Research Article

IoT and Fog Computing Based Prediction and Monitoring System for Stroke Disease

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Abstract: In recent times, stroke is become a considerably health issue for most people throughout the world due to bad dietary habit including smoke and drink, working pressure, lack of physical activity etc. Sometimes, the condition of patients become worst due to lack of information as medical staff are not aware about the physiological attribute of stroke and recovery time will be increased. Nowadays, healthcare domain gets wide attention among research community due to incremental data growth, advanced diagnostic tools, medical imaging process and many more. Enormous healthcare data is generated through diagnostic tool and medical imaging process, but handling of these data is quit tough task due to its nature. Large number of machines learning techniques are presented for handling the healthcare data and right diagnosis of disease. On the other side, IoT, cloud and fog computing are trending research areas for disease diagnosis and prediction and get wide attention from research community. Several healthcare systems have been developed using IoT, Cloud and Fog computing-based technologies. Hence, in this work, an IoT and fog computing-based monitoring system is developed for diagnosis and prediction of stroke. Further, an ensemble classifier is integrated in proposed fog computing-based monitoring system to predict and monitor the stroke infection. The efficiency of proposed monitoring system is tested over stroke disease dataset. This dataset is collected from various hospital located in Delhi-NCR region during 2016-2018. The simulation results of proposed monitoring system are evaluated using accuracy, sensitivity and specificity parameters and provides state of art results.

Keywords: Stroke, Cloud Computing, Fog Computing, IoT, Disease, Diagnosis

1. Introduction

In present time, stroke is the second leading disease responsible for untimely death of human being. In 2030, more than 12 million people could be died due to stroke disease and more than seventy million people could be stroke survivor (Feigin et al., 2010). A recent study showed that developed countries having high rate of stroke disease, but the middle- and low-income countries also having in the risk zone and cases of stroke diseases is rising rapidly in these countries (Kim et al., 2015). It is also seen that the one third stroke survival patients live with long term disability. Most of physicians describe the stroke as injury in brain and spinal code, in turn affects the blood supply. Stroke can be classified into three categories 1) Ischemic Stroke 2) Transient Ischemic Stroke 3) Hemorrhagic Stroke. Most common stroke is ischemic stroke and it is noticed that eighty seven percent strokes are ischemic. The reason behind this stroke is presence of clot or obstacle in the blood vessel of brain. The ischemic stroke having two types – embolic and thrombotic strokes (Pahus et al., 2016). The embolic strokes can be interpreted as the presence of clot in any part of the human body, but this clot blocks the flow of blood towards brain. Whereas, in case of thrombotic clot, the blood flow an artery is restrict due to a clot, in turn blood supply of brain affected. Hemorrhagic stroke is occurred due to burst of weak blood vessels. This stroke typically varies in between 10-15%, but it is more life threaten than ischemic stroke (Dupont et al., 2010; Santos et al., 2016). It is further classified into subarachnoid haemorrhage and intracerebral haemorrhage. Transient ischemic attack can be described as mini-stroke and occurs due to temporary blockage/clot. It causes temporary injury to brain tissues (Shinohara et al., 2011). But it may be a warning message of additional stroke in future. Hence, it can be stated that stroke can considered as a fatal disease. It is observed that the treatment of stroke is risky and physicians can proceed with traditional treatment and examine whether the chance of risk is overcome or not. If, the diagnostic/monitoring tools are available for the treatment/ prediction of stroke patients, then, the current condition of stroke patient is evaluated using the current behavior and also decided some initial treatment measures. Such tools can also predict the recovery rate of stroke patients. But, the tool with high accuracy rate can be very useful, in case of stroke treatment as patients not visit to hospitals or healthcare centers.

In literature, several researchers addressed the prediction of stroke prognosis significantly and also suggested effective treatment and intervention (Longstreth et al., 2001; Khosla et al., 2010; Weng et al. 2017). Some studies also highlighted several features for the prediction of stroke disease such as creatinine level, time to walk, smoke etc. (Lumley et al., 2002; Abdar et al., 2019). It is also observed that medical dataset consists of large number of features and it is very tough task to determine the potential features and verify the risk factor associated with these features manually. Nowadays, machine learning algorithm and meta-heuristic algorithms are widely adopted to determine the relevant features from medical datasets and made the features selection automatic rather than manual. It is observed that combination of feature selection and machine learning classifier improve the prediction accuracy in effective manner. Moreover, a remote healthcare monitoring system can be designed to encourage pervasive healthcare services using rising technologies such as Internet of Things (IoT), wearable equipment's, wireless sensors, cloud computing, fog computing (Logesh et al., 2018). These technologies can be adopted for the observation of vital parameters of patients and provided empathic healthcare services. Nowadays, various wearable devices such as unobtrusive, printable electronic tattoos and smart textiles are utilized in sensing technology (Vijayakumar et al., 2018). The aim of these devices is to collect the health data of individual person for predicting healthy lifestyle (Ghanavati et al., 2017). Moreover, mobile computing and wireless sensors technologies are also widely used in healthcare domain for collection and analysis of medical data. Although, mobile phones have adequate storage space for processing the health data (Vairavasundaram & Logesh, 2018). Cloud computing is also applied in medical informatics due to centralized storage and complex computations facilities (Logesh et al., 2018). It is observed that numerous healthcare application utilizes IoT as a most significant acquisition component to develop a smart environment (Subramaniyaswamy et al., 2015). IoT can tackle large amount of information, its management, storage, and processing. On other hand, Cloud computing provides the various resources on pay per service. These services are utilized by various IOT applications. The remote healthcare monitoring systems is one of them (Logesh & Subramaniyaswamy, 2019). Next, the quality of healthcare services is also improved through various computing facilities such as wireless sensors, cloud computing and mobile computing (Subramaniyaswamy et al., 2017). The cloud computing provides various advantages such as storage capacity, accessibility, cost-effective, scalability and availability. These features of cloud computing are also support the government firms to design remote health monitoring system (Logesh et al., 2018). Further, unprecedented rate of heath information is stored in the centralized cloud data centers. In turn, the cost of healthcare services is reduced significantly (Logesh et al., 2019). Further, the cloud computing enabled framework effectively monitors the patients affected through mosquito-borne diseases. It can be described as effortless usage of medical reports between the medical clinics and effective management of health information (Malathi et al., 2019). But, managing massive information over the cloud is highly complex and further, it delays the transmission over the internet that can cause serious consequences like life threating of patients (Wu et al., 2018). Moreover, computational overhead, network traffic, mobility, location awareness and communication overhead can arise. The privacy attacks and threats are another issue in context of personal information of patients in medical informatics (Pirbhulal et al., 2018). To overcome aforementioned challenges and shortcomings of cloud computing, the fog computing can be considered. It can be acted as a mediator between cloud server and end user to offer the healthcare services and resources (Dastjerdi & Buyya, 2016). Fog computing is an intermediate layer between centralized cloud server and IoT. The aim of fog computing is to address communication overhead, latency, decision making, local storage and data pre-processing issues between cloud server and end user (Malathi & Logesh, 2019). Integration of Fog computing with IoT and Cloud provides more scalability and mobility for the prevention of mosquito- borne diseases by covering the geographical regions and real-time evaluations based on data analytics (Yannuzzi et al., 2014). It can support Nano data centers for data storage and requires less energy as compared to cloud computing. It is due to of time utilization, type of application, number of downloads, data pre-loading, updates and type of network accessed (Wu et al., 2018). From the past few years, the e-Healthcare applications get wide attention from researchers to achieve a healthy lifestyle with confidence and enthusiasm and also to upgrade quality of life. In turn, e-health application should be patient- centric and accurate. These applications require patient health information continuously, but this information is not enough to predict the accurate state of disease. It also requires the contextual information for extracting the diagnosis (Jalali et al., 2016). The contextual information, feedback and patient profile information can be utilized for generating the more accurate patient- centric recommendations and diagnosis (Sodhro et al., 2018). Hence, the aim of this research work is to design fog computing-based health monitoring system for the detection and prevention of stroke disease. The proposed health monitoring system comprises the advantage of fog computing and cloud computing for computation and storage. The objective of fog layer is to reduce the overhead on cloud layer and also address the energy efficiency issue of cloud. The proposed system can help medical staff for diagnosing the stroke disease. The main objectives of proposed fog-based health monitoring system are as follows.

- An IoT and fog-based health monitoring system is developed for prediction of stroke
- An immediate treatment of stroke affected patients
- A record sharing mechanism can be integrated for alert message generations and suggestions.

2. Related Works

This section summarizes the works on IOT, cloud and stroke diagnosis and prediction.

Ali et al. (2019) adopted four popular ML classifiers for predicting the strokes symptoms. These classifiers can be described as DT, SVM, RT and LR. Further, optimal tuning of the parameters can be performed for obtaining the accurate prediction results. Simulation results are evaluated using several well-defined performance measures and it is reported that random forest achieves better accuracy rate than others.

The accurate diagnosis of disease is an important parameter in healthcare. It is seen that many researchers developed efficient diagnostic system for heart disease, but having low accuracy. Khan (2020) considered the accuracy issue of heart disease and developed an IoT based framework for improving the accuracy rate. In this framework, various attributes responsible for heart stroke such as BP, ECG are measured using heart monitor and smart watch. Further, an improved Deep CNN is applied for accurate prediction of heart stroke using collect data. Author claimed that IOT framework achieves more than 95% accuracy rate.

An enhanced deep learning and CNN based model using the internet medical of things presented for effective treatment of heart disease (Pan et al., 2020). The objective of aforementioned combination is to improve the prognostic rate of heart disease. The performance of model is computed using all and minimized attribute of disease. Further, the proposed combination is implemented over IoMT and results are evaluating using accuracy and processing time. Authors claimed that more effective results are achieved through abovementioned model.

Ahmed et al. (2020) presented a real time heart disease predicting system based on data streams including current health status of patients. The other objective of study is to determine the optimal ML algorithms for heart disease prediction. The parameters of ML algorithms are also tuned for achieving improve accuracy. Results claimed that random forest having higher accuracy rate than others ML algorithms.

Yu et al. (2020) developed stroke predicting system based on bio-signals of each individual. Authors claimed that most of stroke detection systems considered the image data rather than bio-signals. Further, deep learning and random forest techniques are integrated into predicting system for selection of optimal features and prediction task respectively. Results revealed that random forest-based system achieves 90.4% accuracy, while LSTM system achieves 93.8% accuracy.

An antlion and DNN based model developed for handling the multimodality in the stroke dataset (Reddy et al., 2020). In this model, antlion algorithm is considered for optimizing the hyper parameter DNN. Further the parameter tuned DNN is applied for predicting the stroke data. Results are evaluated in terms of training time and its revealed that training time of above model is 38.13.

Ali et al., (2020) presented a smart healthcare system for predicting the probability of heart stroke. This system integrates the feature fusion and ensemble deep learning techniques. The feature fusion method can be interpreted as combining the attribute form sensor data and electronic record. Moreover, irrelevant data is eliminated through information gain method. Further, the model is trained using ensemble deep leaning method for producing more accurate results. Simulation results prove the significance of the smart healthcare system for predicting the heart stroke.

As heart disease/strokes is the second highest disease responsible for death (Moghadas et al., 2020). It became more severe, if cannot diagnosed in timely manner. Hence, Moghadas et al., considered the diagnosis rate of heart disease as potential issue and developed an IoT and Fog based framework accurate diagnosis. Further, ECG signals are considered for effective and timely diagnosis of heart disease and k-NN is applied for validating the aforementioned framework.

Yu et al., (2020) presented the impact of stroke severity on elder people having age more than sixty-five using NIHSS. C4.5 algorithm is considered for evaluating stroke severity impact on elder people. Further, thirteen features are taken into account for evaluation instead of eighteen features of stroke scale. Authors claimed that C4.5 achieves 91.11% accuracy.

Selvi and Muthulakshmi (2020) reported optimal ANN (OANN) model for diagnosing the heart disease as it can be described as leading cause of death in world among all age people. OANN model comprises of two technique such as DBMIR and TLBO-ANN. TLBO is used for tunning the parameters of ANN. Apache Spark framework are used for implementing the OANN and works in two modes such online and offline. It’s stated that OANN achieves higher performance than other due to parameter tuning and DBMIR.

Yahyaie et al., (2019) investigated the efficacy of IoT model for effectively predicting heart disease. This study considers the ECG signal for examining the efficiency of model. A total two hundred seventy-one people data are collected using cloud based online application. The collected dataset comprises of ninety features for heart disease. Further, NN model is applied to train the IoT model and it is claimed that acceptable level of accuracy is obtained using aforesaid model.

Healthcare systems can be improved a lot due to smart medical devices, IoT, IoMT and intelligent ML techniques like ANN, DNN, CNN etc. Hence, Akhbarifar et al., (2020) presented a remote health model for effectively monitoring of elder patients using IoT and Cloud environment. A series of ML classifiers are integrated into remote health model. Authors reported that k-NN classifier having higher performance than others.

Surviving rates of heart stroke patients are quite low than other diseases. So, a combination of deep learning, IoT and Modified NN presented for improving the survival rate of heart patients (Sarmah, 2020). The proposed system comprises of three task such as authorization, encryption and classification. The substitution cipher and SHA-512 is used for authorization, PDH-AES technique is used for encryption and transmission of data and for classification, DL and modified NN is adopted. The proposed model achieves 95.8% accuracy with higher security features.

For improving e-healthcare applications and better services, Kumar et al., (2018) presented a hybrid disease diagnosis framework using cloud, IoT and mobile applications. Further, the severity of diseases is measured using fuzzy rule base and neural classifier. Several existing and real medical datasets are chosen for evaluating the framework and observed that it can efficiently handle the medical datasets and accurately identify the disease.

3. Proposed Fog Computing Based Monitoring System

This section describes the fog computing-based monitoring system for the prediction and monitoring of stroke. The architecture of proposed monitoring system is illustrated in Fig 1. It consists of three layers. These layers are Patient Information Layer, Fog Computing Gateway Layer and Cloud Layer. The Patient Information Layer is responsible to collect the information related to such as health, location, activity, personal, behavioral, environment etc. The various sensors are used to collect the aforementioned information. The gathered information is sent to fog computing gateway layer to process and diagnosis the data. In this layer, an ensemble classifier is used to predict the stroke. Once, the stroke is predicted, this information is sent to patients through an alert message and preventive action can be taken. The role of cloud layer is to store the processed information and also share this information with doctors, hospitals and family members of patients. The stored information is also used to calculate the impact of the stroke. Some warning messages can also send to user. The sequence diagram of proposed monitoring system is demonstrated in Fig. 2. he working of each layer of proposed monitoring system is described as follows.

3.1 Patient Information Layer

This layer is responsible to collect the data from users according to symptoms of diseases and surrounding environment. This data can be classified as health data, activity data, personal data, behavioral data etc. The data can be collected through different wearable devices and sensors embed in patient's body and surrounding environment. Further, the sensed data are transferred in real time environment through WSNs technologies. For stroke monitoring, the following types of IoT sensors are used to collect the desired information in terms of dataset.

- Health Dataset: Health dataset contains the information regarding the symptoms of stroke diseases. The symptoms can be described as numbness, dizziness, headache, cholesterol, blood pressure, slurring speech, paralysis, difficulty in seeing, sudden vision loss etc. Such type of information is collected through health sensor for each individual.

- Environmental Dataset: This dataset contains the information regarding the surrounding environment of individuals. In case of stroke disease, air pollution, physical activity, smoke, dietary habit, working environment, nature of job can be considered as environmental data.

- Location Dataset: Location dataset consists the information of stroke affected people including working and residential locations. A RFID tag can be used for close proximity.

- Personal Dataset: This data contains the personal information of each individual. The attributes of this dataset are name, sex, qualification, address, occupation etc. So, all the personal information of each individual is stored in personal dataset.

3.2 Fog Computing Gateway Layer

It is intermediately layer between patient information layer and cloud layer. This layer is responsible to process and analyze the real time data collected through different IoT devices and sensors and also predict the patients with stroke infection. If, patient is stroke affected (Infectious, Positive and Recover), then an alert message will generate and sent to corresponding patient. Further, patient data is stored on cloud layer. This layer consists of two components- Stroke Classification and Alert Generation

3.2.1 Stroke Classification

This component classifies the stroke data into three classes. These classes are Negative, Positive and Recover as shown in Table 1. The patient information layer is responsible to collect the real time raw data regarding health, personal, activity, behavioral a stroke and environmental data from various devices and IoT sensors. This data is processed at Fog computing layer such as missing value imputation. The final dataset is heterogeneous in nature and utilized to predict the stroke. Fog node is used to compile the heterogeneous stroke dataset and converted into a unique format for predicting stroke infection. In fog computing layer, random forest with boosting (RFB) classifier is used to predict the stroke infection in patients. The working steps of proposed RFB classifier is given in Algorithm 1.

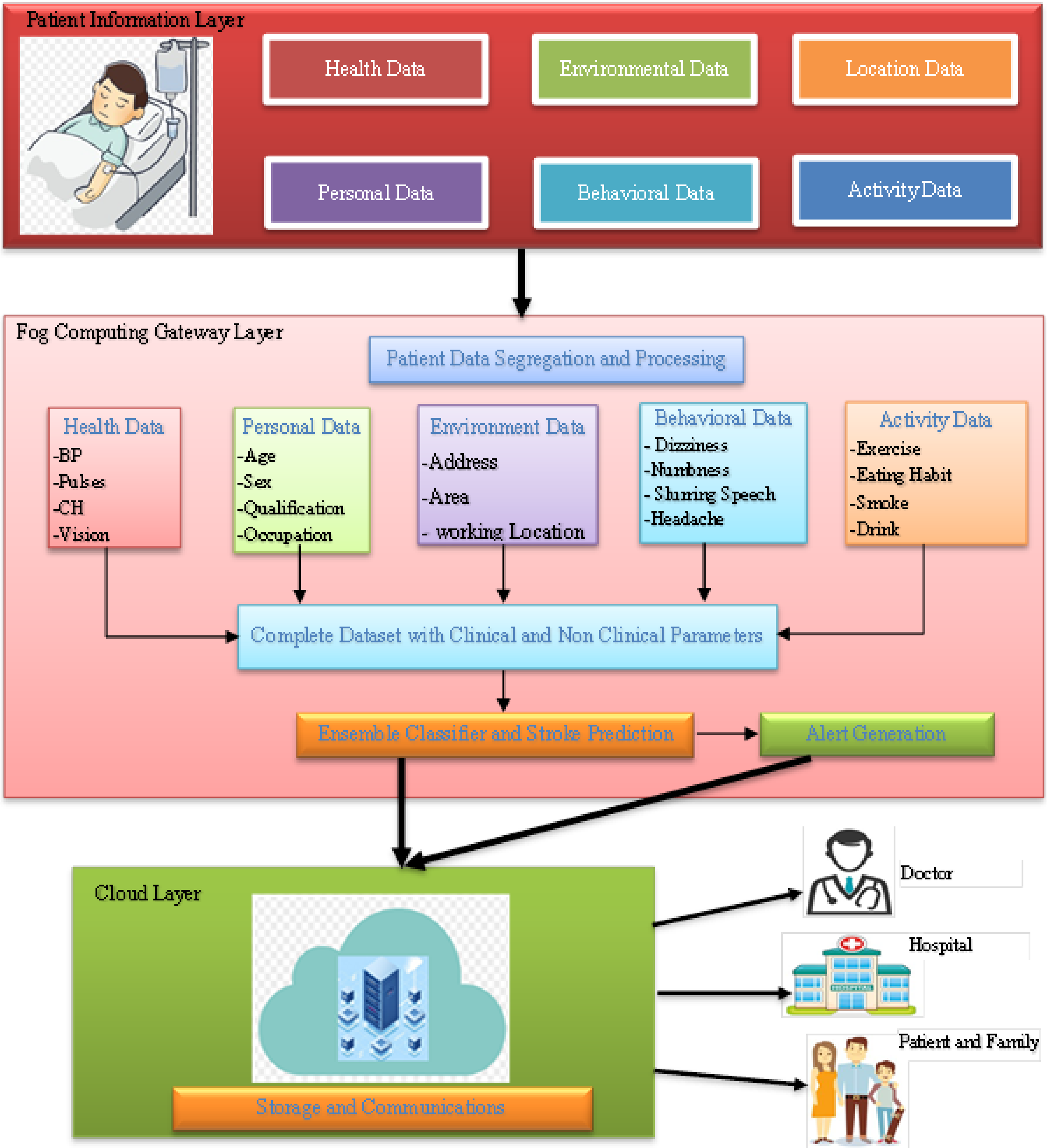

Figure 1. Proposed Fog Computing Based Monitoring System

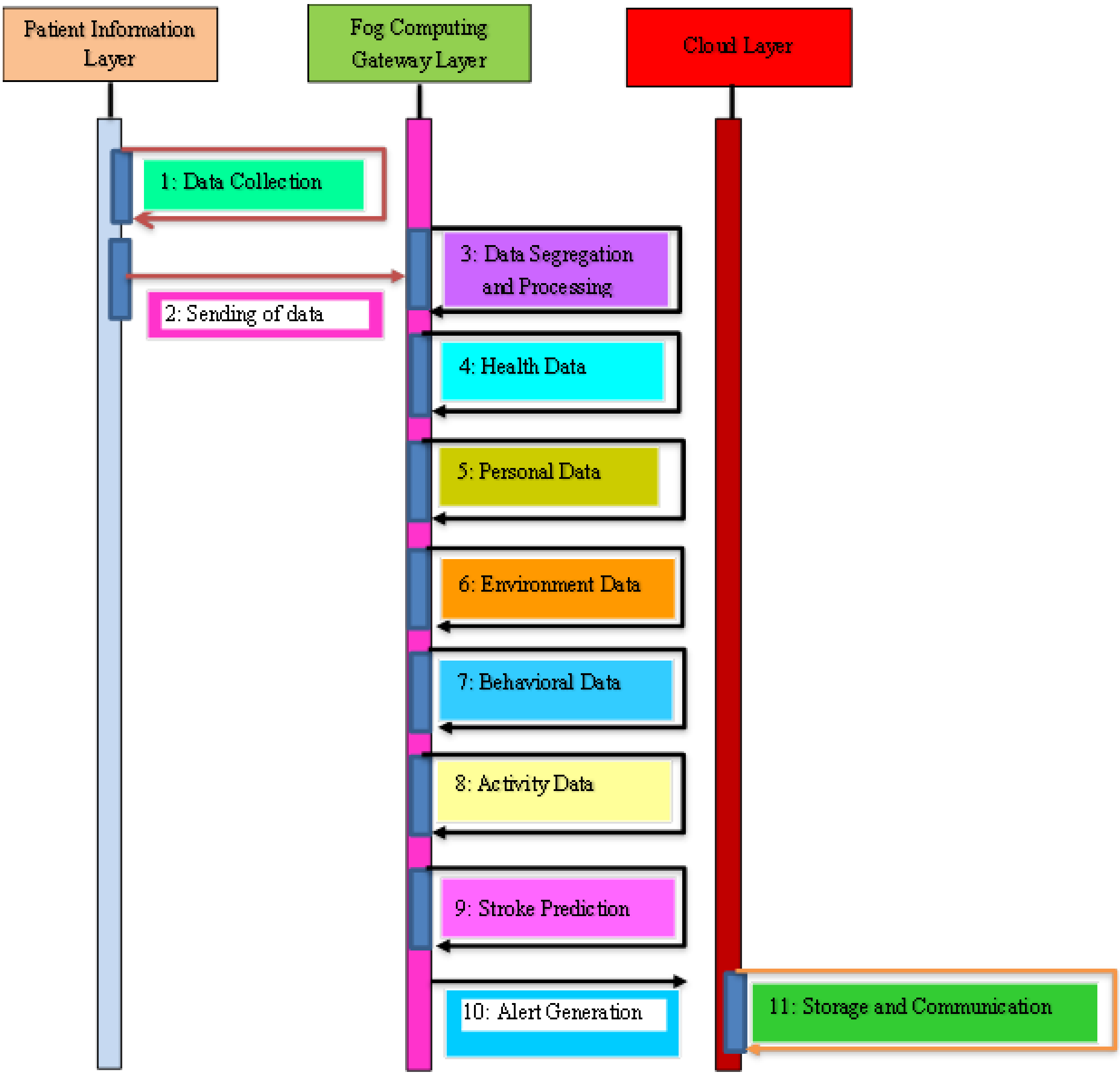

Figure 2. Working Sequence of Proposed Fog Computing Based Monitoring System

3.2.2 Alert Generation and Monitoring

The stroke affected patients are regularly monitored to check the progress and history report. The regular time intervals are considered to monitor the stroke patients. Generally, stroke patients are monitored after every 3 h, Positive after 10 h. There is no specific time interval for stroke recover patients and it may be varied and depend on consulting doctor. Hence, to monitor the patient, probability of stroke index (PDI) is computed and it can be measured using equation 1.

$$\mathrm{PDI} = \mathrm{P}\left(\frac{\mathrm{B}}{(\mathrm{A}_1 \cup \mathrm{A}_2 \dots \dots \cup \mathrm{A}_n)}\right) \qquad (1)$$

Table 1. Types of stroke classes and their description.

Stroke Class	Description
Negative	Patient does not have health symptoms
Positive	Patient has fatigue along with headache, less vision etc.
Recover	Patients that are recovering

In equation 1, P denotes the probability, B is the current stroke class and $\{A_1, A_2, \dots A_n\}$ is the occurrence stroke severity. After, the detection of stroke infection, an alert message is sent through fog computing layer. This alert message comprises of different PDI ranges and sent to end users registered mobile number. End users can be described patients, patient's family members, hospitals and doctors. If, value of PDI is normal, then a stroke negative alert

Algorithm 1: RFB Classifiers

Input: Stroke dataset with attributes and Class labels
Output: Stroke Affected Patients

1: Choose "M" attributes among "N" attributes, such as m << N.
2: Determine node (d) using best split criteria among "k" attributes.
3: Generate the child nodes using best split method.
4: Repeat above steps (1-3), until cannot compute "l" nodes.
5: Construct forest tree using steps 1-4 and this tack repeated n times and generate n decision trees.
6: Compute the class of training set.
7: For each decision tree, determine weighted error rate.
8: Calculate the weight of decision tree's (DT_{weight}) using equation 2.

$$DT_{weight} = {}^{1}\!/_{2} \log \frac{(N-1)(1-e)}{e} \quad (2)$$

9: If (DT_{weight} >0)
Update the weight of training data.
10: Otherwise, reject and repeat steps 7-10

message is sent to end users. If PDI value is abnormal, then warning message is send to end users containing the information regarding possible stroke symptoms. Such alert message can help the doctors to diagnose stroke infection in early stage. In turn, necessary treatment and precaution can be given to patient as per stroke consequence. Further, the proposed fog-based health monitoring system is also capable to re-evaluate the stroke conditions and generate alert message. Algorithm 2 consists of working steps of re-evaluation process of stroke condition.

3.3 Cloud Layer

In the proposed monitoring system, cloud layer is used to store the preprocessed data and communication purpose. Cloud layer provides the ubiquitous storage space to store patient's data and it can be accessed at anytime and anywhere. The database of cloud is divided into non-shareable and shareable modes. The non-shareable mode stores the health status, user's personal data, social contact data and treatment history. This mode consists of highly sensitive data and provides the data privacy from unauthorized access. Whereas, shareable mode contains general data like age, sex and so on that can be share with anyone. Moreover, cloud layer supports two types of authorized users to access the stored data. These users are either patient's/family members or hospitals/doctors. The patients and family members access the patient's health report and give the feedback about the experience, heath status and treatment in the form of comments. This feedback is used for treatment of similar patients and can be accessible for hospitals and doctors for treatment.

Algorithm 2: Re-evaluate the stroke class and generate alert messages

Input: Patient present symptoms and identification number
Output: Revised heath class and generate alerts

Step 1: Get the patients current symptoms and identification number
Step 2: If patient identification number already exist, then new records of patient are updated.
Step 3: Else, new record of patient with identification number is generated and current symptoms of stroke infection is stored in the system.
Step 4: RFB classifier evaluates the class label of patient using current symptoms
Step 5: If new prediction health class = old health class, then alert message will generate and monitoring status also updated.
Step 6: Otherwise, an alert message sent to doctor or hospital regarding appointment and date with time of next appointment is send to the patient.
Step 7: Exit

4. Result Analysis and Discussion

This section presents the experimental results of proposed fog computing-based health monitoring system. The effectiveness of proposed health monitoring system is tested on real time stroke dataset. It is divided into three classes as reported in Table 1. Fig. 3 illustrates two samples, one sample belongs to the stroke patient, while second sample belong to the normal person. Further, in proposed monitoring system, a random forest with boosting (RFB) classifier is implemented for predicting the stroke infection in patients. The performance of proposed RFB is evaluated using various performance parameters. These parameters are F-value, Precision, Accuracy, Sensitivity, Specificity, Error rate and Recall (Gambhir et al., 2017a; Gambhir et al., 2017b). The proposed classifier is implemented in python language using window 10. The performance of proposed g system is evaluated using stroke patients and compared with state of art existing machine learning classifiers such as NB, SVM, RF, Boosting, DT and ANN (Srivastava et al., 2020; Gambhir et al., 2019; Srivastava et al., 2021; Singh and Kumar, 2019).

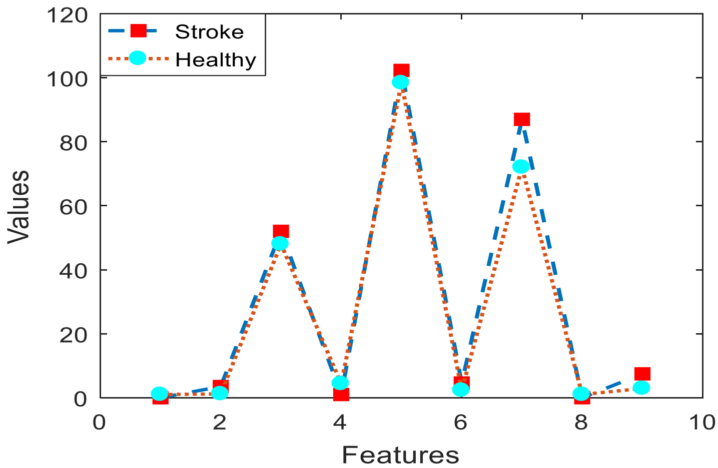

Figure 3. Samples of a stroke patient and healthy person

Table 2 describes the performance comparison of abovementioned classifiers and proposed system. It can be seen that proposed system provides better results in comparison to existing classifiers. It is also observed that RFB based health monitoring system obtains higher recall, precision, sensitivity, accuracy, F-value, specificity rate and lower error rate. It is also noticed that the performance of the DT classier is worst among all classifiers. Further, the ranking of each classifier is also calculated using seven performance parameters and it is observed that proposed fog-based health monitoring system achieves first rank and DT obtains worst rank.

Table 2. Performance comparison of NB, SVM, DT, ANN, Boosting, RF classifiers and proposed Fog based system

Parameters	Classifiers						
	NB	SVM	DT	ANN	Boosting	RF	Proposed System
F-value	49.91	45.40	40.82	74.61	49.62	74.76	86.27
Rank	4	6	7	3	5	2	1
Recall	54.55	50.50	42.00	77.03	56.00	78.94	88.00
Rank	5	6	7	3	4	2	1
Precision	46.00	45.40	40.00	73.34	44.44	71.00	84.62
Rank	4	5	7	3	6	2	1
Accuracy	78.07	75.00	73.63	88.30	79.09	87.27	93.64
Rank	5	6	7	2	4	3	1
Sensitivity	51.50	50.00	41.66	57.80	55.55	68.00	88.00
Rank	5	6	7	3	4	2	1
Specificity	84.04	82.55	81.25	90.05	88.50	92.94	95.29
Rank	5	6	7	3	4	2	1
Error Rate	21.93	25.00	26.37	11.7	20.91	12.73	06.36
Rank	5	6	7	2	4	3	1

Overall Rank	4.71	5.85	7	2.71	4.42	2.28	1

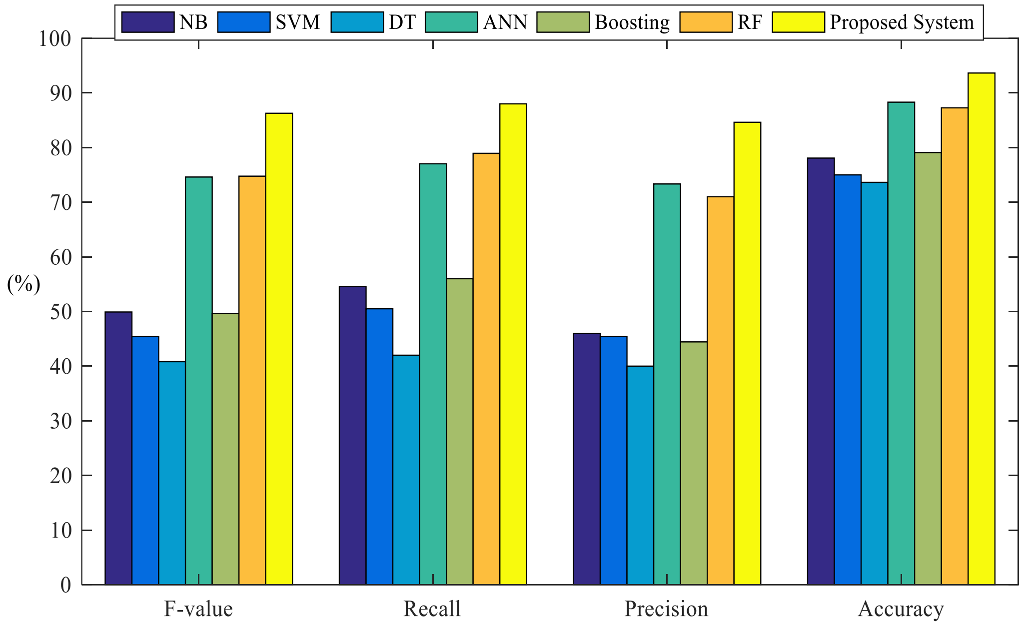

Figure 4. Performance comparison of NB, SVM, DT, ANN, Boosting, RF and proposed Fog based system using f-value, recall, precision and accuracy parameters

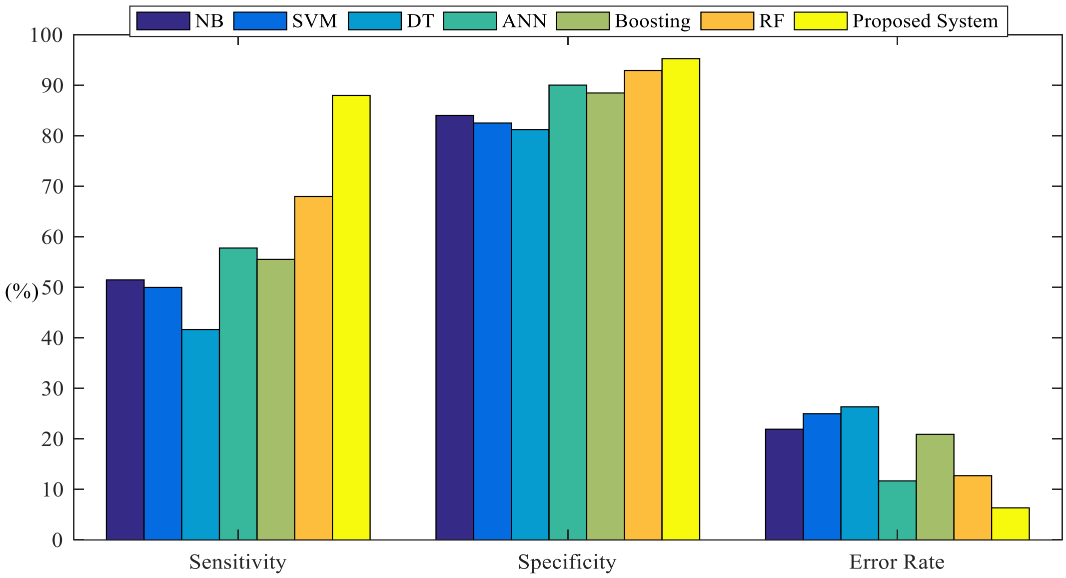

Fig 5: Performance comparison of NB, SVM, DT, ANN, Boosting, RF and proposed Fog based system using sensitivity, specificity and error rate parameters

Fig. 4 illustrates the performance of all classifiers using F-value, accuracy, recall and precision parameters. It is noticed that proposed fog-based monitoring system provides better F-value, recall, precision and accuracy rate. It is also observed that ANN based model second highest accuracy rate as compared to rest of classifiers. But ANN classifier having low f-value, recall and precision rate as compared to RF classifiers. Moreover, it is stated that DT classifier exhibits worst performance among all classifiers. Fig. 5 demonstrates performance of proposed fog-based system and all other classifiers using sensitivity, specificity and error rate parameters. It is noticed that proposed fog-based system achieves higher sensitivity and specificity rate in comparison to other classifiers. It is also revealed that RF classifier have second highest sensitivity and specificity rate as compared to other classifiers. Further, it is also observed that DT classifier exhibits worst performance among all classifiers. Moreover, it is seen that proposed system have low error rate as compared rest of classifiers. Hence, it can be stated that proposed fog-based system accurately predicts and monitor the stroke affected patients.

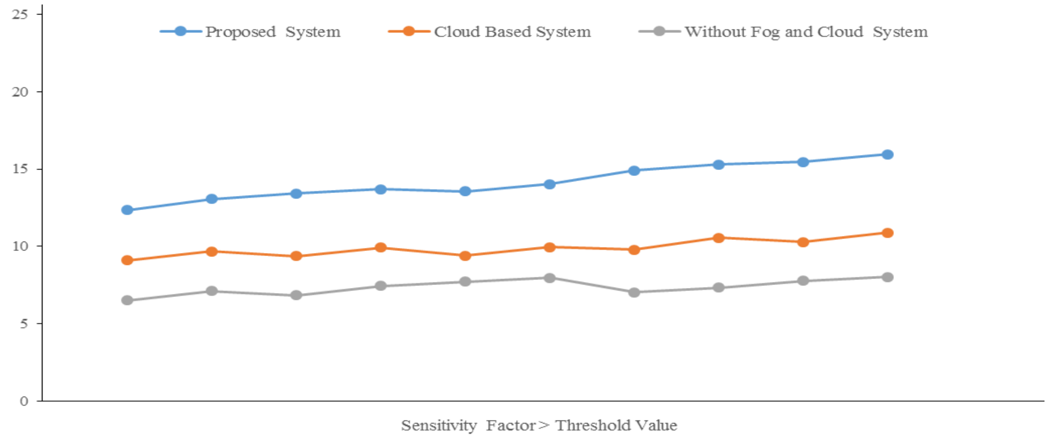

Figure 6. Depicts the efficiency of alert generation of proposed system, cloud-based system and without fog and cloud-based system

The proposed fog-based system is also capable for sending the warning and alert generation messages to users and patients. The efficiency of these messages of the proposed system is also examined in this study. Response Time parameter is considered to evaluate the efficiency of warning and alert generation messages. The other metrics that can be used to estimate the warning and alert generation are precision, specificity and sensitivity. The higher values of these metrics signify that proposed fog-based system more accurately predict and monitor the patients. Fig. 6 demonstrates the efficiency of timely and true warning/alert generation messages based on response time using fog-based system, cloud-based system and without fog and cloud-based system. It is computed using number of delayed alerts generation to the total number of alerts generated. The delay time can be described as time taken to generate an alert from the occurrence of event. It is observed that latency rate of cloud computing and without fog and cloud computing is higher than proposed fog computing-based system. It is due to large number of information processing and transmitted at cloud computing level. Whereas, without fog and cloud computing, a standalone system is responsible for all of the works. Hence, the latency rate of standalone system is maximum as compared cloud-based system and fog-based system. But the fog computing reduces network traffic and bandwidth. In turn provides low latency rate. Further, it is also seen that fog computing works as intermediate layer in proposed system and all the data is processed at intermediate layer. Hence, it improves the efficiency and effectiveness of the proposed system. The following points can be highlighted based on the experimental study.

- In proposed fog-based health monitoring system, RFB ensemble classifier is implemented for stroke infection prediction and this ensemble classifier achieves higher accuracy rate as comparison to RF and Boosting. Because the performance of RF classifier depends on the number of decision tree generated as well as RF cannot maintain the generality on small scale hardware. Whereas, boosting classifier increases the complexity, time and computation. In this work, to overcome the pitfalls of RF and boosting techniques, the boosting technique is integrated with RF technique. The objective of this integration is to maintain the generality of RF even with smaller number of decision tree and to reduce the complexity, time and computation of boosting technique by utilizing the fact that sequential training generate complementary DT for training dataset. Hence, the proposed integration obtains the higher accuracy results as compared to RF and boosting techniques.

- It is noticed that the overall performance of Boosting and NB classifiers is slightly varied especially for F-value and accuracy parameters. It is due to different objective function is used for the prediction of stroke infection in both of classifiers.

- The performance of RF classifier is better than NB, SVM, DT, ANN and boosting classifiers due to parallelism and high dimensionality of RF. Further, RF works non-linear data, unbalanced data, low bias and moderate variance.

- ANN classifier performed better than NB, SVM, DT and Boosting classifier because ANN having complex relationship between input and output. Further, at each layer, the weights of ANN will be more optimized.

- DT classifier achieves worst performance than others classifiers because it can neglect some key values in training data and data is also non-linearly separable.

- The efficiency of the alert generation is also examined using response time. It is observed that proposed fog-based system provides low latency rate.

5. Conclusion

In this paper, fog computing-based monitoring system is developed to predict and monitor the stroke. The proposed monitoring system consists of three layer-patient information layer, fog computing gateway layer and cloud layer. The different IoT devices and sensors are used to collect the stroke data and monitor the health of stroke patients. Moreover, an ensemble classifier is developed to predict the stroke infection. The proposed ensemble classifier is the combination of random forest and boosting technique, called RFB. The proposed RFB classifier is integrated with fog computing gateway layer to reduce the overload on cloud layer. Further, an alert message is also generated at fog layer regarding the health status of stroke patients. It is observed that proposed monitoring system achieves higher accuracy rate in comparison to another algorithm being compared. It is also seen that proposed monitoring system successfully delivers the alert messages to end users. Additionally, the proposed system is also sending proximity message regarding the stroke infection to registered users.

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