In this work, an attempt has been made to predict the health status of an individual based on his vital signs data. The approaches which are based on machine learning techniques include logistic regression, XGB classifier, support vector machine, AdaBoost and artificial neural network.

This work is used to help users improve health risks and reduce healthcare costs by collecting, recording, analyzing and sharing large data streams in real-time medical information on the cloud. Thus making it possible to store and analyze large amounts of data in several new forms and activate context-based alarms. But the scope of this work was limited to ECG, pulse rate, blood pressure, temperature, heart beat and SpO2 detection, some other parameters and remote views of the data collected for a individual patient. Here, the most important specifications are supposedly to be safe to use and to be precisely accurate. This is because the physical information found by our system determines the severity of an important life-threatening condition.

The classifiers used for comparison performed well in terms of the accuracy, precision and recall which is evident from the experimental results. But, the ensemble classifier showed even better results as compared to the individual classifiers. Thus the performance by the ensemble method proved to be the best among all the estimators. When compared with the other classifiers, the ensemble classifier has an edge over them due to its nature of learning from the experts and approve of their vote. This makes it better eligible to be used for the health status monitoring problem used in this work.

The future work would be to deploy this approach of ensemble learning for real-time data from the environment of the patient where the data sent would be directly analysed by the model. In this way, the vital signs of the patient can be monitored from a website, and context-based alarms can be activated to alert about the person's health.

6. REFERENCES

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