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Improved Random Forest And Cuckoo Search Optimization Based Hybrid Approach For Healthcare Monitoring Systems

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Abstract

Wearable sensors are one of the recent advances in the field of Remote Patient Monitoring (RPM), which are capable of recognizing the activities of patients, including their movements. However, the continuous monitoring of patients using wearable sensors tends to create a vast amount of medical data. Existing approaches based on monitoring the healthcare system are insufficient for extracting the required information from patients and lack accuracy. To overcome these issues related to patient healthcare monitoring, this study proposes an improved healthcare monitoring system using an Improved Random Forest (IRF). The IRF approach selects better parameters from every architectural model and provides a better pre-trained model to monitor the patient's health conditions. The hyperparameters of the selected features were fine-tuned using the Improved Cuckoo Search (ICS) algorithm. The experimental outcomes indicate that the proposed method achieved a better accuracy of 99.45%, which is comparatively higher than the existing Federated Learning-based Person Movement Identification (FL-PMI) and FedStack with 97.78% and 98.11%, respectively.

Keywords: *Health care monitoring, hyperparameters, improve random forest, medical data, wearable sensors.*

1. Introduction

In this modern age of technology, medical systems based on the internet play an important role in analyzing the data of patients. There is a rise in numerous technologies getting included in the health care system through the efforts of scientists and researchers throughout the world [1]. Even the medical records are transformed into electronic health records, which comprise data related to disease diagnosis, procedures involved in treatment, and the general details of the patients [2]. The machine and deep learning algorithms act as significant techniques for extracting the hidden parameters. The data utilized to train those algorithms is stored in a centralized location [3, 4]. A large number of data sets related to healthcare applications are being created at the global level with unique properties, and these collected data sets are multi-dimensional in nature [5]. Transferring the patient to hospitals from their home for their regular checkup is a difficult task due to various issues related to travel time and queuing, and there is a probability for the patients to get affected by new diseases due to environmental pollution [6]. Mor[1]eover, remote patient monitoring systems have been developing rapidly and help

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monitor vulnerable patients through remote monitoring. Through a remote patient monitoring system, the clinician performs real-time monitoring, which monitors every movement of the patient. This helps to obtain information about the patient and minimize the time and cost of disease diagnosis [7].

The data related to healthcare is fragmented due to the complexities involved in the processes of healthcare systems [8]. For instance, hospitals and clinics only store the data of their own patients. But, rigorous regulations like insurance portability and accountability of the medical data create a major issue related to mining the data and machine learning techniques that need a greater number of data points to train the model. These issues can be overwhelmed using Improved Random Forest (IRF) due to its capability to hold the fragmented, sensitive data about the patients [9, 10]. The ultimate goal of the random forest model is to provide health care services and enhance the quality of the patient's life using the RF model. The need for hospital-centered care is transformed into home-centered care, which enhances the need for technological advancements in learning models [11, 12]. Moreover, RF offers more advantages than the centralized learning approach. RF is capable of training the global level model by using the distributed informational data, and it is more responsible than other algorithms in maintaining the privacy of the medical data by providing only the mathematical parameters and the metadata [13, 14]. The RF model utilize collaborative technique that obtains the person's information in a secured manner and provides it directly to the clinician or doctor to process the physical condition of their patients [15]. Thus, this research utilized Improved RF as a tool to solve the issues related to telehealth monitoring and help both the doctor and patients.

The main contributions of this research are listed below:

1. An improved health care monitoring system using improved random forest architecture is introduced to monitor the health and activities of the patients.
2. The wearable sensors are used to collect information about the patient's conditions, and the min-max normalization technique is employed to pre-process the data. Moreover, an improved cuckoo search algorithm is used to fine-tune the hyperparameters of the features from the IRF approach.

The rest of this manuscript is organized in the following manner: Section 2 defines the related works based on the health care monitoring system, and Section 3 of the paper provides the proposed method. The results and analysis of this research are described in Section 4 in a detailed manner, and finally, Section 5 discusses the overall conclusion of this research.

2. Related works

Farman Ali et al. [16] have introduced a health care monitoring framework on the basis of cloud environments and big data to store and analyze the medical data of patients with enhanced classification accuracy. The big data analysis introduced was based on mining the data. The data mining techniques pre-process the health care data to diminish the data's dimensionalities. Finally, the introduced framework utilized Bi-LSTM to categorize the health care data to calculate the effects on drug usage and abnormalities in patients. The introduced framework precisely monitors the health condition of the patients and provides a report that is used by the doctor for direct analysis. However, the introduced framework does not suit multimodal data.

Lakshmi Sudha Kondaka et al. [17] have introduced an iCloud Assisted Intensive Deep Learning (iCAIDL) algorithm to provide support to the health care medium of the patients. The patient's data is obtained from the existing health records and provided for training the models with deep learning norms. The collected data is stored in the cloud repository by enabling IoT with iCAIDL. The stored data is collected using the smart medical gadget, and the data in this gadget is accessible for both the patient and the doctor. The iCAIDL helps to maintain the health record in an intensive way, without flaws. However, iCAIDL utilised a single cloud server, which is insufficient to store bulk data.

K.S. Arikumar et al. [18] have developed a Federated Learning-Based Person Movement Identification (FL-PMI) to auto-label data obtained from the wearable sensors. Initially, unlabeled data obtained from wearable sensors was labelled using the framework of the deep reinforcement learning method in FL-PMI. The FL-PMI method stores the parameters of trained data in the cloud using FL-based edge servers. Finally, Bidirectional long-short-term memory is utilized in classifying medical data for the proceeding process. The FL-based edge servers required less memory and cost less for computation. But the FL-PMI is not vulnerable to issues related to privacy.

Thanveer Shaik et al. [19] have introduced a federated learning architecture referred to as Fed Stack, which helps in monitoring the hospitalised patient using a decentralised approach to detect sensor placement. The Fed Stack model utilised three models, like an artificial neural network, a convolutional neural network, and a bi-directional LSTM, to train the data. The Fed Stack model has the capability to analyse the data obtained from the sensors positioned on the bodies of humans, which was able to categorise full motion, partial motion, and activities. However, the variation occurs in the number of labels for each patient due to the use of the same label data.

D. Kavitha and S. Ravi Kumar [20] have introduced a framework to store and process the healthcare data obtained from the sensors. The framework, consisting of context-aware modules, was comprised of two layers known as fog and cloud. Finally, the feature extraction and classification were performed utilising a back propagation neural network along with the Adaptive grasshopper optimization technique. Based on the nature of the classification result, an alarm was sent to the clinician to notify the state of the patients, which effectively minimize the time for detecting the disease. However, the addition of a filter at the pre-processing stage will probably enhance the classification results.

3. Improved Random Forest based tele-health monitoring

This IRF-based tele-health monitoring plays a significant role in detecting the health status of the patients from their homes without their physical experience. An IRF-based smart healthcare monitoring system collects data from the edge devices and wearables of patients. The pre-processing is initiated to remove unwanted and repeated data from patients. After pre-processing, data is fed into the IRF model, and a single output of the pre-trained model is obtained. After this stage, the hyperparameters are fine-tuned, and finally, the performance of the model is estimated. The block diagram of overall process involved in monitoring the patient is described in figure 1 as follows:

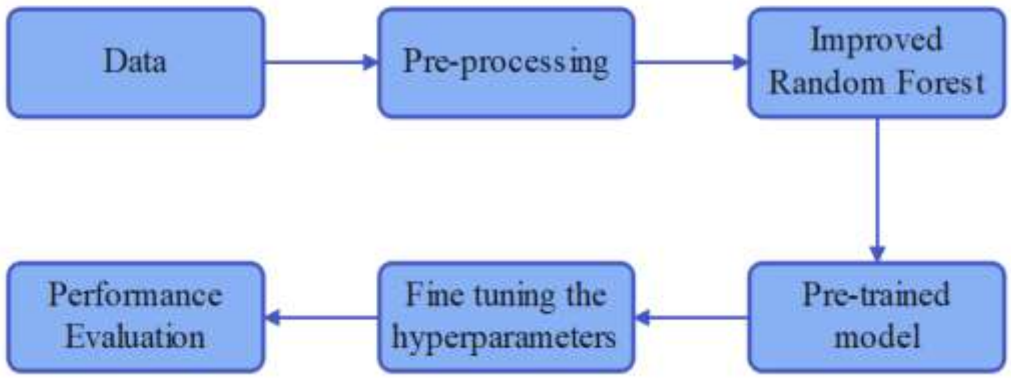

Figure 1 Overall process involved in IRF based healthcare monitoring system

3.1 Dataset

The IRF data in this work is gathered from the patients to analyze and detect their activities. The MobiAct dataset [16] is one of the publicly available datasets that is comprised of random data obtained from patients whose age group lies between 20 and 47. These data are gathered from their mobile phones and the wearable devices that are connected to their smart phones. These devices collect important information like heart rate, Blood pressure, body temperature, and oxygen level in the blood. The sensory data from the mobile phones and the wearable devices is collected and stored in a cloud-based environment for the future use of both the patients and the clinicians or doctors.

3.2 Data Preprocessing

After the stage of data acquisition, the data obtained from smart mobiles and wearables is pre-processed to remove irrelevant information that affects the overall performance of the IRF model. This research utilized the data normalization technique, which is one of the most effective pre-processing techniques in which the data is scaled or transformed to make an equal contribution for every individual feature of the data. Here, the min-max normalization technique (i.e., a type of data normalization technique) is used in this research, and this technique is based on the minimum and maximum values of the un-normalized data utilized in rescaling. The Min-Max normalization technique pre-defines the lower and upper limits in a linear manner, and this data is rescaled within the range of 0 to 1 or -1 to 1. The min-max normalization is performed based on equation (1) as follows:

$$x'_{i,n} = \frac{x_{i,n} - \min(x_i)}{\max(x_i) - \min(x_i)}(nmax - nmin) + nmin \quad (1)$$

Where the maximal and the minimal value of the feature are denoted as, respectively. Similarly, the lower and upper limits of the data are denoted, respectively. The min-max normalization technique effectively preprocesses the sensory data obtained from the smart mobiles and the wearables associated with them. In the next phase, the pre-processed data is fed into the proposed IRF model, which is to be discussed in the upcoming section.

3.3 Improved Random Forest:

The classical random forest method utilizes decision trees as the base learner, like CART, and applies some rules in voting to summarize the whole base learner's results, Because of this, Random forests have better stability. If a smaller amount of data is missing, the Random Forest affects the decision-making processes and certain decision-tree outcomes, and the method results acquired remain accurate. Random Forest has powerful robustness to a smaller number of missing data points produced by machines in bad or failed processing conditions. If there is a larger number of data points missing, they are filled by the mean or default values. Although this process method will change the data distribution, bias in the system is introduced, which minimizes the accuracy of the Random Forest classification algorithm. The method used the information of the decision path to maximize the Random Forest accuracy on the dataset, which contains missing data.

In accordance with the information given above about the decision path, in the sample, when there is a lack of certain features in the decision path corresponding to the sample in the DT, the decision tree predicts outcomes of classification that are unreliable because of missing feature nodes in the decision path, which minimizes reliability of the results of prediction. For defining the influence of adverse events, the reliability score (RS) for the results of prediction of every decision tree for a particular sample is described. In the local importance concept, if the node contains data that is missing, the local importance is high, and the adverse effect on the result is higher. When randomly available missing data is available, the decision path consists of multi-split nodes that contain similar or various data that is missing, and the bias of classification gets bigger when the number of problem nodes increases. In the decision path, the addition of the local importance of whole problem nodes may illustrate the degree of data loss, which is unfriendly to the result of classification. Consider that the distance of various samples in the decision path in the various decision trees is not similar. As a comparison of the reliable weak effect on accuracy of classification, the ratio of the addition of local importance of relatable nodes to whole nodes in the decision path can be measured in the case of missing data. The mathematical representation of the RS of DT can be represented with respect to the sample as given below:

$$\mathrm{RS_t(x,y)} = 1 - \frac{\sum_{\mathrm{k'}} \in \mathrm{DP_{miss}(t,x)LI^t_{k'}(y)}}{\sum_{\mathrm{k}} \in \mathrm{DP(t,x)LI^t_k(y)}} \tag{2}$$

Where,

$\mathrm{DP(t,x)}$ represents collection of whole nodes of decision path in DT t,

$\mathrm{DP_{miss}(t,x)}$ represents the collection whole nodes corresponds to nodes of missing.

In Random Forest, decision path distance of similar sample x is not similar in various decision tress. As calculate the reliability score of decision tress with various decision path distances, every reliability score in the random forest are normalizes and the mathematical representation is given below:

$$\mathrm{RS_t^{norm}(x,y)} = \frac{\mathrm{RS_t(x,y) - RS_{min}(x,y)}}{\mathrm{RS_{max}(x,y) - RS_{min}(x,y)}} \tag{3}$$

Where, $\mathrm{RS_{max}(x,y)}$ and $\mathrm{RS_{min}(x,y)}$ represents the maximum and minimum reliability score values for whole DT in RF and mathematical representation of $\mathrm{RS_{max}(x,y)}$ and $\mathrm{RS_{min}(x,y)}$ is given below:

$$\mathrm{RS_{min}(x,y)} = \min_{\mathrm{t'} \in \{1, \dots \mathrm{T}\}} \mathrm{RS_{t'}(x,y)} \tag{4}$$

$$RS_{max}(x,y) = \max_{t' \in \{1,\dots T\}} RS_{t'}(x,y) \quad (5)$$

In the cases of missing data, the research remains the actual results of the prediction of every classifier; however, certain data in test samples have gone missing, and the balance of the data are still valid and provide significant information. This research utilizes RS to revise the results of prediction in accordance with missing data in the decision path. The particular process of amendment can be described in accordance with two various rules of voting.

On applying the hard voting, input is the test sample, and every DT can acquire the prediction value of the label, which corresponds to the RS described as For various classifiers with similar labels of prediction, the addition of its RS is utilized to acquire the whole reliability prediction in the category. The label with a high RS in every category is taken as the result of the final prediction.

$$H_{DPRF,hard}(x) = \underset{y \in Y}{\operatorname{argmax}} \left\{ \sum_{t=1}^{T} v_t(x,y) \cdot RS_t^{norm}(x,y) \right\} \quad (6)$$

On applying the soft voting, the input is the test sample, and every DT results in the probability of prediction for every category and the RS of the classifier under the missing condition. The probability of prediction of every class is multiplied by RS to acquire the revised probability of prediction of every category, and the revised probability of prediction of every sub-classifier in the random forest is updated to acquire the whole prediction probability of every category. The probability of the highest prediction category is taken as the result of the final classification of the sample.

$$H_{DPRF,soft}(x) = \underset{y \in Y}{\operatorname{argmax}} \left\{ \frac{1}{T} \sum_{t=1}^{T} P_t(x,y) \cdot RS_t^{norm}(x,y) \right\} \quad (7)$$

The rules of soft voting summarize that the probability of whole categories in every DT before voting is high. At first, the rule of hard voting first votes in every DT and then gathers outputs. The rule of the former can better remain the probability of data of every DT to the final result, then the next one first votes in DT, losing data of probability too early. So, the accuracy of the method is theoretically higher under the rule of soft voting.

3.4 Fine tuning the hyper parameters

The features obtained from the IRF-based approach are fine-tuned using the improved cuckoo search optimization algorithm [21]. Hyper-parameters like batch size and the number of units are considered in health care monitoring, and these parameters result in enhanced time consumption and inappropriate values. Moreover, the obtained results are inconsistent, so it is hard to find the optimal parameters. So, this research utilized Improved Cuckoo Search (ICS) optimization to evaluate the parameters of bath size and number of units to enhance the prediction result of monitoring the physical condition of the patients. The fitness of the ICS is evaluated using the equation (8) as follows:

$$F = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (\bar{y} - y_i)^2} \quad (8)$$

Where the number of trained samples is denoted as n, the predicted and the true value is denoted as $\hat{y}_i$ and y_i. The process involved in the ICS algorithm is described in following steps,

Step 1: The hyper-parameters obtained from the IRF approach are obtained and initialized using the ICS algorithm.

Step 2: The initial population in the ICS algorithm is created using Logistic mapping, and the suitable values are initialized for the nest of every individual bird.

Step 3: A communication-based strategy is executed to choose an optimal site of nest which is denoted as X_{best}. The communication strategy accomplished by the bird in searching the nest of bird is represented in equation (9) as follows:

$$X_i^t = rX_i^t + (1-r)X_{best}^t, i = 1,2,\dots,m \tag{9}$$

Where the position of bird's nest after the communication is denoted as X_i^t and the stochastic value which lies in the distributed interval [0,1] is denoted as r.

Step 4: The optimal position of the bird's nest is preserved and the step-size control factor α is evaluated using the equation (10) as follows:

$$\alpha(t+1) = \alpha(t) \times T \times \exp\left(-\frac{t}{T}\right) \times \left(\frac{\alpha_0}{\ln t} + (1-\alpha_0)r\right) \tag{10}$$

Where the step factor at the initial stage is denoted as α_0 and the number of iterations is denoted as t. The maximal count of iteration is represented as T and stochastic value is denoted as r which lies among the interval [0,1].

Step 5: The probability value p_a is updated using the equation (11) which creates a uniform decentralized stochastic value $rand \in [0,1]$.

$$p_a = \begin{cases} p_{amax} - \sin\left(\frac{\pi}{2} \times \frac{t-1}{T-1}\right)(p_{amax} - p_{amin}) \exp\left(-\varepsilon\left(\frac{t+1}{T}\right)^{\theta}\right), t < \frac{T}{2} \\ p_{amax} - \cos\left(\frac{\pi}{2} \times \frac{t-1}{T-1}\right)(p_{amax} - p_{amin}) \exp\left(-\varepsilon\left(\frac{t+1}{T}\right)^{\theta}\right), t \geq \frac{T}{2} \end{cases}$$

(11)

Where the maximal discovering probability and the minimal discovering probability is denoted as p_{amax} and p_{amin} respectively.

After this stage, the probability value p_a is discovered. When $rand > p_a$, vary the value X_i^{t+1} based on the equation (12) as follows:

$$X_i^{t+1} = \omega X_i^t + r(X_j^t - X_k^t) \tag{12}$$

Where X_j^t and X_k^t are the iterations of stochastic solutions. If the value of $rand$ is less than p_a, then no change takes place.

Step 6: Evaluate the updated nest value of the bird and preserve the location of the bird with better fitness values.

Step 7: Then, determine if the arithmetic value coincides with the termination condition. When the values coincide, then proceed to the next step, or else return to step 3.

Step 8: After the completion of iterations, the optimal position of the bird's nest is adapted with an appropriate value as the output of monitoring the patient's activities.

Thus, by employing the ICS algorithm, the prediction of patient activity takes place, and this proposed monitoring system aids in better recognition of patient health care monitoring, including his or her body movements. Moreover, the proposed IRF-based health care monitoring helps the clinician obtain precise medical data and provide treatment to patients.

4. Results and analysis

This section evaluates the results obtained from the proposed health care monitoring system based on their performance. Moreover, the proposed health care monitoring system is evaluated based on the collected data from the MobiAct dataset. The proposed health care monitoring system based on the IRF approach is implemented on Python software in system specifications with an i7 processor at 2.4 GHz, 8 GB of random-access memory (RAM), and the Windows 10 operating system. The results of the proposed IRF-based health care monitoring system are evaluated based on the values of accuracy, precision, recall, and F-1 score.

4.1 Performance analysis

In this section, the performance of the proposed Improved Random Forest architecture is compared with the existing architectures utilized in the process of monitoring the patient's healthcare. The evaluation takes place for two conditions by analyzing the activities of patients with high blood pressure and diabetes. This research focused on detecting the activities of blood pressure patients based on nine features, and diabetes patients were evaluated based on the six features obtained through the proposed improved random forest approach. The performance of the proposed approach is evaluated with existing methods like Artificial Neural Networks (ANN), Recurrent Neural networks (RNN), and AlexNet. The table 1 presented below shows the result of the proposed method with existing architectures for predicting the activities of blood pressure patient.

Table 1 Evaluation of proposed Improved Random Forest architecture for predicting the activities of blood pressure patient.

Proposed architectures and other architectures	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
ANN	71.24	79.37	84.76	82.43
RNN	79.63	80.67	81.62	88.65
AlexNet	83.78	88.93	80.43	87.43
IRF	91.33	90.45	94.65	92.18

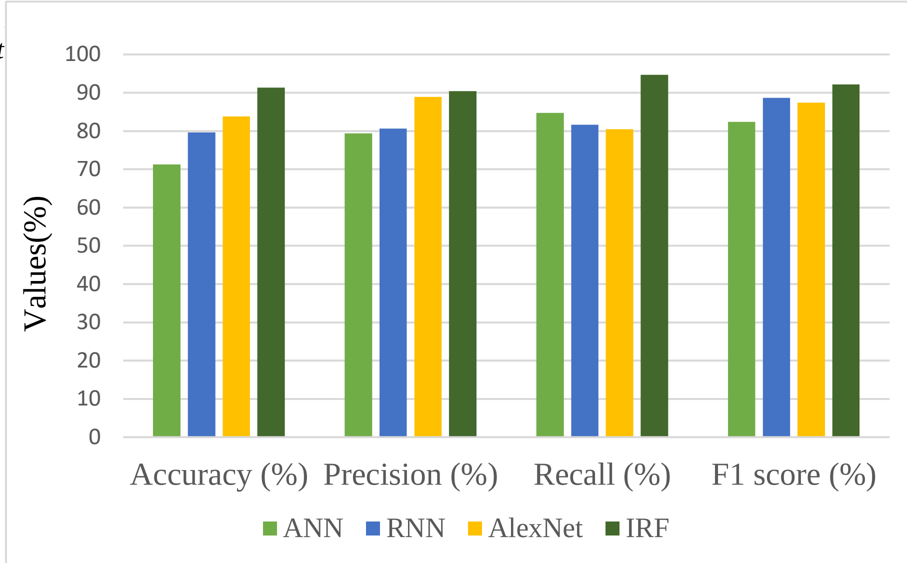

Figure 2 Performance evaluation based on monitoring the activities of blood pressure patients

The results from Table 1 show that the Improved Random Forest architectures have attained better prediction results from monitoring the activities of blood pressure patients. The obtained results show that the proposed IRF architecture has achieved a better prediction accuracy of 91.33%, which is comparatively higher than the existing architectures such as ANN (71.24%), RNN (79.63%), and AlexNet (83.78%), respectively. The graphical representation for the evaluation of predicting the values based on monitoring the blood pressure patient is shown in Figure 2 as follows:

Secondly, the performance of the proposed architecture is estimated based on monitoring the activities of diabetic patients using wearable sensors. The table 2 presented below shows the results of proposed IRF architectures compared to existing architectures. Moreover, the evaluation of results takes place by considering parameters such as accuracy, precision, recall, and F1 score.

Table 2 Evaluation of proposed Improved Random Forest architecture for predicting the activities of diabetic patient

Proposed architectures and other architectures	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
ANN	82.85	75.65	77.12	71.96
RNN	88.59	78.54	76.21	77.26
AlexNet	85.14	82.77	79.99	76.03
IRF	89.48	88.71	85.39	84.32

The results from Table 2 show that the proposed IRF architectures have achieved better results in predicting the activities of diabetic patients. For instance, consider accuracy as a parameter to compare the efficiency of the proposed model. The accuracy of the proposed IRF is 89.48%, which is relatively higher than the ANN, RNN, and AlexNet with 82.85%, 88.59%, and 85.14%, respectively. These results show the efficiency of the proposed model. Figure 3 shows the graphical representation for the evaluation of predicting the values based on monitoring the activities of diabetic patients.

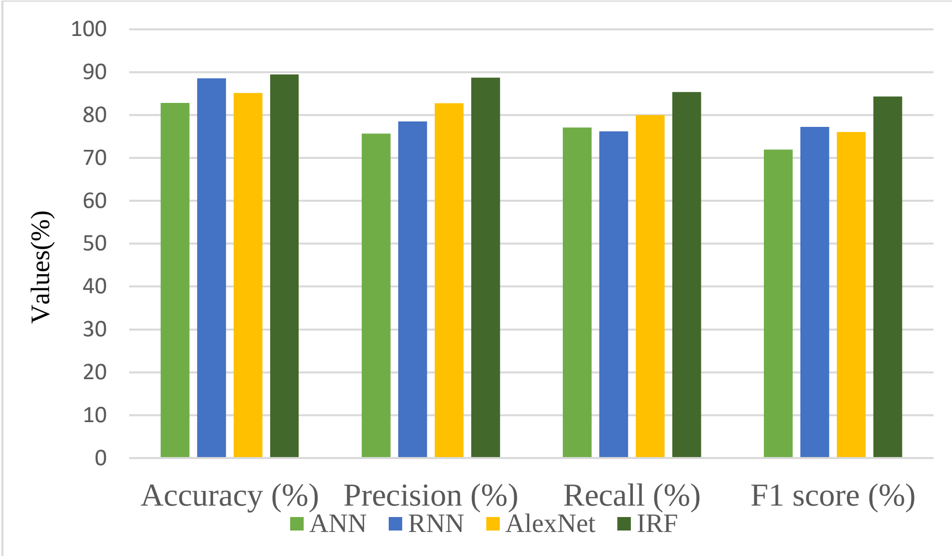

Figure 3 Performance evaluation based on monitoring the activities of diabetic patients

The overall results from figures 2 and 3 show that the proposed Improved Random Forest model achieved better prediction results for monitoring the activities of blood pressure patients and diabetic patients, respectively. The better result of the proposed method is due to its efficiency in providing multiple collaborators to train the model with their own data. Moreover, it considers the better outcomes of the model in various parameters, combines the better results of every individual model, and offers a better result while monitoring the activities of the patients.

4.2 Comparative analysis

This section provides the comparative results of the proposed IRF architectures with the existing methods discussed in related works. The comparison is performed with existing models that utilised a federated learning approach for monitoring healthcare and the activities of patients. The results are evaluated with existing methods such as FL-PMI [18] and FedStack [19]. The results are evaluated by means of accuracy, precision, recall, and the F1 score. Table 3 represents the comparison of the existing methods with the proposed method.

Table 3 Comparing the results of proposed method with the existing methods

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 score (%)**
FL-PMI [18]	97.78	91.72	92.89	90.99
FedStack [19]	98.11	95.24	91.72	94.28
IRF	99.45	97.86	95.32	98.21

The experimental results show that the proposed IRF architecture performs better in all performance metrics than the existing methods. The proposed IRF method achieved an accuracy of 99.45%, whereas FL-PMI and FedStack achieved around 97.78% and 98.11%, respectively. These results prove the efficiency of the proposed model, and this better result is due to the use of Improved Random Forest to train the model with their own data. Moreover, it considers the better outcomes of the model in various parameters, combines the better results of every individual model, and offers a better result while monitoring the activities of the patients.

5. Conclusion

This research proposed the IRF architecture, which is a federated learning-based health care monitoring system that detects the activities of patients by means of wearable sensors. The data is obtained by means of the MobiAct dataset, which is comprised of data obtained from mobile phones and wearable devices. The body temperature, oxygen level, and heart rate are measured by the sensors present in the wearable devices, and then min-max normalization is performed to remove the unwanted data. The proposed IRF architecture selects the best features and provides results to predict the activities of the patients. The experimental results show that the proposed IRF achieved better results in accuracy with 99.45%, which is comparatively higher than the existing FL-PMI with 97.78% and 99.45%, respectively. In the future, the improved random forest approach can be implemented with machine learning models to obtain better results.

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