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Healthcare Monitoring using Machine Learning Based Data Analytics

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Abstract

In this paper, we develop a machine learning based healthcare monitoring and analytics from various Internet of Medical Things (IoMT) devices for possible prediction of cardiovascular risk in patients. The study uses random forest for feature selection and then the fuzzy logic classifier is used for prediction of Cardio Vascular Disease (CVD). The simulation is conducted to test the efficacy of the proposed machine learning based data analytics model over various other methods. The results show than the proposed method has higher rate of classification accuracy in classifying the CVD with higher recall and F1-score than other methods.

Keywords: machine learning, healthcare monitoring, IoMT devices, fuzzy logic.

1 Introduction

The technology that supports the Internet of Things (IoT) is continually undergoing progress. Connecting computers, mechanical and digital devices, objects, animals, and humans with sensors and actuators is essential to achieving the aims of the IoT, such as data collection and enhancing health, productivity, and efficiency [1]. The employment of the IoT based remote patient monitoring is one of the most promising new technical solutions developing to narrow the global health equity gap. Inequitable access to medical treatment is to blame for this disparity. These interoperable medical devices are also known as the Internet of Medical Things (IoMT). The

IoMT has the potential to make an impact in a wide variety of fields, not just healthcare and security. By linking our bodies to the web, we can gain insight into our routines, physical and mental states, and the contexts in which we operate. Thanks to this, doctors can keep a constant eye on patients from afar [2]. Using the collected information to assist detect, diagnose, and treat medical problems early on would be a terrific approach to use the data potential. This is a great approach to put the information to good use.

The human body, on the other hand, is not easily capable of being connected to the internet in the same way that digital or mechanical technology is. Making a digital device that can connect to the Internet without much hassle requires integrating a sensing and networking system. The problem is that even if we were able to properly implant a sensor system in a human being, we still wouldn't be able to link it to the internet. Taking measurements typically necessitates the employment of sizable sensing or measuring equipment.

Large measurement equipment, on the other hand, has a restriction in that it can only be exploited in carefully supervised conditions for a finite length of time at a time. Because of this, it is not possible to connect a human body to the Internet with the extensive range of sensing and measuring equipment that is currently available [3]. This severely limits the IoT utility in critical infrastructure protection and medical care.

As the global population ages, chronic diseases like cardiovascular disease (CVD) become a greater burden on healthcare systems. As a result, there is a growing interest in the development of Remote patient monitoring (RPM) systems, which are intended to support medical professionals in the treatment of chronic diseases through the analysis of enormous amounts of data obtained from wearable sensors and health record data [4,5]. This not only ensures regular operation even if the network connection is weak or nonexistent, but also reduces transmission costs [6]. On the other hand, data analysis from a server in the cloud to a mobile device has its own obstacles and problems. Our goal was to create a system that would be affordable for everyone while still providing accurate results. Recent developments in mobile technology have made local deployment of MLAs possible on mobile devices.

In this paper, the study uses a novel contribution using machine learning algorithms (MLA) that combines random forest with a fuzzy logic classifier, where the data is stored on remote computers, which is capable of performing intensive computing tasks.

The main contribution of the paper involves the following:

1. The authors develop a machine learning based healthcare monitoring and analytics from various IoMT devices for possible prediction of cardiovascular risk in patients.

2. The authors use random forest for feature selection and then the fuzzy logic classifier is used for prediction of CVD.

2 Related works

A lot of research effort has gone into developing smart healthcare IoT-based technologies for health prediction. Anuar et al. [6] describe a wearable Core Body Temperature (CBT) sensor device that operates on the principle of a single heat flux. While testing the sensor in several locations, it was determined that the forehead provided the most accurate estimation of CBT. CBT sensor readings were on average only 0.05 degrees Celsius off from those taken with a clinical thermometer, indicating a negligible discrepancy.

Extending the distance range from 50 to 100 centimetres was demonstrated by Huang et al. [7] using a technique based on neural network regression. Since the automatic face tracking function depends on a well-focused human face, this is an important consideration whenever facial measurements are being taken. The study utilises an app or the Web to get to the data and results.

The wearable temperature monitors that Huang et al. [8] created has found medical applications. Rahaman et al. [9] reviewed the various types of intelligent health monitoring systems and zeroed in on the benefits and drawbacks of the technologies now in use in health care systems. Several IoT-based technologies that could be employed in telemedicine and healthcare services for the treatment and prevention of a wide range of illnesses were studied in depth by Albahri et al. [10]. In order to ensure the safety of patients, researchers looked at the viability of a wireless IoMT system that could immediately notify parents or guardians of any health issues. Certain researchers developed a remote patient monitoring system that featured the detection of important body data like Photoplethysmography (PPG), ECG, and temperature with the goal of detecting the patient present state of health. This investigation followed a similar pattern. Privacy and security issues related to IoT-based smart healthcare systems are also discussed.

Paganelli et al. [11] compared the effectiveness of several topologies for keeping tabs on patients. It possible that any of these designs will lead to the discovery of the virus. The proposed architecture consists primarily of three layers: the application layer, the data collection layer, and the data transmission layer. The IoT-based healthcare solutions, however, have some restrictions, including communication delays, latency, and other problems.

Bassam et al. [12] demonstrated the use of a wearable health monitoring system in patients. The system has an in-built GPS that allowed for real-time tracking. The system is connected to an Android interface via an API in order to track the health of a discharged patient. All these issues can be addressed and a solution found with the help of fog computing and data mining methods. Any IoMT smart health system must ensure the confidentiality of patient information. A block-based encryption method could be utilised to secure cloud-based data storage. Body language, facial emotions, and gestures may be picked up by non-invasive remote monitoring to help diagnose epilepsy seizures. This would supplement the standard practise of examining vital signs to determine a patient health condition.

Disease management, patient experience, effective treatment, and the importance of 5G in communication are all discussed in [13] that foresees the usage of IoT in health monitoring of humans. IoT (IoMT) is important to all of these discussions. Traditional approaches to disease diagnosis rely on measuring key bodily functions. IoMT-based home systems are utilised to forecast the onset of urinary tract virus infections, as shown by Bhatia et al. [14]. There are many different kinds of diabetes, cystine, hepatitis, liver disease, and other similar illnesses. In order to solve concerns such as cloud security, storage allocation, communication delay, data retrieval, etc., Li et al. [15] made a detailed assessment on the efficacy of machine learning utilising big data analytics. Predicting an individual behaviour in the future may be possible by using machine learning algorithms to information gathered through the IoMT about that person activities, facial expressions, and health, among other things. Kondaka [16] emphasises the necessity of machine learning in effectively assessing and managing the data kept on the cloud in order to create accurate forecasts regarding diseases. Utilizing deep learning technology can assist reduce the number of errors that arise in IoMT smart health systems.

The cloud system presented by Onasanya et al. [17] uses the IoMT and wireless sensor networks to identify and treat cancer at an early stage. To better pinpoint potential COVID-19, researchers have created a second IoMT system. In order to distinguish between the symptoms, this system employs a total of eight distinct learning algorithms. In order to shorten the amount of time it takes for an ambulance or other sort of medical help to reach a patient throughout a smart city, researchers are examining how an IoMT system could be used to track patients in the city.

Uslu et al. [18] describe these factors in detail. The improper use of patient information, cybercrime, data aggregation, and so on are among the most significant problems that can arise during the development of an IoT-based health monitoring system. It is of the utmost need to have a case monitoring system that is dependable and accurate in order to maintain track, as this will help government officials to keep track of patients and, maybe, limit the spread of the disease. IoT, or the IoMT, might form the backbone of this infrastructure. Using massive volumes of data acquired on biological signals to carry out real-time monitoring of individual patients should significantly reduce the frequency.

Wan et al. [19] designed a wearable IoMT health monitoring system with its own network. This network is referred to as a body area network, and it is on this network that numerous sensors continuously measure and store characteristics. Each of these locations creates a distinct set of difficulties for the system, yet all IoMT technologies have found their way into healthcare, the home, or wearables. There are a number of considerations that must be made during the design and deployment of the automated IoT health monitoring system.

3 Proposed Method

The conventional ML systems were little more than signal gathering platforms, sending real-time physiological data from a single sensor to a server that is placed in distance location. The proposed model automatically analyse the data and improve forecast accuracy with fewer assumptions than traditional statistical approaches, they are finding increased usage in monitoring systems.

The proposed monitoring system is seen in Figure 1. The study begins by manually gathering and classifying the training data. It is necessary to perform preprocessing on the data, collect features, and maybe combine the data with additional dataset before using them as inputs to a classifier. The machine learning algorithm is put through its paces in a number of settings after it has been trained.

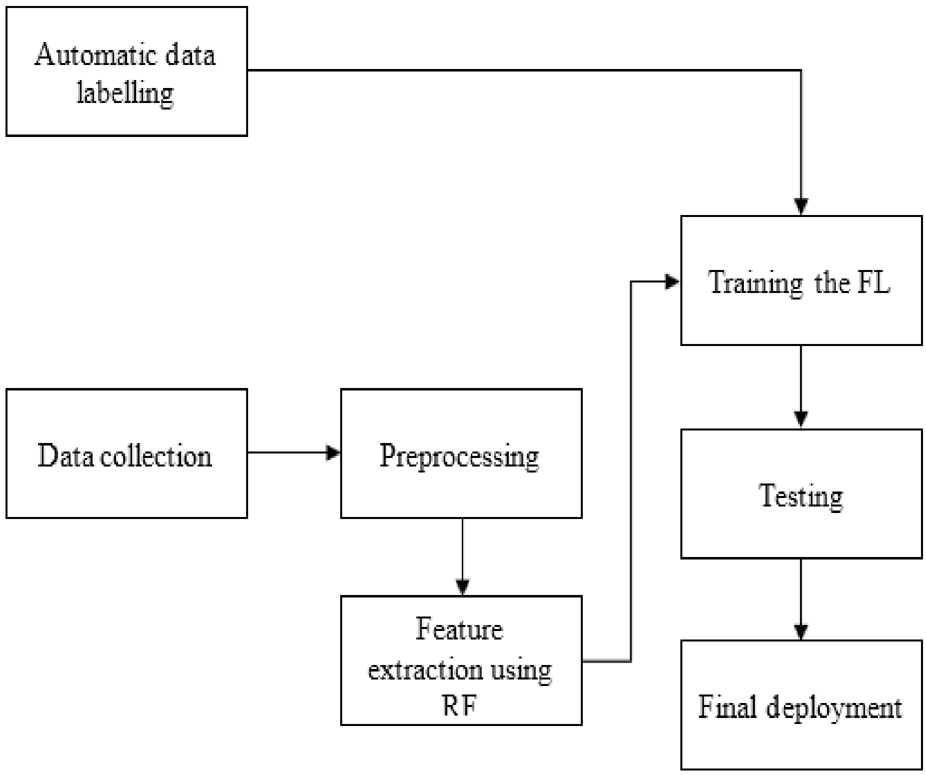

Figure 1: Proposed Model

In this investigation, we explore the feasibility of integrating a mobile platform into the structure of a remote monitoring system. Ultimately, we aim to streamline the process so that it more convenient for users.

During the process of creating a mobile ML system, there are four major decision milestones that have a domino impact on the whole system efficiency. There are four major checkpoints to consider:(1) the method used to label training data,(2) the data split, (3) the classifier selection, and (4) the modification of classifier requirements to account for the available computational resources.

The study initiates automatic labelling with training data. The study proposes testing classifiers namely fuzzy logic on mobile devices to provide accuracy-computational profiles of each potential model. The system will choose a model dynamically based on the available computing power.

Data Acquisition/Collection Layer

The proposed healthcare system incorporates insights from two substantial databases. During normal health monitoring, a variety of physiological measurements are taken, including but not limited to heart rate, blood pressure, glucose level, blood sugar, blood oxygen, respiratory rate, activity level, cholesterol, electromyogram, electrocardiogram, and electroencephalogram.

These records are then transmitted wirelessly via Bluetooth to a remote gateway device, where they undergo preliminary processing before being employed in a health risk assessment. The patient whole medical record is kept in the cloud, from their smoking and diabetes histories through their observation reports and complete clinical reports.

Pre-Processing Layer

University of California, Irvine researchers are examining patient data from Cleveland and Hungary stored in the institution machine learning repository for indications of cardiac disease.

Due to the inherent inconsistency, incompleteness, and noise of real-world data, data pre-processing has become a precondition for the use of machine learning techniques. Correct heart disease prediction utilising the heart disease dataset requires processing of missing data, standardisation of the data, and feature selection. Problems with missing values and noise in data from wearable sensors might make it difficult to anticipate heart disease and increase the risk of an inaccurate diagnosis or incorrect classification.

In this specific case, the widely-used data-cleaning method of Kalman filtering is put to use. Using this method, we may efficiently clean up the data by getting rid of extraneous information like noise, duplicates, and outliers. Because to its straightforward layout, it necessitates comparatively little processing time. This unsupervised filtering technique is optimised to return values that are free of noise and closer to what the sensor is actually telling you, making it useful for processing large amounts of real-time sensor data. Also, the figures it returns are closer to the sensor true measurements. We additionally employ two additional unsupervised filters during this stage of processing to remove superfluous values and complete gaps in the data, respectively. The initial filter retains as much as 90% of the maximal variance while excluding unnecessary features. The second filter fills in missing values in the structured dataset by using its mean and median.

Random Forest based Feature Selection

Feature selection is the first step in machine learning, occurring before any actual learning takes place. A more precise machine learning system can be achieved through the use of feature selection. By selecting features using a random forest, the chances of under- and over-fitting are minimised.

When a number of decision trees representing several classifiers are utilised, the likelihood that any single tree would fail to correctly forecast the target value is eliminated (an ensemble of classifiers). The RF draws its conclusion by averaging the data from all of the trees.

The RF margin function is described by Equation (1), the generalisation error by Equation (2), and forecast confidence by Equation (3).

$$mg(X, Y) = a_v I_k(h_k(X) = Y) - max_j(h_k(X) = j) \tag{1}$$

Where I - indicator function. The error in generalisation, can be expressed as follows in Equation (2):

$$PE^* = P\_X, Y(mg(X, Y) > 0) \tag{2}$$

when a coordinate system with X and Y axes is used to plot the probabilities. With an increasing number of classifiers (decision trees) in random forests, $h_k(X) = h(X, \Theta_k)$ holds true for all repetition sequence (TR) sequences.

Probability of convergence (PE) to Equation (3) is given below, as predicted by the Strong Law of Large Numbers and the tree topology.

$$P\_X, Y(P_\Theta(h(X, \Theta) = Y) - max\_j(Y\_P\Theta(h(X, \Theta) = j) < 0) \tag{3}$$

Where

Θ – random vector

X – input vector

Y – random vector distribution

Here, we send training data comprised of X and Y vectors to a set of classifiers called decision trees, denoted $h_1(x)$, $h_2(x)$, etc. Equation (1) provides an expression for the margin function. The RF bagging algorithm is also part of the bootstrapping procedure with the base classifiers. Several trees, rather than simply one, are generated using this strategy, which is typical of ensemble learning. As the degree of similarity across trees increases, the robust classifier favours a lower rate of error.

The attributes extraction and the number of decision trees are crucial factors in RF classifier training. This approach prevents overfitting and takes noise and outliers into account without sacrificing accuracy.

3.3. Data Prediction Layer

Sequence prediction issues have been present for some time, and their difficulty is widely acknowledged as being among the highest. The data prediction layer consists of the following machine learning algorithm that is discussed below:

The fuzzifier, inference engine, knowledge base, and defuzzifier are the four main parts of a typical Fuzzy Logic (FL). Typically, input to a fuzzy system might be either numerical data or textual descriptions (fuzzy sets).

1. The term fuzzification is used to describe the process of feeding a clear input into the appropriate fuzzy set.
2. The inference engine uses expert knowledge, represented as a set of fuzzy conditional rules in the knowledge base, to translate the values of the input variables into the language values of the output variables.
3. Knowledge bases include domain-specific expertise and formalise it in a database and set of rules. The language control rules are stored in a database, and domain expert knowledge is incorporated into the rule set.
4. Defuzzification adds discrete data to the fuzzy set that is created, providing numerical data along with the linguistic values.

The first method is a FIS (fuzzy inference system) algorithm, and its goal is to classify patient medical histories in accordance with the risk that they would develop cardiovascular disease.

Algorithm 1: Classification using FIS

1. Determine fuzzy using input and membership function μ_1

2. Find the risk state of CVD using μ_1 (MaxHeartRate1, LowHeartRate1, BP1) as low or normal or high
3. If the risk = high
   (a) Alert the patient and doctor
   (b) Save the health record of the patient
4. Else save the health record of the patient
5. End the process

The inputs for maximum heart rate, ECG, and blood pressure, are created and member function are fed, which are fuzzified into fuzzy sets using a fuzzy value range. The variable risk of high is determined based on exceeding the value of MaxHeartRate1. An individual highest and lowest recorded heart rate and blood pressure are all sent into a member function that enables the decision making. The inputs are converted into fuzzy sets with a corresponding value range. The FIS receives the produced fuzzy sets as input and uses them to categorise patients based on their medical records.
In the DB, these procedures are codified as fuzzy conditional rules. The combination of the rule base member functions and the fuzzy rules determines the final ranking of the outcomes. In the prediction process, information on people who have previously been identified as being at high risk for cardiovascular disease is analysed in greater depth.
Membership Function
This sigmoid function is used as a activation function and it is defined in the following equation:

$$\text{sig (x;a,c)} = \frac{1}{1+\exp[-a(x-c)]}$$

whereas :
c - degree of membership.
a - slope.

4 Results and Discussions

The RF-FL is trained and tested on a PC running Windows 7 with MATLAB 2014A, with a 2.2 GHz Intel i7 processor and 12 GB of RAM.
Software developers now have access to a novel training method for gauging the efficacy of their classifier creations. In this way, our approach may be used to train classifiers for any mobile app, expanding the utility of the RF-FL training method. Our approach would require more time to train the model than would be necessary using 5-fold training. The methods we have proposed require the development of an automated system that can transfer the classifier to the mobile device and assess its computational efficacy.
The purpose of this research was to use a machine learning model on a dataset related to heart disease to evaluate the performance of sequential prediction models. Both the Cleveland and the Hungarian heart disease datasets are employed in the system, and both may be found in the online ML and data mining repository at UCI. There are a total of 303 and 294 records, respectively, in the Cleveland (https://archive.ics.uci.edu/ml/datasets/heart+disease) and Hungarian heart disease databases (https://www.kaggle.com/sid321axn/heart-statlog-cleveland-hungary-final), and each record has 14 unique properties. As a way to test the robustness of the proposed RF-FL model, we used the dataset generator Mockaroo to raise the record count to 100,000. An example of this is dividing a dataset of 100,000 records into a training set of 70,000 and a testing set of 30,000.
The training of the model is carried out from the Cleveland and Hungary and then the testing is made from the IoMT devices. Depending on the precision requirements, the optimal number of IoMT nodes is chosen automatically. The learning rate is 0.16 times slower than the decay rate of 0.96. We have a momentum parameter of 0.82, an epoch size of arbitrary precision, and a batch size of 128 transactions. Wireless Body Sensor Networks (WBSNs) are responsible for transmitting data collected from IoT devices to the cloud, where it will be analysed and organised. Using Apache Spark and Cassandra as the server and storage architecture for the TensorFlow ML package, the experiment was conducted on the I2K2 Cloud Platform. The major limitations involve the use of limited IoMT devices as increasing data may lead to poor pre-processing and thereby the precision would reduce.
Evaluation Indices
Accuracy, precision, sensitivity specificity, and F1-score are the few indicators used when determining a model value. Accuracy evaluates how well the proposed RF-FL model performs by comparing the actual outcomes with the expected ones.
We measure the classifier model performance in determining if a patient has heart illness by comparing the true positive (TP) and true negative (TN) rates. How well a model predicts is measured by the proportion

of false positives (FP) and false negatives (FN) it produces. False positives (FP) and false negatives (FN) are abbreviations for these types of errors. Examining the proportion of true positive observations to total positive cases reveals the accuracy.

Accuracy defines the overall correctness of the proposed model as in following expression:

Accuracy=(TN+TP)/(TP+FP+FN+TN)

Sensitivity defines the correctness of classifying the specific class as in following expression:

Sensitivity = (TP)/(FP+TP)

Specificity defines the how many times, a specific class is classified correctly as in following expression:

Specificity=(TN)/(TN+FP)

F1-score is the harmonic mean of the precision and recall and it is expressed below

F1 Measure=(2TP)/(2TP+FP+FN)

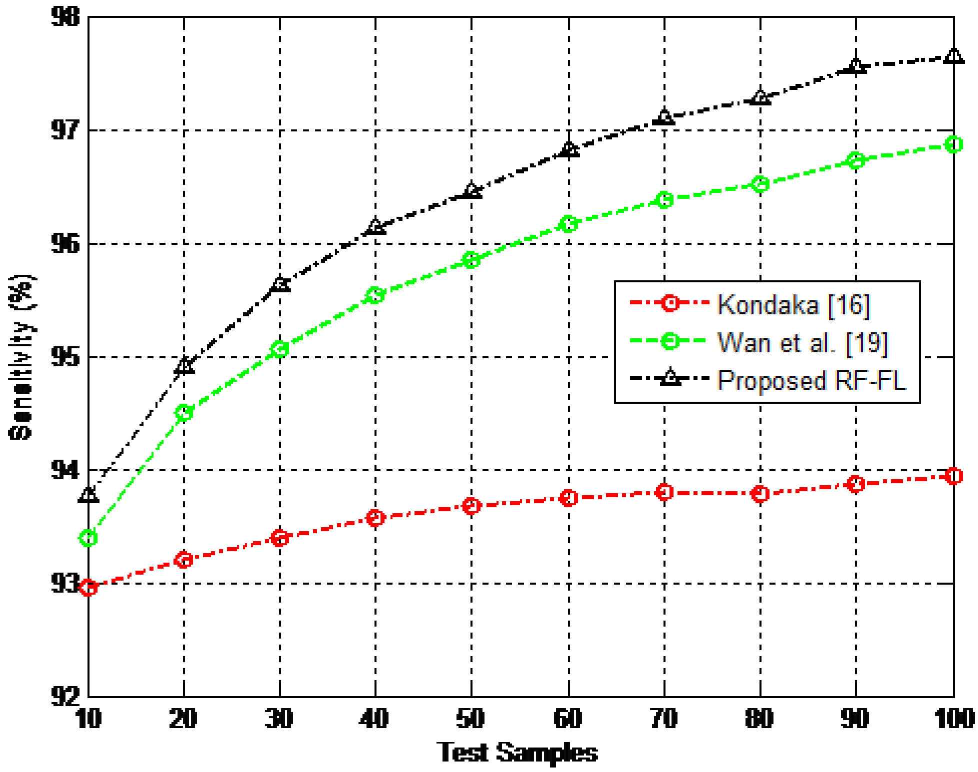

Figure 2: Sensitivity

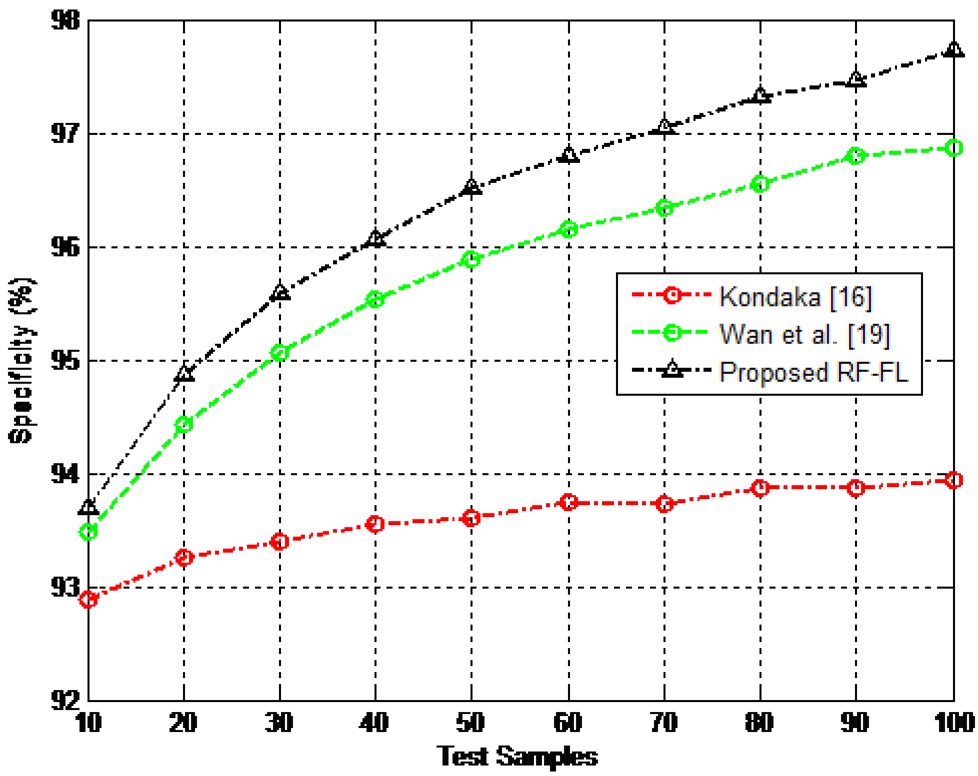

Figure 3: Specificity

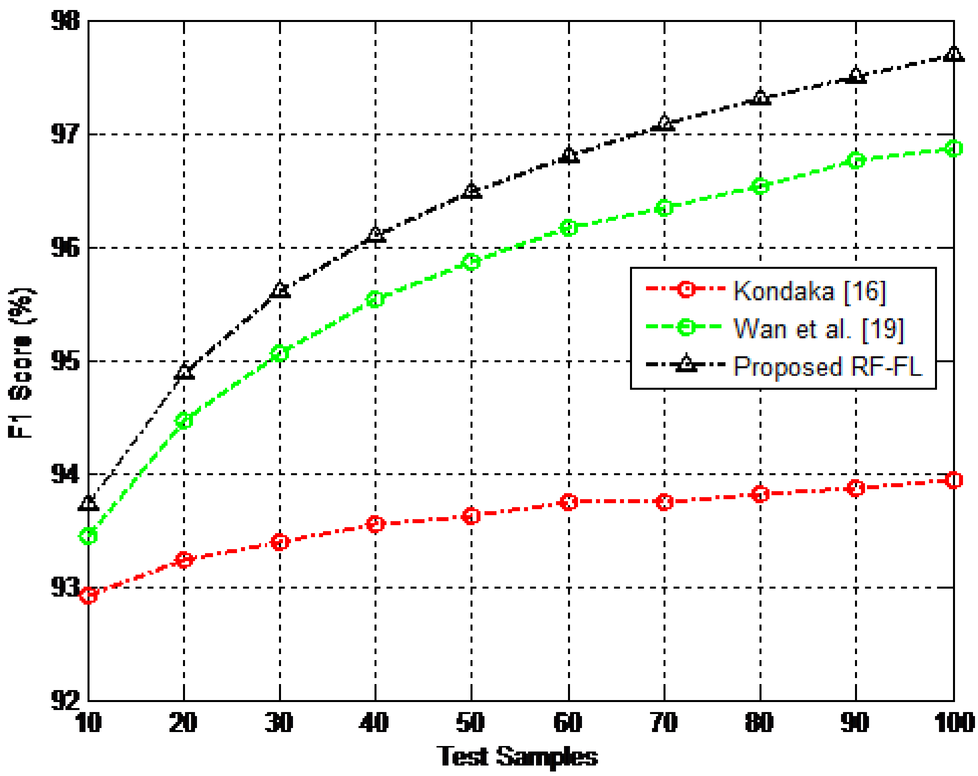

Figure 4: F1 Score

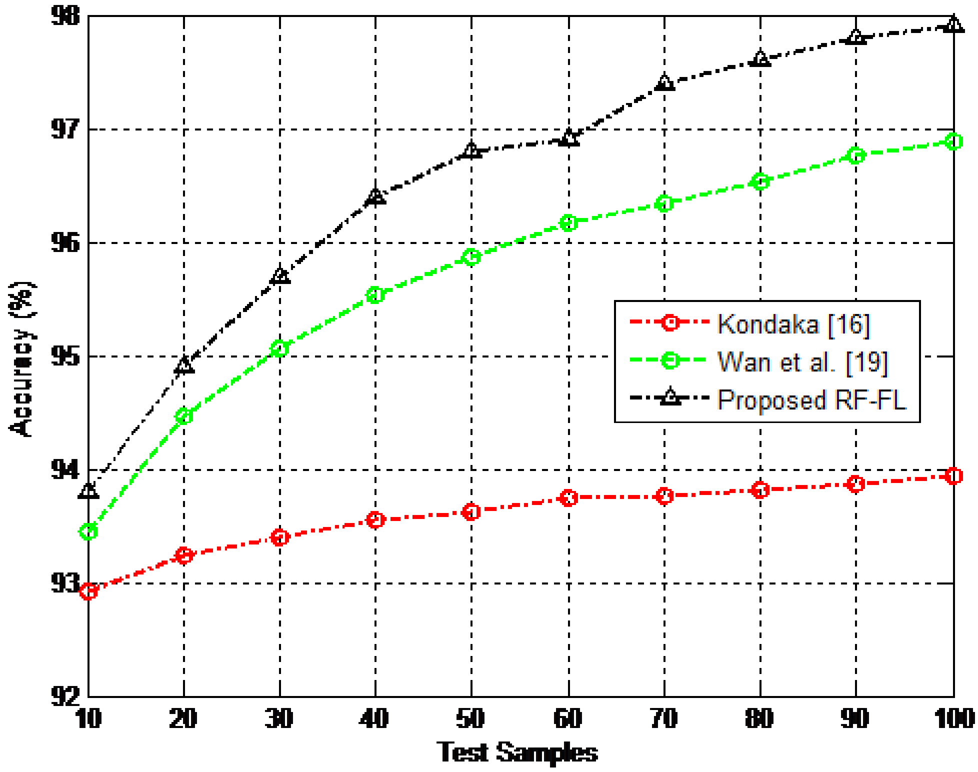

Figure 5: Accuracy

Figure 2-5 shows the results of various metrics of the proposed classifier with existing methods. The simulation shows that the proposed method has higher classification accuracy than the existing methods.

5 Conclusions

In this study, we assessed the classifiers based on accuracy and computational performance is universal, in contrast to the majority of our recommendations, which are tailored to particular stages. Here, RF features are ranked according to how much of an impact they have on model correctness on available system resources. These results pave the way for the next generation of personalised predictive monitoring systems. The classification using fuzzy logic enables proper classification of instances than other methods and the selection of correct features improves the process of obtaining proper classified results. From the results of simulation, it is seen that the proposed method achieves a higher rate of accuracy in classifying the dataset than the other existing methods. The model achieves a higher degree of F1-score than other methods that shows a better efficacy of the model in classifying the dataset. In future, real-time applicability of the model is tested when the proposed RF-FL is applied over various types of dataset.

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