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IOT-INSPIRED SMART HEALTHCARE FRAMEWORK FOR DIABETIC PATIENTS: FOG COMPUTING INITIATIVE

Abdulaziz Aldaej

College of Computer Engineering and Sciences
Prince Sattam Bin Abdulaziz University
Al-Kharj 11942, Saudi Arabia
a.aldaej@psau.edu.sa

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Abstract. *Diabetes is characterized by a high prevalence of vulnerable food habits and poor management, resulting in a high risk of premature death. Maintaining a healthy blood glucose level has several health advantages which lower the risk of diabetes. Continuous monitoring of blood glucose levels in real time is a big issue. Monitoring just glucose levels without taking account of other indicators such as ECG and physical activity, on the other hand, might lead to incorrect treatment. As a result, the ever-increasing need for an all-encompassing healthcare system has prompted the use of prominent innovations including fog-cloud computing and wireless communication network. However, complex computation, delay, and portability issues come from the use of these approaches. This paper proposes a fog computing-inspired health framework to regulate human diabetic levels to solve the aforementioned concerns. The J48Graft decision tree is utilized to forecast diabetes vulnerability with a greater level of classification accuracy. An emergency signal is issued instantly for preventive actions when fog computing is utilized. The suggested framework performs better in terms of precision, energy effectiveness, computing complexity, and delay, as evidenced by the experimental findings concerning state-of-the-art decision-making techniques.*

Keywords: IoT, Fog computing, J48 decision tree, Diabetes, Smart healthcare

1. **Introduction.** Maintaining a healthy lifestyle necessitates monitoring blood glucose levels on a regular basis [1, 2]. When blood glucose levels rise over normal, it can lead to serious complications such as cardiac arrhythmia, stroke, heart attack, and blind vision. Hypoglycemia occurs when the blood glucose level falls below 59 mg/dl, resulting in cardiac arrhythmia [3, 4]. Hyperglycemia occurs when blood sugar levels are elevated beyond 129 mg/dl, causing heart impact, blind vision, and renal loss [5]. As per the reports of the Centers for Disease Control and Prevention, a substantial percentage of persons aged 59 and above suffer from arrhythmia, and anyone can develop diabetic disease [6]. However, while diabetes cannot be entirely diminished, it may be managed. The possible care is to keep the glucose in the blood at a stable level by continuously sensing and adjusting the insulin level in a time-sensitive manner. Internet of Things (IoT) is an inter-network for connecting computational devices, and physical things ensuring interaction, communication, and sharing data [7, 8]. Users are becoming bombarded with information as web-based services increase fast in tandem with the growth of IoT. In recent years, decision support systems have been widely utilized to provide users with relevant information in a variety of sectors, including travel and tourism, healthcare, e-commerce, movies, and sports [9]. The proliferation of intelligent IoT sensors, in particular, has fueled the innovation of smart medical frameworks. The Health Internet of Things (HIoT) interconnects

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body sensors to an intelligent sensor for continuous detection, collection, and sending data via a network [10-12]. However, managing the massive volume of data created by IoT might be a difficult challenge for a service provider [13]. However, enhanced-service computational facilities and enormous repository infrastructure are need-of-the-hour owing to a shortage of energy, storage constraints, processing delay, transmission costs, and effective assessment of sensing devices [14, 15]. In this context, cloud computing's promising potential has been utilized to enhance the effectiveness of healthcare frameworks [10]. Cloud servers are a pivotal aspect of medical data repository in the next generation's IoT-medical framework [16]. It is a centralized data center in which several computer resources deliver services through the Internet [17]. Healthcare service providers employ cloud-based services to make the most of available resources, reducing processing time and cost [18, 19]. It has a significant impact on the number of users and service requests. However, customized diet and medication recommendations based on consumers' present circumstances are a big concern [20, 21]. Moreover, because it carries users' sensitive information, the centralized data repository, data analysis, organization, and administration of health information over cloud-base is particularly vulnerable to privacy threats [22, 23]. Effective data processing is required to overcome the aforementioned concerns [24]. An effective approach to making use of cloud computing is to conceal the user's true identity. It causes issues such as excessive latency, network traffic, mobility, and dependability [25].

1.1. **Research motivation.** Cloud computing in addendum with fog computing presets novel aspects, especially in the healthcare domain. Moreover, the data generated by the IoT biosensor are required to be analyzed in real time for effective service delivery. Limited work in the categorization of diabetic levels is an open research challenge that can be addressed by the revolutionary technology of cloud and fog computing. To analyze and handle large data, using a fog computational paradigm as an intermediate between the cloud storage layer and application layer has become a vital aspect.

Time-sensitive assessment of a patient's medical state allows for better and timely healthcare. HIoT is used to create a huge quantity of health-related information to analyze the situation for real-time analysis of medical information. It increases network data, complexity in computing, and delay substantially. As a result, an effective fog platform is employed as a gateway among IoT devices and cloud databases to optimize the healthcare system (Figure 1) [7]. Fog computing efficiently decreases latency and saves bandwidth by minimizing transmission among end-node and cloud-base. It also makes abnormality detection, interoperability, and mobility more convenient.

1.2. **Major contribution.** A fog-based medical framework for the mobile diabetic user is presented in the current article. The proposed framework not only monitors physiological parameters but also incorporates contextual information to enhance classification accuracy. The suggested fog-inspired medical framework is designed to recognize diabetic vulnerability levels and issue a medical signal to prevent early death. More lives can be saved instantaneously since the obtained medical conditions are assessed and evaluated at the fog layer during data creation. It saves a lot of storage space as well as network traffic and latency. Based on the aforementioned aspects, the major contributions of the current research are as follows.

1) Propose a fog computing-inspired model for real-time monitoring, prediction, and control of distant diabetes patients' risk depending on physiological conditions.
2) Diabetes patients' risk is assessed at regular intervals to look for any changes in glucose levels, for immediate response.

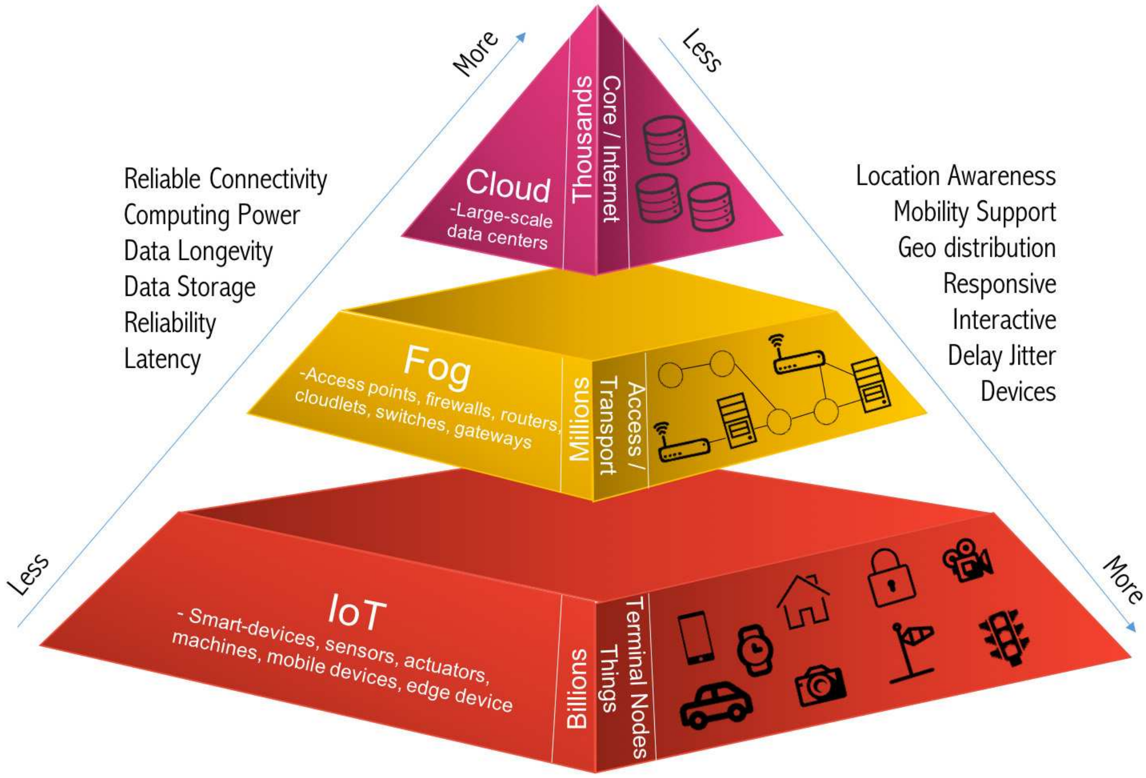

FIGURE 1. IoT-fog-cloud framework

3) Effective alert generation procedure is presented for medical alerts if health condition deteriorates.

1.3. **Paper organization.** The literature on fog-inspired medical decision-making in the realm of healthcare is described in Section 2. The prerequisites of IoT-inspired healthcare are provided in Section 3. The services presented by the fog environment in the medical domain are highlighted in Section 4. The major components of the presented fog-inspired medical framework are discussed in Section 5. The diabetic case study with the J48Graft classifier and alert generating is presented in Section 6. Section 7 discusses the experimental assessments and outcomes. Section 8 concludes with a summary of the findings and recommendations for further research.

2. **Related Work.** The user's physiological status is tracked using HIoT and communicated to a medical server regularly. Any interruption in transmission or the absence of crucial signals might have significant repercussions. As a result, numerous attempts were undertaken to properly transfer health data to a distant server to increase diagnosis precision. Emerging technologies including sensing devices, intelligent preceptors, HIoT, servers, and healthcare data analysis are employed in the presented medical framework to reduce computational costs and delay, therefore improving the well-being of mobile patients. Because of its capacity to link and communicate with other devices through the Internet, the IoT is regarded as a revolution. Many researchers have suggested IoT-based approaches for tracking patients' health. Kiran et al. [26] suggested an IoT-enabled data gathering and communication framework based on ECG data and rule mining. The suggested method uses less electricity and decreases network traffic, according to the results of the performance evaluation. Yang et al. [27] introduced the intelligent home (iHome) framework, which combines telemedicine with intelligent medication boxes (iMedBox)

and pharmaceutical packaging named iMedPack, and biological devices termed as Bio-Patch to improve medical services. Rathore et al. [7] devised a comprehensive plan for transforming a city into an intelligent health-oriented city by utilizing big data analysis. Data gathering, aggregation, communication, and decision-making are divided into 4 layers in the suggested architecture. For ProTrip, Subramaniyaswamy et al. [28] created an ontology-inspired meal recommender algorithm and tested it in a time-sensitive medical framework. Selvan et al. [29] used fuzzy theory and an ontology-based recommender framework to decrease the manual labor involved in diet and medication prescription and suggestions for chronic patients. Cloud computing, as a potential developing technology, has provided huge storage, processing, and resource exchanging facilities at minimal expenses in recent years. Luo and Ren [30] investigated the use of cloud platforms in the sensing and administration of medical data. The suggested architecture improves efficiency by 50%, according to simulation findings. Abawajy and Hassan [31] offered a ubiquitous health monitoring framework for congestive heart failure patients that integrates cloud and IoT paradigms for time-sensitive monitoring of ECG data. The suggested model enables energy efficiency, scalability, and adaptability, according to experimental results. Hassan et al. [32] developed a hybrid network approach for effective medical media data exchange that incorporates both cloud and body sensors. To decrease packet loss, an adaptive streaming approach was employed. Simulation results demonstrate that the model is feasible for reducing delay and time-sensitive healthcare data transfer. Malathi et al. [33] suggested using case-based reasoning with fuzzy logic, and KNN to create a disease prediction assistance system. The authors also added Paillier Homomorphic Encryption to the system to protect user privacy. As more healthcare service providers seek to employ central cloud storage, challenges such as delay, network congestion, computational complexity, and delayed transmission become increasingly prevalent. The characteristics and attributes of the fog layer for crucial IoT applicability are presented by Bonomi et al. [34]. Authors explored the cloud's complicated security problems and proposed fog computing as a potential approach for compacting enormous storage and processing to enable IoT-based applications. Gia et al. [35] offered a case study that shows how the fog layer may improve ECG parameter abstraction in a health monitoring system. Because many attributes are similar to mosquito-originated diseases, correctly identifying the bacteria aids in the right treatment of the patient. Vijayakumar et al. [36] presented a smart method for mosquito-borne illness identification and categorization. As a result, a fog-based remote patient-oriented framework is proposed in the current study for diabetes to increase the efficiency of the medical framework.

Research gaps. The comprehensive related work presented in the current work focuses on utilizing smart technology for the detection of diabetes in patients. However, numerous research gaps have been identified that have presented the motivational aspects for the current research. Some of the limiting factors in the state-of-the-art literature review works are as follows.

1) Even though researchers have presented work in the direction of diabetes analysis, limited work has been performed utilizing fog computing for time-sensitive analysis.
2) The predictive classification has been minimally explored by the researcher in the current domain. Henceforth, utilizing the machine learning technique presents novel aspects for the current research.
3) Limited work has been performed in the direction of generation of alert signals for the diabetic emergency in the patients.
4) Categorization of diabetic level is another vital novel aspect of the current research that has been minimally explored.

5) Real-time analysis is critical for the monitoring of the diabetic level of patients. Conspicuously, it depicts vital to assess the patients in a time-sensitive manner.

3. **Preliminaries.** Preliminaries and technological background necessary for a full comprehension of the presented fog-assisted medical framework are provided in the current section. The J48Graft classifier is used in the presented medical framework to accurately identify and determine diabetes risk levels, so that remote patients may keep blood glucose levels stable and avoid an early death.

3.1. **Fog computing paradigm.** IoT creates a tremendous quantity of medical data due to the fast growth of wireless technologies, smart devices, and tailored healthcare applications. Medical big data may take many forms, including text, video, and images, which must be stored, analyzed, and processed on a cloud server. When dealing with medical big data on the cloud, there are difficulties with latency, network traffic, and security. As a result, a new computing platform known as fog computing is incorporated to reduce the cloud's burden [37]. The fog layer works as a bridge between the end-device and cloud database, bringing cloud services closer to the edge of the network and allowing for more sophisticated and secure healthcare services. The network edge, where data is created, is an appropriate location to evaluate real-time health data [38]. Distributed computing, decentralized data repository, minimization, analysis, storage, processing, security, and privacy are the fog layer's main characteristics and advantages. To execute big data analytics successfully, several IoT domains, such as medical perception systems, demand decentralized fog computing and centralized cloud storage. By utilizing fog computing as a middle layer in a time-sensitive healthcare system, several advantages can be harvested including.

1) IoT devices are energy-constrained devices; therefore, mobile services and data processing at the fog layer are energy-efficient techniques.
2) It is vital to assess and respond in a medical emergency to avoid permanent health loss. IoT-fog computing presents minimal delay in such scenarios.
3) Information accumulation, assessment, and service delivery occur at the fog layer, making cloud platform less complex.
4) Millions of IoT devices create massive amounts of data all around the world. As a result, fog computing is vital for reducing network traffic and bandwidth.
5) Low latency is achieved by sending reduced, processed, and compressed data to the cloud.
6) Security measures for data privacy and intrusion prevention can help ensure reliable data transport.

3.2. **J48Graft classifer.** Because of its capacity to manage a dataset with a high error rate, the decision tree is regarded as a significant contender for classification and decision-making. Classification is done using similarity measurement in k-nearest neighbor and it works effectively for minimal datasets. The random tree constructs a decisive tree with k-heterogeneous features; however, it is readily overfitted [39]. The multilayer perceptron is a well-known neural network technique for classifying non-linearly separable datasets [40]. For multiclass datasets, J48Graft delivers better categorization results with minimal error. The main benefit of utilizing the J48Graft classifier with raw data is that it increases the likelihood of categorization accuracy while lowering the error rate. On the multiclass dataset, it is recommended because it takes less time to execute [41]. The J48Graft decision tree classifier is utilized in the presented fog-based medical framework to determine a diabetic patient's risk level as hypoglycemia, normal, pre-diabetes, and hyperglycemia by taking account of factors including physical activity, body weight, blood glucose level, and nutrition [42]. The proposed system uses the J48Graft classifier to forecast the vulnerability of diabetes in a time-sensitive manner, allowing the user to avoid premature death.

4. **Fog Computing Services.** Localized data accumulation, processing, communicating, and service-specific decision-making are made easier using the fog computing paradigm. Reliability, remote monitoring, time-sensitive data analysis, security, and authentication are a few of the requirements for a health monitoring system. Generic fog layers are highlighted in Figure 2 and each service is described in depth ahead.

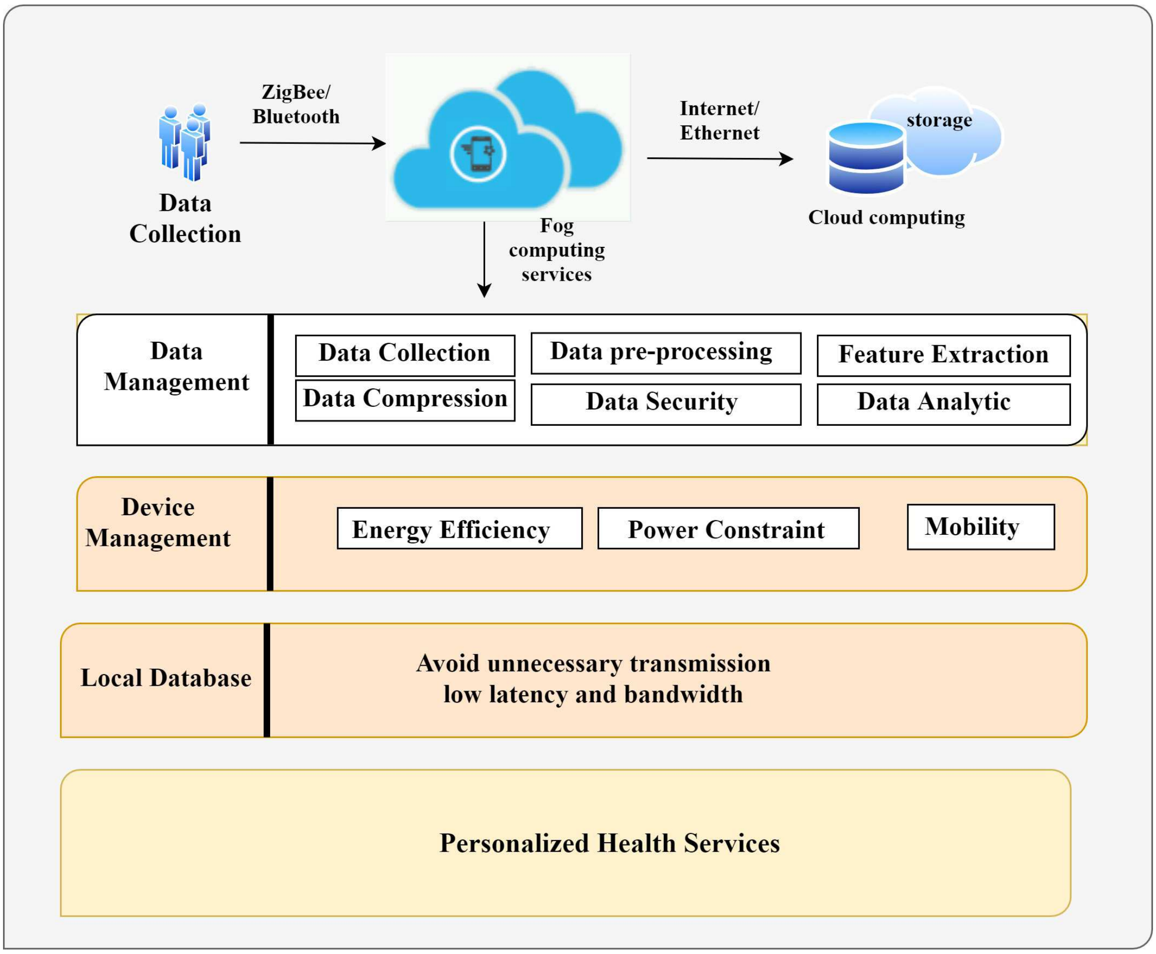

Figure 2. Services provider by fog layer

4.1. **Time-sensitive healthcare data assessment.** Local processing of real-time medical data received from multiple sensors extracts useful data for assessment and record creation. Based on the presented design, the fog layer gets sensed data continuously; therefore, data handling is critical in the current layer for providing an alert during a medical emergency. Data management becomes easier in the healthcare system since delay and ambiguity can lead to unfavorable outcomes. The fog smart device's operating system has a local data storage for compressed form [7]. Pre-processing, assessment, attribute abstraction, and security is among the other functions performed. Data filtering is the vital aspect of an input module when it receives sensory data to eliminate noise and distortions. The filtered data is then compressed using a lossless algorithm to decrease sensor transmission overhead and computing complexity. Sensory data is fused to get reliable and efficient information by eliminating redundant and unnecessary data. As a result, data reduction allows for local data analysis, which enhances the healthcare system's efficiency by decreasing delay, network utilization, and needless data transfer to the storage. A localized data repository acts as a cache memory, allowing for a continuous data flow.

4.2. **Fog node analysis.** The presented model is made up of resource-constrained devices that require careful control. To extract features, the fog gadget uses sophisticated algorithms and calculations. It delivers appropriate feedback and reports while performing clinical diagnoses utilizing data obtained from wearable sensors. As a result, it uses more energy, and adequate fog device management is required. Once a day, it must charge the battery-powered gadget. Another issue to consider is mobility to minimize decision-making disruptions and loss of data. If a diabetic person wears medical sensors and moves from one area to another, the monitoring procedure at the new location should not be affected [43]. Device discovery aids in the identification of new devices entering the domain and ensures that service is not disrupted.

4.3. **Delay and energy consumption.** Medical sensors are limited in terms of resources; therefore, they must be developed for a specific purpose rather than broad activities to save energy. It greatly decreases data processing overheads at the sensor end. Likewise, the delay is an important need since any delay in illness detection or service delivery might result in a loss of life. Sensed data is collected and analyzed in the fog node, from which an alert is transmitted to experts and caregivers in the event of an emergency. To minimize transmission delay, a filtering approach is employed to eliminate falsified and unnecessary data.

4.4. **Personalized medical care.** Several events occur with the mobile medical framework, including patient health status, physical activity, and the surroundings. When a major incident occurs, the event management ensures that medical assistance is provided immediately, as well as notifying specialists, family members, and patients. The time-sensitive medical framework must be adaptable for heterogeneous medical service delivery by the patients' health status and requirements. Personalized medical care requires setting a framework attribute on a priority basis and the medical status of the individual. To provide individualized healthcare, adaptive rule-mining and sophisticated machine/deep learning techniques are utilized. For example, if aberrant cardiovascular data is noticed while sensing, the framework understands the importance of the situation and assesses the heart-related attribute.

4.5. **Data security.** In general, security is critical for any time-sensitive medical service delivery framework since falsified health attribute integrity might result in serious repercussions. An attacker can disable the entire health monitoring system if any medical sensors are compromised. As a result, for confidentiality, dependability, and integrity, robust cryptography techniques should be used at IoT and fog-node level. Furthermore, each sensor in the network must verify its authenticity with the IoT network, and key management functionality is used to ensure safe data transfer. Furthermore, because real-time monitoring systems include sensitive information about patients and are frequently transferred via an insecure communication path, it is critical to avoid unwanted access by unauthorized personnel.

4.6. **Discussion.** As mentioned before, fog computing presents a ubiquitous network for time-sensitive computation for time-sensitive analysis. With the incorporation of the machine learning-inspired classification technique of the J48 classifier, the categorization of the diabetic level can be achieved at the fog computing layer. Moreover, the fog computation nodes can extract useful features from the data instances for effective categorization in real time. Furthermore, since most of the computation is performed at the fog nodes, the energy utilization in the current model is determined to be minimal as compared to cloud-based computation. Finally, as far as customized healthcare is concerned, a fog computation node can be deployed in the ambient environment of the patient so that personalized healthcare can be ensured successfully. Additionally, healthcare recommendation is another vital aspect that can be explored.

5. **Fog-Inspired Medical Framework.** IoT in medical applications is projected to inter-link humongous resource-constrained, bandwidth-restricted, and power-limited devices to the communication channel and transfer Internet-based data. Medical sensors are an example of such gadgets that continually detect health-related data but are unable to store or analyze the information. As a result, the cloud platform has offered a centralized data repository solution for the processing of healthcare information. The widespread use of cloud computing increases latency and network traffic substantially. Fog is a cloud-to-end-device intermediate computing platform that adds to the cloud-assisted Health-IoT by providing extra services. Figure 3 depicts the proposed fog-assisted healthcare system. Data collecting, fog computing, alarm production, centralized storage, and data analytics are all part of it. Wearable sensors monitor users' physiological parameters including health activity, diabetic levels, blood pressure, and fever in the presented fog-inspired medical framework. Contextual data such as temperature, time, location, and humidity may be combined with health data to better forecast odd trends in the scenario. The raw data from multiple sensors is then regularly transferred to the fog layer through smart devices via Bluetooth, Wi-Fi, or ZigBee. The intermediate fog layer performs operations such as anonymous encryption, aggregation, feature selection, and classification. The network layer is responsible for securely transferring assessed medical data from the fog node to the cloud platform across multiple applications. Data analysis, directional innovation, broadcasting, and human-oriented suggestions are all conducted at the cloud computing

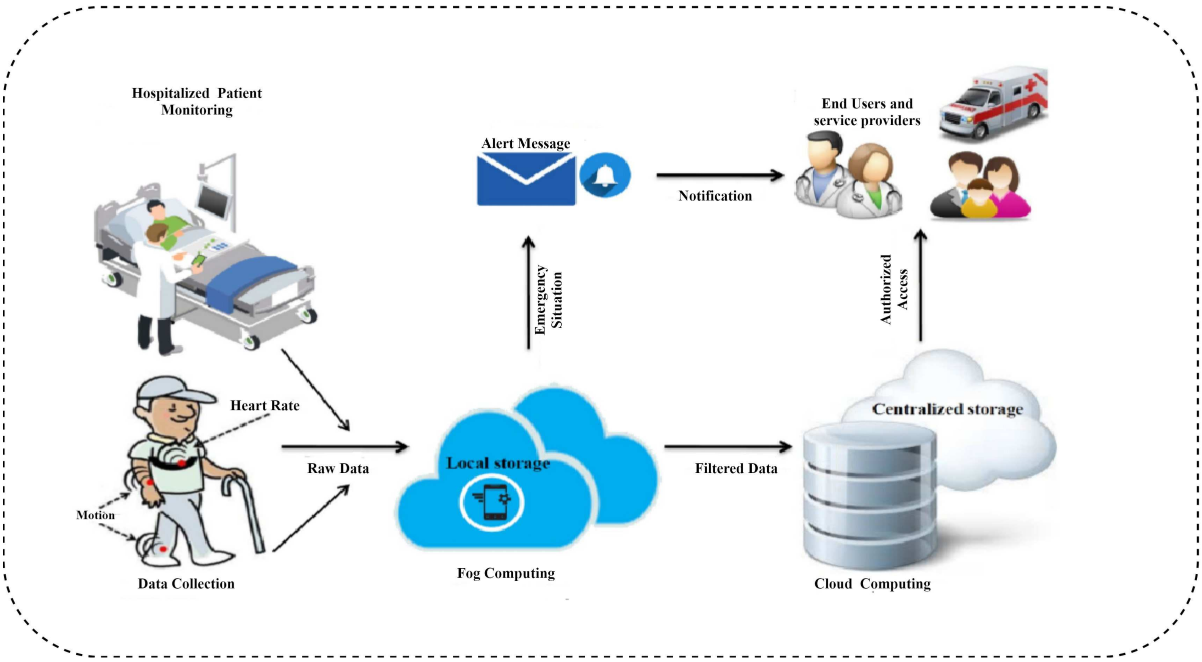

Figure 3. Fog-assisted healthcare system

layer. Finally, user-friendly online services for responses, report visualization, and feedback is provided by the service layer. The following sections present the vital modules of the presented fog-inspired medical framework.

5.1. **Perception layer.** Data sensing and acquisition are functions at the perception layer. Sensors linked to the human body regularly gather important physiological data including diabetes level, fever, pulse rate, blood pressure, perspiration, mobility, and contextual data such as humidity, air, and pressure. As a result of the temporal granularity of the health data, the categorization of events is performed in terms of static and dynamic. Static data are related to physiological data instances of the patients including walking time, standing time, and sleeping time. For dynamic data, the parameters include heart rate, body temperature, sugar level, and nutritional value of the meal. Moreover, data is stored in a specific format as shown in Figure 4. Specifically, UID depicts patient ID, Time depicts a temporal instance of data acquisition, and Q-Value indicates the quantified value of the parameter. Ambient data aids in the detection of odd trends and improves the precision of healthcare services. After then, the detected data is sent to the cloud layer for local processing. An intelligent hub is utilized to accumulate and combine the varied data sensed by multiple IoT devices to make the system energy efficient. Devices in the Health-IoT are dynamically arranged in a mesh format, depending on the circumstances. Hospital patients would benefit from this topology. A star topology is required for outside patients, where every IoT device interacts with the hub directly. Because energy-constrained data perception devices are utilized, an intelligent module is used as an application platform. To avoid security risks like eavesdropping and man-in-the-middle attacks, each sensor must verify authenticity to the hub. The hub wraps the varied data in a particular form and appends information to identify the patient and IoT device after successful verification. Through Bluetooth or ZigBee, the data is transmitted to the fog node for computing.

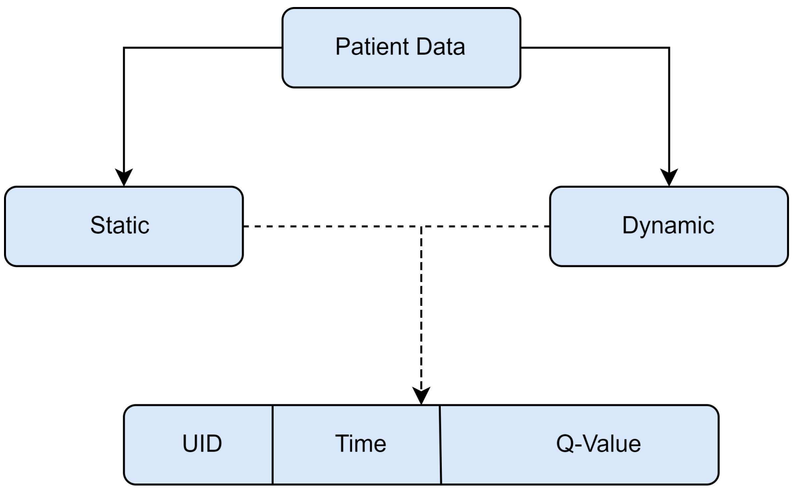

Figure 4. Uniform data acquisition format

5.2. **Fog layer.** The suggested remote patient healthcare system's fog layer is the most important component. HIoT creates a tremendous quantity of medical data as the number of users grows with the development of wireless technologies, smart devices, and personalized healthcare applications. The fog computing layer serves as a bridge between user-end devices and the standard cloud database, bringing computing closer to the network and allowing for more sophisticated and secure healthcare services. The edge, where data is created, is the best location to look at real-time health data. Distributed computing, distributed storage, mobile analysis, assessment, pruning, intermediary storing, data security, and privacy are some of the fog layer's major characteristics and benefits. Fog allows location awareness, local computing, low latency, and local storage because it offers localization, whereas the cloud server provides worldwide centralization. The fog layer's controller/hub collected the detected data and sent the processed health data to a cloud server for worldwide storage and administration. The fog can evaluate and forecast unexpected patterns by processing data locally. If it detects that a crucial parameter is above a certain threshold, it sends an emergency alert to medical professionals and family members through a smart device. Delivering early assistance, greatly avoids catastrophic outcomes such as death. For acquiring data instances from the sensors, the fog node acts as a gateway module for data analysis. Raspberry Pi, is used as the fog node in the current study which is programmed to acquire data instances after a delay of 7 seconds. Fog gateway comprises broker and worker module for data analysis. The fog broker acts as the resource provider intermediary from the local and cloud resource. Moreover, data security is ensured using the cryptography techniques at the current module. The proposed prediction mechanism is performed in the fog worker module. It comprises the embedded circuit for computation purposes. The classification results are communicated to the cloud platform of Amazon EC2 for alert generation procedure. The collective integration of fog-cloud is necessary for the realization of the overall objective of the proposed model.

5.3. **Data networking layer.** Comprehensive linking between IoT networks in the medical framework is provided by the network and communication layer. It serves as a link between the edge and the cloud layer for data transfer. The network layer, like the conventional OSI model, receives medical data from the fog platform and safely transmits it to the cloud server. Smartphones and other local networks make up the communication layer. A smartphone serves as a coordinator, collecting sensory data and encapsulating aggregated sensory information into a single packet in the correct format, which is then ready for communication to the cloud via wireless protocols. Flexible and scalable transmission and communication are possible thanks to the use of multiple networks and smart devices. To transfer data securely and enable competent connection among devices, robust routing protocols and MAC protocols can be widely used. Fog computing eliminates needless transmission, leading to reduced delay and network hindrances in the proposed healthcare system.

5.4. **Cloud computing layer.** In the presented medical framework, the cloud layer allows for central data repository, computing, managing, and analysis. The cloud server stores and manages the health data transmitted by the fog layer via multiple networks. Caregivers will use an application interface to provide warnings, notifications, reports, comments, and other health-related recommendations. Authorized users, such as general practitioners, specialists, research institutions, and emergency services, can log in and submit requests by giving patient data. Consumers are granted access to health information once the validity of the consumer and the requirements of the request have been verified. In summary, by combining the fog computing paradigm with cloud-assisted Health-IoT, intelligent healthcare services are provided. Patients and family members can receive reports and notifications from the cloud server via a mobile application. Though fog computing can provide sophisticated healthcare services, it lacks the storage capacity, accessibility to completely updated health records, the ability to run complicated algorithms, and the ability to reply to queries with desired data that can only be handled by cloud computing. Henceforth, the integration of fog-cloud platforms has been incorporated to realize an effective medical framework.

5.5. **Service layer.** Communication between healthcare facilities, medical organizations, immediate response services, and diagnostic labs is facilitated by the application layer. It provides chronic illness monitoring, surgical patients, physical activity advice, and emergency assistance, among other things. The application programming interface may be used by application developers to create service-related apps. A smartphone application is also being created to assist the healthcare system by offering notice and feedback services. When an alert message is received at the cloud-end from the sensing framework, it sends a message to the smartphone to inform them of the emergency. Smart devices enable healthcare service providers and users to freely access cloud services. Finally, it provides a graphical interface for response and visibility to the user.

6. **Monitoring Patients for Diabetes.** This section explains how the proposed fog-assisted healthcare system can be used in real time. The main goal is to demonstrate the efficacy of the proposed system's principal components. In the current paper, user monitoring is focused to detect diabetes risk levels. Consider the case of multiple users, each of whom is given an identification number for documenting, reporting production, and functions. To create an exact healthcare service, the user must ensure the security of personal data, medical status, curative services given, and medications used. Users' profiles include sensitive data, making them the potential for security breaches. As a result, pseudo identification is used to hide the user's true identity to protect privacy. On the cloud server, users' profiles are indexed based on pseudo-identity. The objective is to protect the users' personal information. As a result, all patients' identities are obscured, and information may be sent from the computing node into the cloud at any time.

The registered personnel is composed of a set of IoT devices, each with its novel identification, that is used to track a variety of physiological parameters. A smartphone with GPS (global positioning system) sensors to position users is also required. A medical preceptor attached to the patient's body transforms the acquired data into machine learning format and delivers it through ZigBee or Bluetooth to the smart device. To create a sequence file, the fog-node wraps the acquired data into a singleton packed by abstracting needed information and removing superfluous and flawed data. It records each sensory value in a local database after comparing it to the set threshold value. If a vulnerable value is identified, the fog device creates an alarm signal and informs the concern about the situation. If it is normal, it will be saved to the database for further examination. Finally, when the aggregated data acquires a health-threatening value and limits delay, it is forwarded for analysis, categorization, illness prediction, and prevention via a cloud platform. The fog device's authenticity is verified by the cloud server, and the report is saved for further study. The associated user's health record is updated regularly and stored safely in the cloud repository. The entire workflow is depicted in Figure 5.

6.1. **Categorization of diabetic level.** The diabetic level in the blood stream is classified into 4 categories based on a pre-defined threshold value: *normal*, *hypoglycemia* (reduced glucose level), *hyperglycemia* (enhanced glucose level) and *pre-diabetes*. *Hypoglycemia* is defined as an empty stomach blood glucose level of less than 59 mg/dl. It is *normal* if the result falls among 59 and 99 mg/dl. It varies from 99 to 119 mg/dl in *pre-diabetes*. Diabetes is diagnosed when the level exceeds 125 mg/dl. Before breakfast, the fasting glucose value is usually checked. Moreover, the oral glucose tolerance test measures glucose levels before and after 2 hours of eating (OGL). According to the American

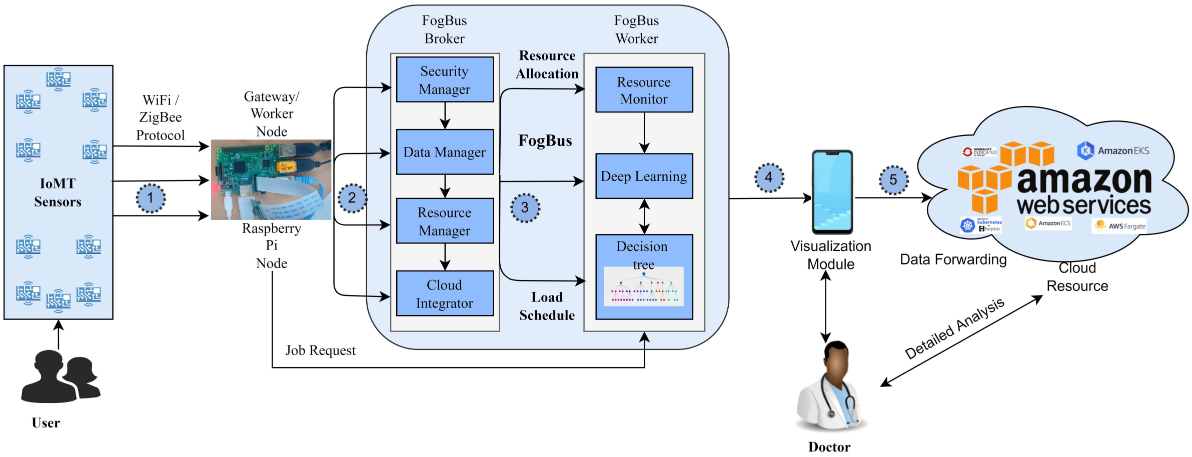

Figure 5. Workflow

Table 1. Diabetic patient's blood glucose level

Date	Time	Code	Value
01-02-2018	8:00	78	245
01-02-2018	11:05	56	1
01-02-2019	11:05	34	102
01-02-2018	11:05	67	121
01-02-2018	11:05	89	132
01-02-2018	11:05	54	110
01-02-2018	11:05	90	98
01-02-2018	11:05	17	60

Diabetes Association, glucose levels less than 139 mg/dl are normal, among 139 and 199 mg/dl are pre-diabetes, and more than 199 mg/dl are diabetes.

6.2. **J48Graft-based user classification.** Physical activity, nutrition, habitat, and environmental factors all affect the user's blood glucose level. To avoid catastrophic effects such as death, a trained model is required to estimate the medical vulnerability level. For multiclass datasets, J48Graft delivers better classification results with a low error rate. The J48Graft classifier has the benefit of taking less time to run on a multiclass dataset. Decision tree grafting is a technique for improving classification results while avoiding the creation of complicated trees. Grafting is used to reclassify instances in the decision tree that have misclassified data or no training data. It decreases the prediction error by a substantial amount. The J48Graft decision tree classifier is utilized in the proposed fog-assisted healthcare system to determine the diabetic patient's risk level by evaluating influential variables such as blood glucose level, body weight, physical activity, and food. The suggested system uses the J48Graft classifier to forecast the risk level of diabetes with increased accuracy in real time, preventing the user from dying prematurely. Table 2 presents the pseudo-code for the J48Graft classification technique.

6.3. **Generation of emergency signal.** Alert generation is a key part of the planned fog-assisted healthcare system since it sends notifications to users' smartphones regarding the present condition and danger level. It also maintains all information regarding the alarm production on the cloud server, including physical activity, location, time, food, habit, and contextual information relevant to the bad scenario. These actions are

TABLE 2. J48Graft decision tree (DT) algorithm

J48Graft decision tree (DT) algorithm
Input: Health parameters, Time instance
Output: Health parameter class
Initialize DT = Empty For each data parameter at time instance T, do Estimated Data Entropy = $-p_i \log_2 p_i$, where p_i is the probability that p belongs to the category i Estimated Calculated Entropy for all data instances = $\sum_{i=1}^{m} p_{ij} \log_2 p_{ij}$ On the branch Attribute C, present the entropy Estimate Split information = $-\sum_{i=1}^{w} \frac{p_i}{p} \log \frac{p_i}{p}$ *where w is the total number of attributes* Estimate gain information = $\frac{\text{Total entropy}}{\text{Split}}$ Identify parameter with maximum gain information Update the DT with next root node Remove the root node for a specific class End

automatically tracked by wearable sensors or a smart device at regular intervals. Predetermined threshold values are an important aspect of a well-functioning healthcare system. An alert is issued if the glucose level in the bloodstream exceeds the threshold value, alerting the user to the critical condition. If the user is in a normal state, the system will suggest preventative measures to reduce the risk of diabetes. If the user is at risk, the system will prescribe the appropriate medicine. Algorithm 1 describes the algorithm that is utilized to produce alert messages. Initially, numerous diabetic parameters are acquired from the patient in real time at a specific time instance. Each of the parameters is compared with the predefined threshold measure to determine the vulnerability of the specific parameter in terms of *safe and unsafe*. For specific time instances, the state of the patient is determined. Algorithm 2 is presented to generate the alert signal using the state of the patient. Descriptively, the current state acquired from Algorithm 1 is assessed. If the state is *unsafe*, then the alert signal is generated to the concerned caregiver and doctor. Else, if the state of the patient is assessed as *safe*, then the checkpoint is created. In other words, all the activities performed by the patient are acquired and stored in the database. The quantified value of an activity is compared with the patient-specific threshold measure. After ΔT time window, the entire procedure is repeated.

Algorithm 1: Patient state determination

Input: X number of diabetic parameters measures
Step 1: Determine parameters for the real-time time
Step 2: For $i = 1$ to X
Step 2.1: If (Parameter-value(i) > Threshold Value(i))
Then (Patient-State = Unsafe)
Step 2.2: Else (Patient-State = Safe)
Step 3: Return Patient-State and Exit
Output: Current State of the patient

Algorithm 2: Alert generation

Input: Event Set = (Health ∪ Environmental)
Step 1: Using Algorithm 1, Acquire health state of the patient
Step 2: Determine current timestamp
Step 3: If Patient-State = Safe, then Jumpto Step 4 Else Jumpto Step 7
Step 4: Do
Step 5: If Any-Event-Occurance = True If diabetic-level > β (threshold), Generate Warning Alert
Else, Add Event to Log
Any-Event-Occurance is a variable for acquiring events
β is per-patient personalized threshold
Step 6: After ΔT time space, Goto Step 1
Step 7: Do
Step 7.1: Generate Emergency Alert Signal
Step 7.2: Transfer (Log ∪ Information Health Attributes) to Doctor
Step 8: Exit

7. Experiment Evaluation.

This section assesses the fog-assisted healthcare system's performance efficiency in real-time settings. To estimate a user's risk level, the dataset is first collected and the relevant health parameters are evaluated. The user is then categorized as diabetic or not, and treatment recommendations are generated based on the circumstance.

7.1. Dataset specification.

The blood glucose level and physical activity datasets are not available in the repository. 2 distinct datasets from the UCI repository were used to verify the efficiency of the proposed healthcare system. The UCI diabetes dataset[1] is used, which comprises 70 sets of data on diabetic individuals' blood glucose levels over many weeks. At regular pre and after breakfast, snacks, lunch, and dinner times, the blood glucose level is measured for analysis. The major goal is to keep blood glucose levels stable through diet and physical activity. Henceforth, UCI PAMAP2 Dataset[2] is used for the experiments and analysis of diabetic patients. The PAMAP2: Physical Activity Monitoring Dataset contains 9 subjects, i.e., 1 female and 8 males, aged between 29 and 33 years, and BMI (body mass index) range between 25 and 28 kg/m^2 was used. Cycling, lying, ironing, standing, vacuuming, walking upstairs, walking downstairs, regular and Nordic walking, sitting, jogging, watching TV, computer work, playing soccer, automobile driving, rope jumping, folding laundry, and home cleaning are among the 18 physical activities. For analysis, the number of calories eaten after each action is determined. More than 10 hours of activity were tracked and offered for experimentation.

7.2. J48Graft efficacy.

J48Graft classifier is used to determine the risk level of diabetes, such as hypoglycemia, normal, pre-diabetes, or hyperglycemia. The J48Graft classifier was incorporated in Weka 3.6 after an experiment was done on a diabetic dataset to estimate the user's risk level. Several statistical metrics were used to assess the effectiveness of the J48Graft classifier. The improved performance of the J48Graft classifier may be seen in the greater success rate and decreased failure rate. The success rate is the proportion of properly categorized users to the total number of users, whereas the failure rate is the proportion of incorrectly classified users to the total number of users. To demonstrate the correctness and completeness of classifiers, evaluation measures such

[1] https://archive.ics.uci.edu/ml/datasets/Diabetes
[2] Source: http://archive.ics.uci.edu/ml/datasets/PAMAP2+Physical+Activity+Monitoring

as precision, recall, sensitivity, specificity, and accuracy are utilized. An examination of such statistical measures reveals that the suggested method is capable of accurately determining the risk level of diabetes. If the classifier is capable of producing high recall and accuracy numbers, it will also provide high precision values. The accuracy number indicates how well the classifier can reduce the error rate.

The suggested fog-assisted healthcare support system with J48Graft classifier has a high recall value, as the statistical measurements show that the proposed fog-assisted healthcare support system with J48Graft classifier is capable of accurately categorizing diabetic patients. There are fewer classification mistakes when the sensitivity is higher and the specificity is lower. To demonstrate the increased performance of the J48Graft classifier, 3 distinct methods are utilized for experimental evaluation: K-nearest neighbor, random tree, and multilayer perceptron. In terms of statistical assessment measures, the J48Graft decision tree classifies the risk level of diabetes more efficiently than other classification algorithms, as seen in the comparison chart of assessment metrics. Figure 6 and Figure 7 depict a comparison of several algorithms in terms of classification accuracy. It demonstrates that on multiclass datasets, J48Graft-based classification outperforms other classification methods.

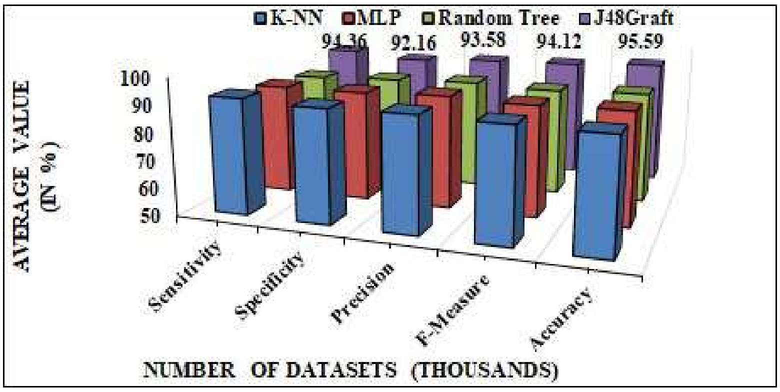

Figure 6. (color online) Categorization efficacy

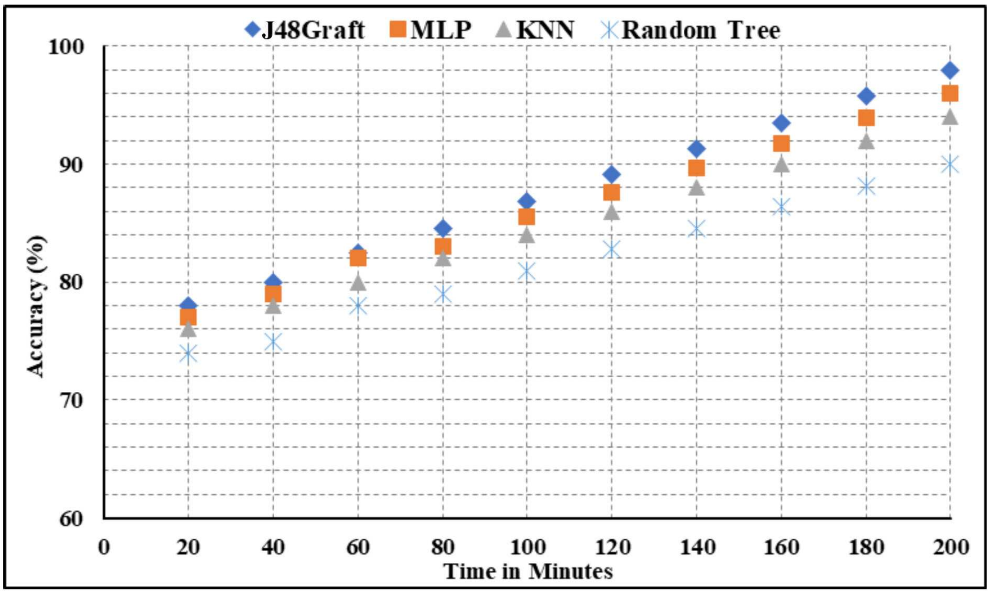

Figure 7. Accuracy prediction

7.3. **Experimental results.** On a smartphone with a Snapdragon 410 Quad-Core clocked at 450 MHz and 2 GB of RAM, the fog-assisted remote patient healthcare system is tested. Activity monitoring has been done using sensory data collected by wearable sensors over a certain period. The health data collected by sensors is sent to a fog device, where it is compiled and wrapped into a single packet, supplemented with header information, and then sent to a cloud server for storage. Following that, medical professionals provide recommendations to improve a patient's wellbeing based on the readings and calories eaten during physical exercise. After collecting all the raw data, it is subjected to pre-processing for removing redundant data and filling missing values. Then the intermediate data is shared with the medical experts for proper treatment and suggestions. 2 categories of diabetic patients should be considered when examining diabetes patients: elderly users who remain at home and active users. Type II diabetes mellitus is strongly associated with obesity and hypertension. A glycosylated hemoglobin level of more than 7.0 is typically regarded as a positive diabetes diagnosis. Table 1 displays the few patients' records with the characteristics of date, time, code, and value. Pre-supper is coded as 62, regular insulin dose is 33, NPH insulin dose is 34, pre-snack is coded as 64, pre-breakfast is coded as 58, and pre-lunch is coded as 60. Figure 8 depicts the graph for pre-breakfast blood glucose level measurements of a patient. When looking at the pre-prandial data, it is seen that the majority of the pre-dinner readings exceeded the upper limit, but very seldom before breakfast. As a result, the patient is advised to burn more calories before dinner and modify dinner eating habits, therefore increasing insulin production through physical exercise. The beta islet cells of the pancreas can produce very little or no insulin in diabetic patients. The primary goal is to lower blood glucose levels to a normal range through diet and physical activity. Blood glucose levels might drop during physical activity and exercise or remain constant after some time. Calculating the number of calories ingested per exercise and subtracting it from total intake can assist the doctor or nutritionist in determining how many extra calories should be burned. Table 3 and Table 4 display a subject's personal information and actions in seconds, respectively.

To sustain a healthy lifestyle, an average individual needs approximately 2500 kcal per day. Physical activity and a healthy diet are 2 of the most effective ways to lower

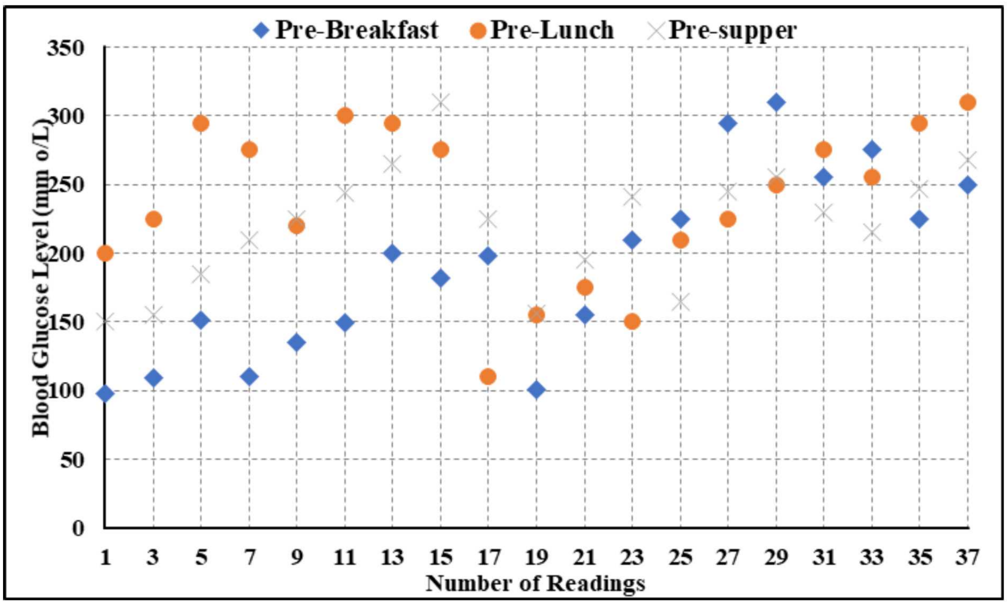

FIGURE 8. Blood glucose level monitoring

Table 3. Subject information

Subject ID	101
Gender	Male
Age	35
Height (cm)	182
Weight (kg)	83
Resting heart rate (bpm)	75
Maximum heart rate	193
Dominant hand	Right

Table 4. Physical activity monitoring

Physical activities	Duration (in seconds)
Lying	271.89
Sitting	234.76
Standing	217.65
Walking	218.32
Running	178.9
Cycling	235.78
Nordic walking	202.76
Watching TV	836
Car driving	545.9
Walking upstairs	158.7
Walking downstairs	148.7
Vacuum cleaning	229.3
Ironing	372.5
Folding laudary	216.8
House cleaning	540.2
Rope jumping	540.2

blood glucose levels and enhance pancreatic insulin production. The number of calories burnt per calorie consumed is determined based on the kind and duration of physical activity. Figure 9 depicts a graph for 15 distinct physical activities carried out by subject 101 throughout the period given in PAMAP2 Dataset. Subject 101 did not do any work and also did not participate in soccer. Assume the patient ate 2500 calories but only burnt 1617 calories throughout his physical activity. As a result, he must burn the remaining 883 kcal to maintain a healthy lifestyle and avoid diseases such as hypertension, diabetes, and cardiovascular disease. The information is subsequently shared with domain experts for tailored recommendations and ideas. Furthermore, approved domain specialists continually access the activities done as well as the number of calories eaten for suitable comments and recommendations. Figure 10 depicts the activities completed and the number of calories burnt for each activity during a period. A subject's actions take up 4693.07 seconds in total. After evaluating the patient's physical activities and the number of calories burned, it is recommended that the patient changes his or her diet and increases his or her exercise for a longer period. The suggested fog-assisted healthcare system is thoroughly investigated to ensure that alert creation is effective. The reaction time is an important metric for estimating the efficiency of alert production. Precision, sensitivity, and specificity are some additional statistical assessment measures employed

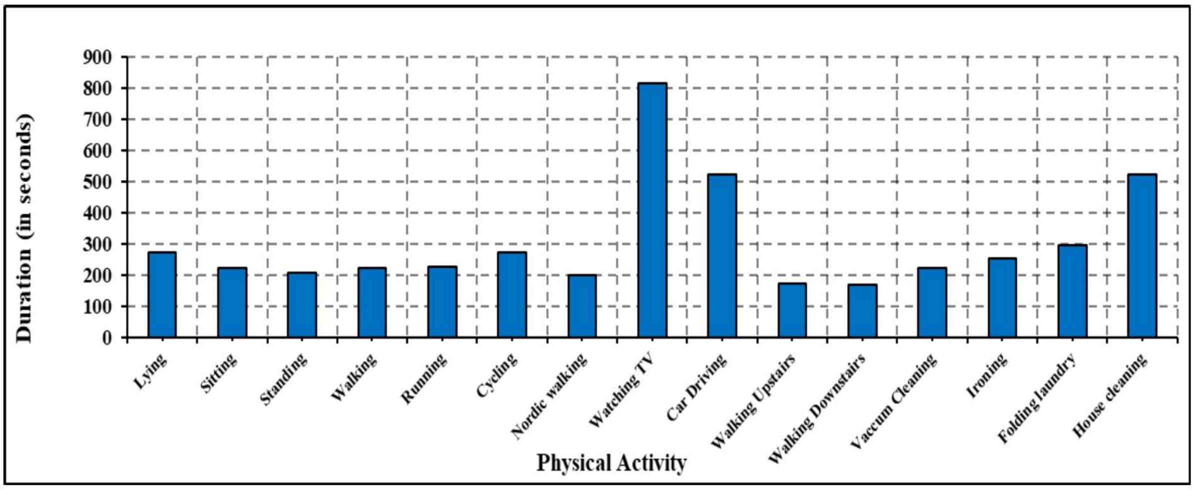

FIGURE 9. Physical activity specification

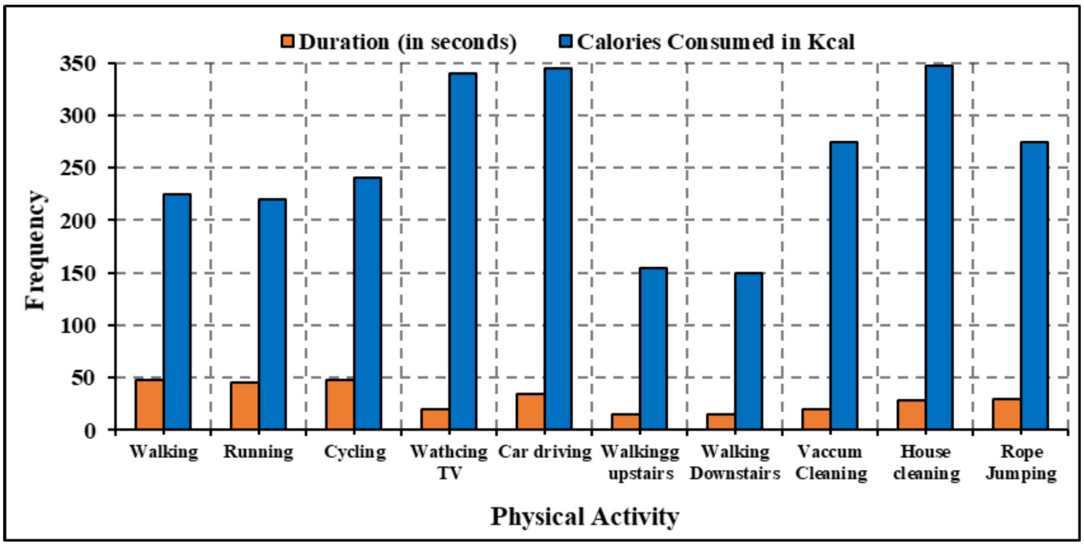

FIGURE 10. Consumption of calories

for this purpose. The improved performance of the suggested system may be seen in the higher accuracy, sensitivity, and specificity values.

Alert Generation Efficacy. To determine the efficiency of warning production, the system is assessed analytically. To put it another way, numerous statistical criteria are assessed for various warnings sent to concerned clinicians. The proposed system generates two sorts of notifications, as described in the preceding section: warning alerts and emergency alerts. The primary goal of statistically evaluating the warning generating process is to identify "false positive" alerts based on the overall number of alerts produced. Other metrics for the proposed system are also examined, such as accuracy, sensitivity, and mean absolute error. The statistical findings obtained for the proposed model across the whole monitoring method are summarised in Table 5. The proposed system had a low rate of false positive alerts, which totaled 3.15 percent, suggesting good alert generating accuracy. Furthermore, the suggested system's high precision (91.20 percent), sensitivity (87.41 percent), coverage (97.56 percent), and specificity (94.33 percent) values demonstrate its excellent performance. Furthermore, for the alert generating process, low error rates were achieved in the form of mean absolute error (3.11 percent), root mean square

Table 5. Statistical results

S. No.	Parameter	Value (in %)
1	False positive alert	3.15
2	Sensitivity	87.41
3	Specificity	94.33
4	Precision	91.20
5	Coverage	97.56
6	Mean absolute error	3.11
7	Root mean square error	2.56
8	Relative absolute error	7.87
9	Root relative squared error	3.43

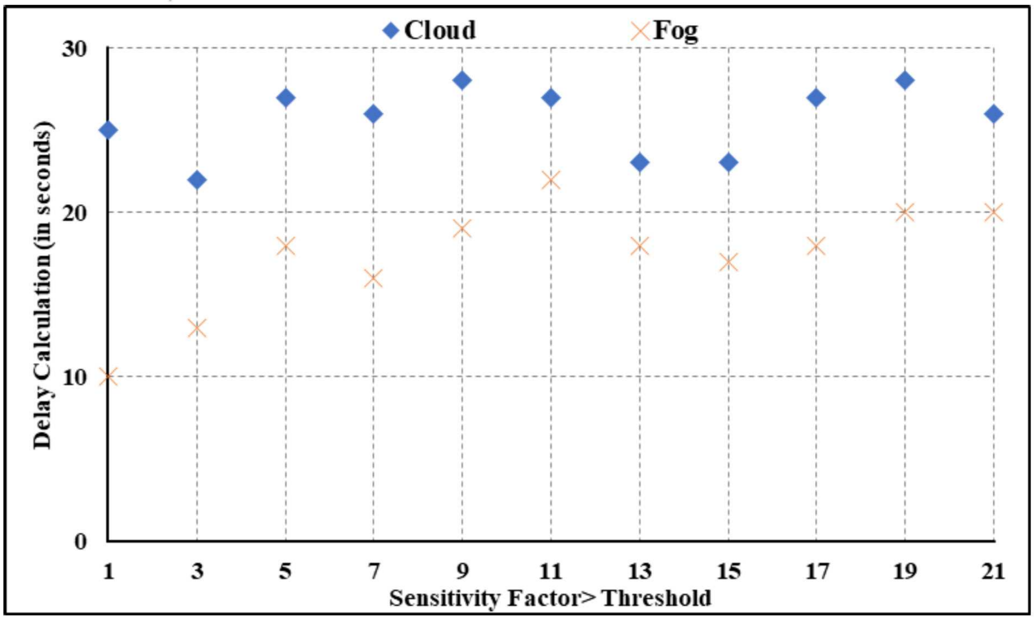

Figure 11. Alert generation efficacy

error (2.56 percent), relative absolute error (7.87 percent), and root relative squared error (3.43 percent). Also, the number of delayed alerts generated divided by the total number of alerts generated is used to calculate alert generating efficiency. The time it takes to create an alert after an event occurs is called delay time. When comparing cloud computing to fog computing, the graph (Figure 11) reveals that cloud computing has a higher latency rate. Because a large volume of data is transferred for data processing in cloud computing, network congestion occurs. However, because of the proximity of fog computing, communication and computation take place at the network's edge. It lowers latency by reducing network traffic and capacity.

System Stability. Furthermore, the suggested system is tested for stability measurement in addition to the results obtained in the preceding sections. Because the system is impacted by the timing of numerous occurrences, determining the temporal stability performance is critical. This type of measurements is usually described in terms of mean absolute shift (MAS). A lower shift value suggests that the system is less stable over datasets, whereas a larger shift value indicates that the system is more stable. The suggested system's MAS was in the range of (0.51-0.74), indicating that it is quite stable (Figure 12).

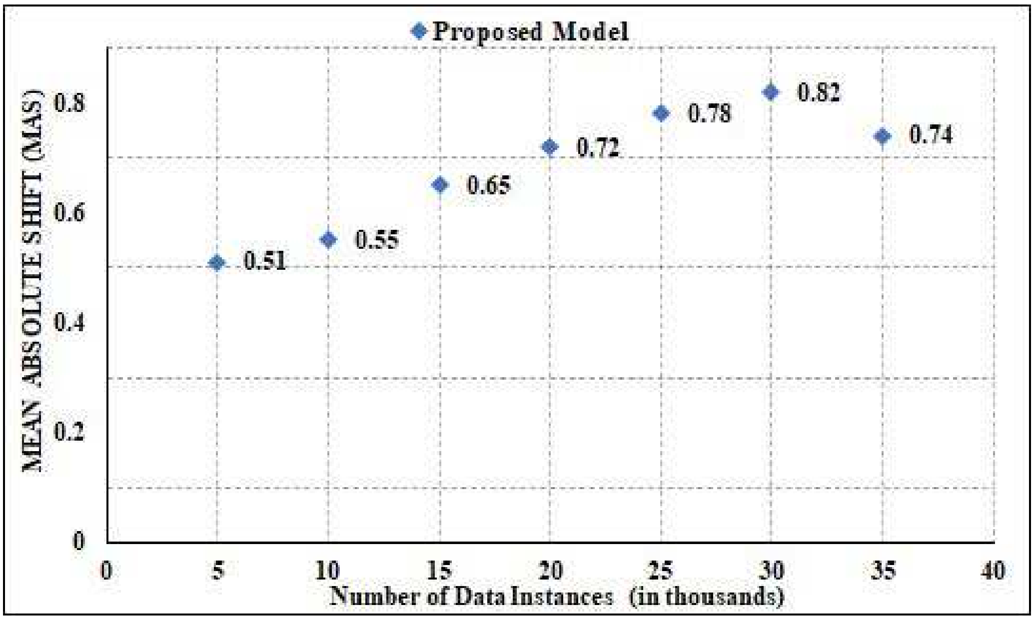

FIGURE 12. System stability

The remote patient health monitoring system relies heavily on fog computing as an intermediary layer. Because health data is handled at the intermediate fog layer, the health monitoring system's performance and efficiency are improved. Duplicate information and needless interactions are removed, resulting in a performance boost. Due to low latency and network bandwidth, the execution time is decreased. The delay rate is calculated as the time it takes to categorize a user's diabetes risk level.

7.4. **Medical significance and future perspective.** Diabetes is becoming more prevalent, and it is now considered a common condition in the modern world. Diabetes is one of the 15 main causes of early death. Diabetes can affect people of any age or gender, and it can lead to cardiac arrhythmia, heart attack, renal failure, stroke, and blindness. This occurs as a result of fluctuations in blood glucose levels. Hypoglycemia occurs when the glucose level falls below the usual range, whereas hyperglycemia occurs when it increases over it. Although medicines are available, they cannot be entirely healed; the only way to prevent catastrophic effects is to keep the amount of glucose in the bloodstream under control. To live a healthy lifestyle, it is necessary to continuously monitor and regulate insulin levels in real time.

Future Perspective. Using the J48Graft classifier, a fog-assisted healthcare assistance system is suggested to determine the diabetes risk level. However, several issues must be solved in the future. The suggested method was created specifically for diabetes, and it has to be developed to do effective assessments on many illnesses at the same time based on important characteristics and risk factors. Because the suggested method makes use of sensitive patient data, it is vulnerable to privacy and security concerns. As a result, there is a great need for research into powerful cryptography solutions that can protect users' sensitive data without jeopardizing the system's performance and efficiency. The study will be expanded to give timely and user-centric suggestions for registered users by utilizing contextual information and expert knowledge.

8. **Conclusion.** Due to advances in information and communication technology, it is now possible to monitor blood glucose levels in real time to regulate diabetes and avoid catastrophic repercussions. We suggested a fog-assisted healthcare system for diabetic

patients who live in distant areas in this paper. The suggested healthcare system uses a fog computing layer to link the IoT to a cloud server for continuous real time monitoring of physiological signals and contextual data. J48Graft decision tree classifier is used to generate an accurate prediction of blood glucose risk levels. J48Graft outperforms other baseline methods by acquiring 98.56% in classification accuracy. Local data storage, mobility, scalability, and interoperability are done by using fog computing as an intermediary fog computing layer. Furthermore, it extends cloud computing capabilities to the network's edge and simplifies the creation of emergency alerts. To validate the efficacy of the fog computing-based method, the experimental findings are compared to the cloud computing healthcare system. The experimental findings demonstrate performance enhancement of fog over cloud computing for bandwidth efficiency, low latency, and greater classification accuracy.

Future Research. For future research directions, the current work can be expanded to include edge devices for temporal efficacy. Moreover, fog-based resource optimization is another aspect that can be addressed in the current domain. Furthermore, network security over fog computing is another open challenge that can be addressed.

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Author Biography

Abdulaziz Aldaej received the M.Sc. and Ph.D. degrees in information systems from the University of Surrey, U.K., in 2010 and 2015, respectively. He is currently an Assistant Professor with the Department of Information Systems, College of Computer Engineering and Sciences, Prince Sattam Bin Abdulaziz University, Saudi Arabia. His research interests include semantic Web technologies, network security, AI, the IoT, and human-computer interaction.