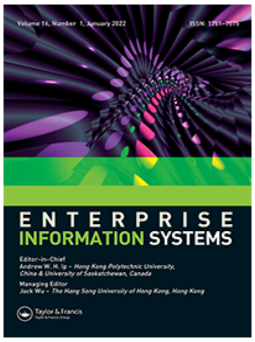

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IoTPulse: machine learning-based enterprise health information system to predict alcohol addiction in Punjab (India) using IoT and fog computing

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ABSTRACT

This paper proposes IoT-based an enterprise health information system called ***IoTPulse*** to predict alcohol addiction providing real-time data using machine-learning in fog computing environment. We used data from 300 alcohol addicts from Punjab (India) as a case study to train machine-learning models. The performance of IoTPulse is compared against existing work using various parameters including accuracy, sensitivity, specificity and precision which shows improvement of 7%, 4%, 12% and 12%, respectively. Finally, IoTPulse is validated in FogBus-based real fog environment using QoS parameters including latency, network bandwidth, energy and response time which improves performance by 19.56%, 18.36%, 19.53% and 21.56%, respectively.

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KEYWORDS
Enterprise health information system; internet of things; alcohol abuse; healthcare; machine learning; fog computing; IoT; information system

1. Introduction

The increasing trend of alcohol addiction is simply not a condition that affects the individual but can have huge repercussions on work culture in enterprises across the nations. The use and abuse of alcohol drugs has caused great concern as it has affected working human resources in diverse age groups, employed in different enterprises. According to the World Health Organisation (WHO) informed the death of more than 3 million people due to damaging use of alcohol in 2016. It represented 1/20 deaths and approx. 5% of the global disease burden (Global Status Report on Alcohol and Health 2020; Lipari, Hedden, and Hughes 2014). Approximately, twenty six billion dollars was exhausted in 2015 in the US alone (The Federal Drug Control Budget: New Rhetoric, Same Failed Drug War 2020). Alcohol addiction if detected well in time can be treated at early stage. However, the prolonged alcohol use could result in health hazards like abdominal disorders, leukaemia, eye ailments, pancreatic cancer, chronic lung infections, dental infections, coronary heart and cardiovascular diseases (Tseng et al. 2018). Other harmful

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effects are related to the reproductive system, childbearing capacity, frequent miscarriages in women, and sudden infant death syndrome (Chhabra, Hussain, and Rashid 2019). Injurious health hazards and the damaging effects of alcohol are proportional to the amount of alcohol consumed with time. Moreover, excessive use of alcohol has badly affected the personal as well as professional lifestyles of working individuals in enterprises. Enterprise health information systems (EHIS) (Shang et al. 2016) are focused on exploring solutions to detect alcohol addiction with higher efficiency and accuracy at its early stage to avoid future problems and maintain a healthy work culture in enterprises (Armstrong 2007).

Observations of alcohol consumption patterns and the correlation between the alcohol consumption and consumer's health features from real-time data, addiction in its early stages can be predicted (Global Status Report on Alcohol and Health 2020; Lipari, Hedden, and Hughes 2014; Armstrong 2007; Chhabra, Hussain, and Rashid 2019). Early detection using such data may aid a physician's diagnosis or an expert system's judgement (Hong et al. 2018). Although this is beneficial, the lack of frameworks that can continuously collect real-time personal data from user-devices and derive meaningful insight for accurately detecting alcohol addiction is a major challenge (Chatrati et al. 2020; Tang et al. 2019a). The Internet of Things (IoT) in this context is beneficial (Chen et al. 2018; Dumka and Sah 2019; Varghese et al. 2016), sensors, Radio-Frequency IDentification (RFID) chips, smart devices and microprocessors (integrated as a health monitoring device) are employed in an EHIS for collecting individual's health-related data (Sharma and Singh 2019; Singh and Singh 2019). The data can then be processed and used for detecting alcohol addiction using Machine Learning (ML) (Baig et al. 2019; Souri et al. 2020). This requires advanced connectivity of devices (Hong and Varghese 2019), and hence a number of health monitoring frameworks have been proposed to collect physiological information of a patient using EHIS (Tuli et al. 2020b; Wang et al. 2018).

1.1. Motivation and our contributions

Earlier, several EHIS have been proposed to utilise employees' health data/information held in EHIS to strategize employee health plans and policies in an enterprise system (Chatrati et al. 2020; Tang et al. 2019a; Tang et al. 2019b). State of the art technologies like ML and IoT have not been exploited to its full potential in predicting the employees' health status (Hosseinzadeh et al. 2020; Chen et al. 2020). Moreover, the employee health data, real-time data collection and processing has not been fully addressed since it is challenging to continuously monitor an employee's health (Chen, Lughofer, and Polikar 2018; Vijayakumar et al. 2019). Motivated by the successful applications of IoT (Xu and Buyya 2017; Shukla et al. 2019; Mutlag et al. 2019) in other fields of technological development integrated with the fortes of ML, an IoT-based EHIS called ***IoTPulse*** has been proposed to predict the alcohol addiction using ML model with high accuracy. An alcohol consumer can be monitored using IoT-enabled health monitoring devices. Fourteen healthcare monitoring devices such as Zig-Bee, Bluetooth etc. when equipped with IoT technologies are used to sense and pass on the employee health data to the EHIS. The collected data from health monitoring devices has been fed to ML models to predict whether the individual under study is an alcoholic or not. Further, IoTPulse is validated in a real fog environment using FogBus to test in terms of energy, latency, response time and network bandwidth as compared to existing techniques. Also, various open challenges as future directions have been highlighted that needs to be addressed while architecting IoT- and ML-based EHIS. The ***main contributions*** of this research work are:

•Propose an IoT-based EHIS called ***IoTPulse*** for detecting alcohol addiction in employees of an enterprise.

•Implement well-known ML models such as Bayesian Network, Neural Networks and k-Nearest Neighbour (KNN) to effectively predict alcohol addiction.

•Performance of three ML models is evaluated based on various performance parameters such as recall or sensitivity, accuracy, specificity and precision.

•In our alcohol addiction case study, we classify the consumer as an addict or not based on training data collected from 300 individuals from Punjab (India).

•IoTPulse is validated in real fog environment using FogBus to test the performance in terms of QoS parameters such as energy, latency, response time and network bandwidth as compared to existing technique.

1.1.1. Article organisation

The remainder of the paper is organised as follows: Section 2 presents the related work. ML models are described in Section 3. Section 4 presents the IoTPulse, an EHIS. Section 5 presents prediction mechanism for alcohol addiction. Section 6 discusses the performance evaluation of various machine-learning models. Section 7 presents the validation of IoTPulse on fog computing environment. Finally, Section 8 summarises the paper and highlights promising future directions.

2. Related works

Alcohol is a toxic and psychoactive substance capable of producing addiction or dependence (Global Status Report on Alcohol and Health 2020). Alcoholic beverages have become a routine part of today's society (Poongodi et al. 2020). The people who are employed in enterprises where alcohol frequently accompanies socialising fall prey to ill effects of alcohol consumption (Zhao et al. 2019). The list of alcoholic beverages is big and is controlled by the law of different nations (Fedorova et al. 2019). Addiction is defined as a disorder, which affects the physical as well as the psychological health of a person. It is characterised by compulsive usage of toxic and psychoactive substances despite the known adverse consequences. WHO and other national health organisations conduct surveys periodically to study the behaviour of alcohol consumers and effects of alcohol on society. The epidemiologic studies have identified many different patterns and trends in alcohol consumption and its harmful effects on personal, professional and societal fronts (Fedorova et al. 2019). These studies found that adolescence is the common age when addiction of alcohol or alcoholic beverages typically commences. It is a challenging task to study and find the exact and appropriate reason or cause of such addiction. By studying the behaviour of alcohol consumers at home and offices, affected areas, and relating the consequences on enterprise work culture and enterprise health policies, strategists can create effective enterprise health systems and models (Magno et al. 2019). The advancement in artificial intelligent technologies and health informatics, various tools and techniques are adopted to examine the underlying patterns of alcohol consumption to enable a well in time prediction of alcohol addiction (Dhillon and Singh 2019). Early prediction is an extremely significant component in the EHISs as accuracy remains a prime aspect in assessing the overall performance of the EHISs (Kaur et al. 2018). The recent relevant studies in physiological health systems reported vitro models creating leveraging tools for predicting effects in drug discovery (Venkatakrishnan, Moltke, and Greenblatt 2001). On the other hand, the vitro model suffers from misinformation, which mislead the prediction results (Terasaki et al. 2003; Venkatakrishnan et al. 2003). For example, Liver is the most probable organ that may damage by the over-consumption of alcohol and researchers are exploring DILI (Drug-Induced Liver Injury) (Andrade et al. 2005). The authors work on mechanism-specific biomarkers to improve the physiological metrics (Lin and Khetani.2016 2016). Authors suggested using Neural Networks (NN) to discover DILI as their work performed with accuracy more than 85% on the data set of 198 drugs patients (Xu et al. 2015). In other significant work, researchers were able to identify a drug addict using NN (Zhang et al. 2018). The data collection and availability of physiological data remains key concerns while working with ML models for EHIS. As the number of alcohol consumers are increasing day by day, so as the demand for alcohol addiction prediction has seen an uptrend. The researchers studying the behaviour of alcohol consumers in enterprise systems have also indicated genetics, environmental and social factors that can lead to alcohol addiction. The United Nations Research Institute for Social Development (UNRISD) survey showed that alcohol abuse correlated positively with the broken families than with poverty and scarcity of resources (Jerak 2018). According to (Saingam 2018), urbanisation and fast cultural changes are the key factors identified behind the increase in alcohol consumption. With the advancement of sensor technologies (Geng and Du 2020), IoT based devises have become a prominent solution to 24 $\times$ 7 health data collection. Sensors have revolutionised the real time healthcare systems (Subramaniyaswamy et al. 2019). RFID enabled devices integrated with medical devices can be employed to continuously screen patients and consequently can improve various e-health services deployed at hospitals or other enterprises in a cost effective manner (Mahmud, Koch, and Buyya 2018). Wireless Sensor Networks (WSN) can also be used in hospitals for real-time continuous monitoring of patients. Health and Insurance enterprises can deploy such systems for keeping a close watch on the patient and follow up for medications (Farahani et al. 2018; Singh and Singh 2018).

The EHISs also use the multi-agent technology integrated with IoT environments that concentrates on using heterogeneous devices and further collaborates with multiple users (Ali and Roudsari 2017). A project named SAPHIRE, clinical decision support system has been developed capable of sending patients' data remotely (Hein et al. 2006). These systems can mitigate the human-error risks (Kaur, Kaur, and Singh 2020). Various applications of the IoT in healthcare are advantageous in remotely monitoring and analysing the health of the patient. Researchers have developed an IoT-enabled system having biomedical sensing devices with cloud storage of continuously generating data (Wan et al. 2018). An IoT-based real-time Electrocardiogram (ECG) monitoring system has also been developed to analysis the health of heart patients (Tuli et al. 2020a; Gill et al. 2019). The component architecture, implementation, component integration and various artificial intelligent algorithms are also considered in Cypress WICED IoT-based technology (Armstrong 2007). Such architectures for healthcare-based systems has found its scope of application in smart cities and smart enterprises (Tuli et al. 2020a). Another IoT-based smart hospital-based framework has been proposed for remote data collection (Cáceres, Rosário, and Amaya 2018). IoT-based systems are used to monitor the effects of toxic and psychoactive substance on individual's health. In (Jara et al. 2010), researchers proposed an IoT-based drug interaction checker to explore hazardous consequence of alcohol. Information systems integrated with edge devices such as smartphones, laptops and tablets were utilised to explore the ill effects of overconsumption of psychoactive substance and their reactions. To improve the accuracy of such prediction systems for EHIS, researchers have implemented a distributed forecast movement approach for Healthcare applications using IoT (Zamanifar, Nazemi, and Vahidi-Asl 2017). Mario et al. (Gutierrez et al. 2015) proposed Smartwatch Sensor Data-based Prediction (SSDP) system that predicts blood alcohol content. Drunkenness of a person can be predicted using SSDP system which gathers sensor data, and NN-based approach is applied to analyse the statistics. It is capable of finding the user's intoxication level and suggesting the health consequences. With such real-life applications of IoT in enterprise health systems, IoT has come up as an excellent and realistic technology to be used for alcohol addiction prediction.

2.1. Critical analysis

Table 1 shows the comparison of IoTPulse with previous research works. All the above-related works have presented alcohol prediction techniques using ML models without considering the computational component concurrently in a single framework, but it is very significant to incorporate computation model such as cloud or fog computing (Bitam, Zeadally, and Mellouk 2018) to optimise the various QoS parameters in a controlled and holistic manner. None of the existing works validated against specificity and recall and only three frameworks (Wan et al. 2018; Cáceres, Rosário, and Amaya 2018; Zamanifar, Nazemi, and Vahidi-Asl 2017) considered IoT devices for data collection at runtime. As per literature, there is a no existing EHIS, which considers IoT-based data collection module, three important ML models (KNN, Neural Networks and Bayesian Network) simultaneously and fog computing to improve computation during predictions, which validates the proposed system IoTPulse using FogBus (Tuli et al. 2019a) i.e. real fog environment. The proposed EHIS, IoTPulse is validated against similar technique using four QoS parameters such as energy, latency, response time and network bandwidth. Due to this, the current alcohol prediction systems become inefficient to respond in these situations. Thus, IoTPulse uses an EHIS leveraging both ML models and integrated IoT and fog computing for optimum results.

3. Machine learning models

Machine Learning aids to determine basic patterns and extract the required information from the large volume of data using computation and statistical process (Bansal et al. 2020). The use of machine learning models can be used for prediction of alcohol addiction to improve current EHIS (Tuli et al. 2019b; Naranjo et al. 2017). Further, these systems help to monitor and diagnose the other related disease using various IoT devices (Tuli et al. 2020a). Based on anomaly detection, regression, clustering and classification, the existing ML techniques can categorised into four types and we used classification category in this paper to predict alcohol addiction. For classification process, three most effective ML

Table 1. Comparison of IoTPulse with existing research works.

			ML Model			Performance Parameters for ML Models					QoS Parameters			
Work	EHIS	IoT	KNN	NN	BN	Accuracy	Precision	Sensitivity	Specificity	Fog	Energy	NB	Latency	Response Time
(Lin and Khetani.2016 2016)			√			√								
(Xu et al. 2015)				√		√								
(Zhang et al. 2018)				√	√	√	√							
(S. Ali and Roudsari 2017)			√			√	√							
(Wan et al. 2018)		√			√	√	√							
(Cáceres, Rosário, and Amaya 2018)		√												
(Zamanifar, Nazemi, and Vahidi-Asl 2017)		√			√	√								
(Gutierrez et al. 2015)				√		√								
IoTPulse	√	√	√	√	√	√	√	√	√	√	√	√	√	√

Abbreviations: KNN: k-Nearest Neighbour, NN: Neural Networks and BN: Bayesian Network, EHIS: Enterprise Health Information System, IoT: Internet of Things and QoS: Quality of Service; NB: Network Bandwidth algorithms including Bayesian Networks, KNN and Neural Networks are used (Tuli et al. 2019b).

3.1. Bayesian networks

A Bayesian network is a network of connections that uses statistical methods to describe relationships of likelihood between different elements. This methodology is helpful in modelling an uncertain domain. Bayesian Networks indicates the likelihood of the occurrence of the event that arise from the previous event. e.g. e_1 -> e_2 represents the likelihood of the occurrence of event e_2 from event e_1. The equation for Bayesian networks is written as follows:

$$P\left(\frac{h}{e}\right)=\frac{P(h).P\left(\frac{e}{h}\right)}{P(e)} \tag{1}$$

Here, P(h/e) denotes the likelihood of occurrence of h given e, P(h) is the prior probability of hypothesis. P(h/e) is the likelihood of occurrence of *e* given *h*. P(e) is the events prior probability. P(e) should not be equal to 0 and sometimes its value is fixed i.e. P(e) = 1. Events can recursively cause additional events in an IoT environments. A chain reaction of these events is formed in which their likelihood of occurrence depends on the event proceeding them and is given as follows:

$$e \rightarrow e_n \rightarrow (e_n-1) \rightarrow (e_n-2) \rightarrow \ldots e_1 \rightarrow e' \tag{2}$$

The likelihood of such an occurrence can be determined by a\pplying the Bayesian method as:

$$P\left(\frac{e_n}{e_n-1}\right)*P\left(\frac{e_n-1}{e_n-2}\right)*P\left(\frac{e_n-2}{e_n-3}\right)\ldots\ldots\ldots P\left(\frac{e_n}{e_{n'}}\right) \tag{3}$$

3.2. Neural networks

Neural Networks (NN) is an efficient machine-learning algorithm that operates on the theory of human brain structure. These structures help in performing some important operations like data mining, pattern recognition and classification (Mancini et al. 2019). Neural Networks are also known for their fast parallel-distributed computations. Figure 1 shows the structure of neural network.

For a training set, $\left\{i_j, o_j | i_j \in R^c, o_j \in R^m\right\}_{j=n}^{n}$, if n describes total observations, c specifies the covariates dimension, o_j denotes the target variable, then NN can be written as follows:

$$f_L(i)=\sum_{L}^{j=1} a\left(i, wt_{j,} b_j\right) t_j = hd(i)t \tag{4}$$

Here, *a* states activation function, Wt_j describes weights provided to input nodes, b_j outlines the bias value, hd(i) describes hidden layers for input variable, *t* states the target variable (Dhillon and Singh 2020). Figure 1 shows the structure for neural network. Neural Network with hidden layers is defined as:

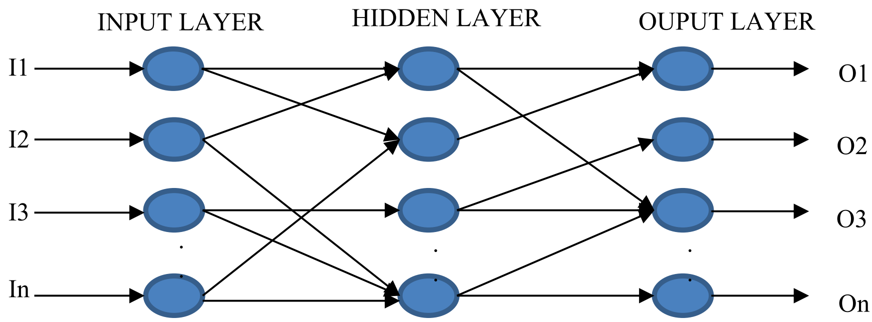

Figure 1. Multilayer perceptron neuron network.

$$HD = \begin{bmatrix} hd_1 \\ hd_2 \\ . \\ . \\ hd_n \end{bmatrix} = \begin{bmatrix} a(wt_1,b_1,i_1)\ldots\ldots a(wt_L,b_L,i_1) \\ a(wt_1,b_1,i_2)\ldots\ldots a(wt_L,b_L,i_2) \\ . \\ . \\ a(wt_1,b_1,i_n)\ldots\ldots a(wt_L,b_L,i_n) \end{bmatrix}_{(n*l)} \quad (5)$$

The target matrix is specified by:

$$O = \begin{bmatrix} o_1^T \\ o_2^T \\ . \\ . \\ o_n^T \end{bmatrix} = \begin{bmatrix} o_{11}\ldots\ldots o_{1m} \\ o_{21}\ldots\ldots o_{2m} \\ . \\ . \\ o_{n1}\ldots\ldots o_{nm} \end{bmatrix} \quad (6)$$

With the given equation, the output weights can be:

$$t = HD\left(\frac{I}{C}HDHD\right)^{-1} O \quad (7)$$

Where *I* denotes *n**m* matrix.

For the prediction of alcohol addiction, neural networks play a significant character in unfolding the hidden layers which are probabilistic in nature. There are various forms of artificial neural network, we have focussed on the Multi-Layer Perceptron (MLP) Neural Network Model in the present research. In ML the learning process is vital. Therefore, feed forward propagation learning method is used for building the model in the proposed work. This learning method works iteratively by feeding input with computed error and output (Mancini et al. 2019). The total number of neurons to be used in hidden layer are calculated by the given formula:

$$\text{Number of Neurons} = \frac{(\text{attributes} + \text{classes})}{2} \quad (8)$$

3.3. *K Nearest Neighbour (KNN)*

KNN is a supervised classification algorithm, which works by finding the nearest possible class for the elements, and classify it based on a hypothesis that closer lying elements belong to the same class. KNN works by calculating the difference two instances using Euclidean distance function (Jiang et al. 2007). It works as follows:

For a given instance x_j, y_j can be:

$$y_i = \operatorname{argmax} \sum E\left(y_n, c\right) \tag{9}$$

Here, $c \in \{c_1, c_2, \ldots, c_m\}$, y_i is the predicted class for x_1 and n is the number of classes. Where E is the Euclidean distance d(x,y) between two points x and y and is given by following equation:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} \left(a_i(x) - a_i(y)\right)^2} \tag{10}$$

KNN Algorithm can be summarised below [Algorithm 1].

Algorithm 1: KNN Pseudocode

Input: Training Set (x_i, y_i), where x_i are the instances, y_i is target value
Output: Class label
Begin:
1.For i = 1,2, …, n
2.Compute Euclidean Distance D(x,y)
3.End For
4.Obtain set s for all nearest values
5.Calculate $y_i = argmax \sum^{E} (y_n, c)$
6.Return y_i//Class label
End

Various results are generated after the data have been processed. Based on those results, predictions are made to classify an individual into specific class

4. IoTPulse: enterprise health information system

IoT seeks to link different objects (IoT devices) across the networks. Connecting these heterogeneous devices for development of Enterprise Health Information (EHS) System and predicts the alcohol addiction using Service-oriented Architecture (SOA). Such an IoT-based EHS architecture is flexible to allow devices dynamically communicate with items and exhibit real-time heterogeneous nature. Figure 2 shows the SOA-based EHS system for the prediction of alcohol addiction in an IoT-based environment comprising four different layers. The significance and functionalities of each layer has been discussed below:

4.1. Sensing layer

IoT is intended to be a complex global network composed of various transmissible machines, which are proficient in exchanging information, detecting, storing information etc. The devices fitted with the tags, sensors, etc. will automatically detect the environment in the Sensing layer, and communicate and pass information between various devices. In this paper, the solution to address the prediction of alcohol addiction is focused on opportunistic sensing. Health monitoring devices will be fitted out with RFID chips, cameras, smart devices or sensors to control and monitor the patient's

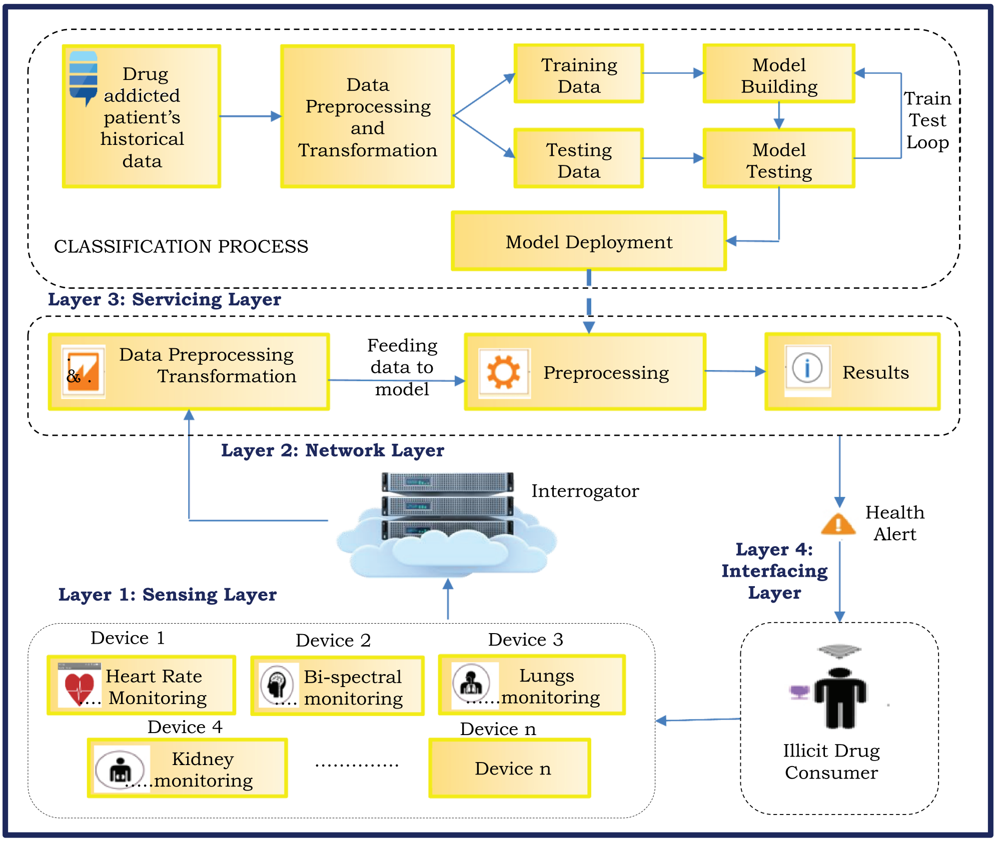

Figure 2. SOA-based EHS for alcohol addiction prediction.

health-related measures for data collection in real-time. These sensors, cameras, and smart devices detect the several measures and alterations in the human body and scan for some specific variations or an actual time interval for occurrence of an event. While the use of such IoT-based technologies differs from one application to another and relies on a preference of user, the potential to observe and recognise objects in the world has vastly enriched with the technology innovation.

4.1.1. *Sensing layer hardware components*

In this section, various health monitoring devices are discussed which can be used in IoT-based health information system. Following are some of the main IoT devices that can be implemented in the present research for the prediction of alcohol addiction prediction:

(1)*Bluetooth*: Bluetooth is a short-range wireless communication methodology that equipped with several smart devices including laptops, wearables, a smartphone etc. This technology is most appropriate for transfer of data among various devices.

(2)*Ethernet*: Ethernet has been emerged in 1970's to satisfy the communication and networking needs. It is a wired technology that can relay high speed data, but security, synchronisation and services would remain an essential part for the potential development of Ethernet.

(3)*Wearables Devices*: Wearables like FastTrack reflex smart band will control and maintain tracks of your physical exercises such as jogging, cycling, workouts, running etc. These devices are lightweight and endorse wireless networking including Infrared waves and Bluetooth. Using these devices inside an IoT-based program may help in monitoring the patient's physical activity.

(4)*Ultra-Wideband (UWB)*: UWB is a wireless system which requires small amounts of energy (Xu and Buyya 2019b) and offers large data rates (Shojafar et al. 2019). These technologies may be very useful for short distance wireless communication when implemented inside an IoT-based network.

(5)*Smartphones*: Smartphones are very helpful in collecting data when implemented in an IoT-based healthcare information system. In smartphones, a vast number of sensors as Global Positioning System (GPS) Tracking, Compass, accelerometer, Barometer or microphone are embedded to collect the data.

(6)*RFID*: RFID is an advanced sensor-based system that uses a compact RFID chip and Reader to recognise and monitor products and people in the real-world environment. Healthcare monitoring systems are now switching to RFID chips due to their low expense, reliable input in real time and compact design, etc.

(7)*Zigbee*: ZigBee is an industry-based wireless networking system of IEEE 802.15.4 specification which is used to connect WSN property to offer low data transfer speeds, scalability and efficiency. Many Healthcare monitoring devices are equipped with ZigBee for wireless transmission of data and Health monitoring services for patients.

(8)*Wifi*: Wifi is one of the most common technologies, which can be easily implemented in any platform because to its various features such as durability, cost effectiveness, availability of components with IP addressability, durability, and scalability.

(9)*Wi-Max:* 'Worldwide Interoperability for Microwave Access (WI-Max) is a wireless broadband methodology, which can enhance the performance of IoT-based system with the long-range wireless networking capabilities for both fixed and mobile connections.'

Table 2 gives the comparison of various IoT technologies discussing transmission speed, security, communication range.

Table 2. Comparison of various IoT-based technologies.

S. No.	IoT Technology	Transmission Speed	Security	Communication Range
1.	Bluetooth	1 Mbps	Less Secure	10 m
2.	Ethernet	2 Mbps	Moderate	_
3.	Wearables	30–45 Mbps	Moderate	100 m
4.	UWB	50 Mbps	Moderate	30 m
5.	Smartphones	50 Mbps	Moderate	130 m
6.	RFID	424 kbps	Less Secure	>50 cm/3 m
8.	Zigbee	256kbps/20kbps	Less Secure	10 m
7.	Wifi	50–320 Mbps	Moderate	100 m
9.	Wi-Max	70Mbps	More Secure	50 km

4.2. Networking layer

The network layer in the SOA for prediction of alcohol consumer integrates both aspects and is essential for simple networking assistance such as data transfer over wired or unwired devices. Furthermore, the data originates from a large amount of IoT-based devices linked to a diverse network. This layer for such framework is often accountable for aggregating data from specific IT networks to assurance stable services to various customers. In the present work, several network technologies have been selected which can be implemented in an IoT-based healthcare information system. Following are some of the significant innovations that can be used:

(1)*Ad hoc Network*: While WSN is evolving, the medical ad-hoc sensor network is a real software and hardware that can be utilised in such an IoT-based system to capture alcohol data practically.

(2)*Wireless Sensor Network (WSN)*: In the proposed work, lightweight, low-power and portable smart spatially dispersed medical sensors mounted devices such as pulse oximeters or accelerometers form a WSN. There are a range of WSN mechanisms which can be utilised in such healthcare programs like MEDiSN and CodeBlue and can be used to map and control environmental and physical factors.

(3)*Mobile Network*: This network is a ubiquitous, reliable and efficient solution for an IoT environment. Nevertheless, the cell networks are built to control downstream data. A variety of models has been developed already for the integration of IoT environment with a mobile network.

(4)*Cloud Technologies*: Cloud computing is a paradigm for a centralised network of configurable computers that can be accessed on request. Compared with the technology accessible today, Cloud is the key aspect of IoT which delivers useful business-specific infrastructure in multiple real-time environments and device domains. The cloud-based intelligent system enabled by IoT will also track, capture and process data. Microsoft's research lab, IBM IoT, ThingSpeak, Oracle IoT Cloud, Ayla's web network and Arrayant link are some of the big cloud technologies.

(5)*Social Networks*: IoT with a social network or SIoT is acquiring popularity because of its broad service area and flexible rule setting. Parallel processing, centralised data management, load balancer are some of the key characteristics of SIoT.

4.3. Servicing layer

Service layer is based on middleware technologies and is the primary instigator for IoT infrastructure and applications. The system's fundamental functions and operations are supported by the service layer. Within this layer, all the service-oriented tasks such as information sharing, knowledge retrieval, data collection, data integration, data pre-processing and data protection, are performed. Servicing layer plays a crucial function in the proposed solution. Data obtained from different devices like Bi-spectral (Zhang and Wang 2020) and Sphygmomanometer is deployed to estimate alcohol addiction.

4.3.1. Data acquisition

In this tier, the device network or body sensor network can be used to collect data from different aspects of the patient i.e. blood pressure or body temperature monitor. Such systems are focused on bodily parameters such as temperature, sound, current, light reflecting angle etc. to monitor the measurements or gain details from the human body with the aid of sensors, mobile systems, etc.

4.3.2. Data collection and transmission

The data collection and transmission layer within the three-layered architecture addresses networking and data communication. This layer is able to gather data from different sensors that are then transferred through protocols and system devices such as Ethernet, Zigbee, Bluetooth etc. Improving the functionality and productivity of this kind of IoT-based network is a significant task which is the evolving IoT research field. The Algorithm 2 shows the basic process introduced in this research to gather and transfer patient data in real time using cloud technologies. As there are numerous devices for data collection, device failure may be possible. Monitoring of these devices for effective prediction and analysis of information is very critical as inaccurate or noisy results may cause severe health risks. In the conducted study, movement detection algorithm is proposed that can be used to track the performance of these health monitoring systems.

Movement in such a method is identified by transmitting a message within a fixed time period to the mobile sensor node and Received Signal Strength Indicator (RSSI) is calculated. Changes in health condition was determined on the basis of historical records. These changes are mainly the difference between the two cases. If the difference is significantly higher, then master node will consider it as a substantial change and send a signal to the nearest predicted master node.

It should be remembered that the NN notification will sense a difference depending on a combination of safety characteristics or health tracking readings and if the message's RSSI dropped below the level, the response will be transmitted in the form of hidden states. There is a significant chance that any physical activity or changes in environmental conditions may lead to a particular characteristic. Using just one attribute will contribute to resource wastage and defective performance (Xu and Buyya 2019a; Tang et al. 2019b). Therefore, this range of health characteristics determines a threshold (Shukla et al. 2019). The nearest Master node will send the requests and acknowledgements recursively until the message about current and the next hidden state is not received by destination. These two current and next state values are bind in the message and are used to calculate the

Algorithm 2: Movement Management Algorithm

```
Previous Master Node (PMN) tracks change in Mobile Sensor Node.
PMN transmits Neural Networks messages to identified master node.
Identified Master Node directs Request to the mobile sensor node
if Request is received by Sensor node then
    Sensor node transmits Request to the Identified Master Node j
    Predicted Master Node j acknowledges the PMN by sending NNACK message.
else
    Broadcasts FindNode message which contains ID's of both Predicted and Previous Master node.
    Calculates RSSI if any static Node j receives the FindNode message from mobile sensor node
    if calculated RSSI value is greater than threshold-value then
    Send Response to the mobile sensor node
    j:static node having maximum RSSI value responds by sending NNACK to PMN
    PMN sends the current & previous hidden state to j
    endif
endif
```

variation. The value is updated when the current applicant node decides the next hidden state by observing the HSTable containing details regarding the hidden states (previous and next), and about next observation etc. Eigenbackgrounds Prati Mediod, and Zivkovic AGMM are some other motion detection algorithms that can be used to enable the network, capture data and move data in such IoT based environment.

4.3.3. Data synchronisation

One of the essential tasks is to develop consistency in the data before the actual processing starts. The number of IoT devices is consistently expanding. Since the different devices produce data with different speeds, data synchronisation should be carried out to continuously monitor the patient's health for the prediction of alcohol addiction. Data synchronisation can be file synchronisation, Mobile device synchronisation, distributed file systems and version controlling. In the present research, mobile device synchronisation is used.

4.3.4. Data pre-processing & transformation

With such an IoT-based program, automation can be accomplished to some degree as the data is repeatedly obtained from the patient and inevitably transmitted for diagnosis of alcohol addiction. These results, still, can include noisy components, other missing values etc. Following are data pre-processing techniques:

(1)*Data Cleaning*: Data is cleaned by processes such as replacing missed values using different methods like smoothing the noisy data, binning, filtering, outer identification and correction of conflicting data.

(2)*Data Integration*: In this, data is combined from various sources into a cohesive data repository, for example data centre.

(3)*Data Transformation*: Data normalisation, data generalisation and data aggregation are some of the activities included in data transformation.

(4)*Data Reduction*: In this, data size is reduced for building the model because actual data size will take more time to process.

Pre-processing of data is a vital activity before the final data analysis, because data may be inaccurate, noisy and could have certain missing values. The attribute's Most Probable Value (MPV) is used to treat missed values. i.e.

$$P(i)=\frac{n(i)}{n} \tag{11}$$

$$MPV=Mazimum(p(i)) \tag{12}$$

where i denotes instance value. Figure 3 presents the processing of alcohol addiction data using ML. The processing of alcohol addiction divided into three components dedicated to a different set of functionality and services. We then used box plot and five-number overview to look at the data distribution and outlier identification. The box plot for such an analysis gives O (n logn) time complexity.

4.3.5. Data analysis and knowledge extraction

One of the new fields for data mining and analysis is ML. A variety of ML techniques or algorithms can be used for prediction purpose. In the present research, Bayesian Networks, Neural Networks and KNN are used for the prediction of alcohol addiction.

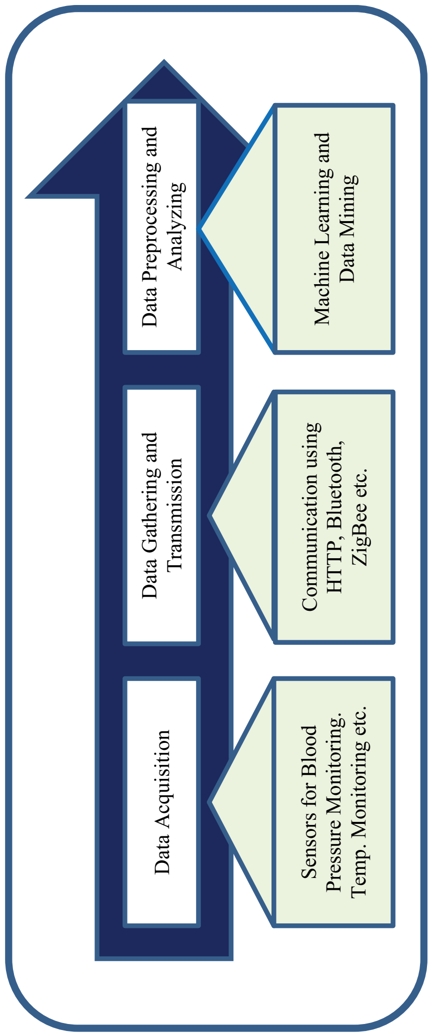

Figure 3. Processing of alcohol addiction data using ML.

4.4. Interfacing layer

An interface layer is a software specification that enables limited interference with the programs operating on the application layer. It offers the data abstraction so that the customer does not require to think about the system's internal details. The Interface layer includes four essential functionalities in the proposed architecture:

(1)*Alert to patients*: The important alerts related to health are generated using different technologies like email, SMS, auto-generated messages etc.

(2)*Health Reports for Patient*: A short medical report on the patient's problems and various health issues and risks is prepared.

(3)*Health Reports for the physician*: A comprehensive health details on the history of patients and current diagnosis for validation and consultation advice is prepared for the physician.

(4)*Data for research and surveys*: For medical research and survey, the patient data and outcome is used.

5. Alcohol addict prediction mechanism

There is no other direct user interference needed to capture or produce data within the current enterprise health information network. The basic idea is that sensors are installed within the different health monitoring devices and can interact directly. Algorithm 3 shows the proposed working mechanism. The program may continue to search for data from different devices on a specific occurrence or timestamp. This will test if the device that sends the data is inaccurate or not. As the data demonstrates a critical character in these healthcare systems, corrupt or inaccurate computer data may have major implications. Time is one of the main factors which must be taken into concern while operating on such an EHIS. As with a predetermined time period, the program must obtain data from the patient again. Therefore, if the data is not obtained during a predetermined time period, then one of the associated devices would be considered defective.

Consumer fitness is measured using ML algorithms and if the estimated fitness is below a certain Margin-of-Safety (MOS) value then the device would be in normal condition. However, if the fitness value is lower than MOS value then user may be warned by sending alert message that he/she might be seriously affected by alcohol addiction. This should be remembered that the MOS value relies on all health tracking systems along with their weight.

5.1. Pre-processing of dataset

The dataset obtained is in raw form and needs to be pre-processed to remove the missing and redundant values. In the present research, missing values are treated with MPV method as described in Section 4.3.2.

Then the normalisation of dataset is performed with the help of z-score normalisation. Further, feature selection is performed to choose the most relevant features.

Algorithm 3: Alcohol Prediction Mechanism

Input: Set of health care devices: N
Output: Alert Consumer
Begin:
1. Set value of time = c_t
2. Initially set value of j = 1
3. if (Device ($\rho_m = \sum_{i=1}^{2} a_i \rho_i$) = = Defective)
4. Alert administration and technician
5. Increment value of j i.e. j=j+1
6. Go back to step 4
7. Else
8. set device_value = value of device j
9. Pre-process device_value
10. Set d[j] = device_value[j]
11. if (j = = N)
12. Fetch consumer's historical data from storage (*Hj*)
13. Compute fitness value (d[], time, H) with the help of ML models
14. if (Computed fitness value < MOS)
15. Alert consumer
16. Save the data to future reference for backup
17. Else
18. Go back to step 6
19. end if
20. end if
21. end if
22. Wait for an incident or time interval to happen
23. Go back to step 2

End

5.2. Feature selection

For Feature selection, we have worked on forward selection technique. Forward selection is an iterative approach which works by adding features iteratively. Initially, we have an empty model. In each iteration, feature selection adds one feature at a time to the model. Features are added until all features have been included (Sutter and Kalivas 1993). The performance of model is enhanced for each model and we get the efficient features. Algorithm for forward selection for 8 key features is given as Algorithm 4.

5.3. Machine learning models

In our proposed approach, we have used Bayesian networks, Neural network and KNN algorithms for the accurate prediction of alcohol-addicted patients. The dataset is divided into 70:10:20 ratio for training, validation, and testing. First, the models are trained on the

Algorithm 4: Feature Selection

Input: Set of Attributes [*A1, A2, A3, …….. A14*]
Output: [*A1, A4, A5, A6, A8, A9, A10, A14*]
Begin:
1. For each feature i
2. Start with empty set such that, Y = {ϕ}
3. Select next best feature x_i = argmax [J(Y_i + k)]
4. Update feature set $Y_{i+1} = Y_i + x_i$
5. End for

End

alcohol dataset which is then passed to validation test for tuning the parameters and then testing is performed in order to check the performance of trained model.

6. Performance evaluation

We used *R* language to implement various machine-learning models. 'bnlearn' package was used to implement Bayesian Networks in which person's probability of being an alcohol addict is calculated given the likelihood of an alcohol addict on a particular reading of health monitoring. To implement neural networks,*'mlp'*package is used on 13 attributes for prediction of alcohol addiction. The selection and collection of hyper parameters is therefore totally trivial. The usage of deep learning and Neural Network with many hidden layers can contribute to greater accuracy and substantially better performance. Also, the amount of time and the computational speed for such a method would be increased. The followings are the parameters after tuning based on the neural networks:

•Input layer size: 13 (the total number of attributes i.e. features selected as given in Section 5.2)

•Output layer size: 2 (Whether a patient is alcohol addict or not, i.e. binary classification)

•Total number of hidden layers: 5

•Learning parameter (α): 0.0001

•Activation Function used: ReLU

For KNN, the value of *K* used is 5 i.e. 5 clusters are made to predict the behaviour of an alcohol patient. To implement this, 'knn' package is used. Table 3 describes the system configuration for experimental testing of proposed approach.

6.1. Dataset

In this tier, body sensors like blood pressure and blood temperature monitor are used to collect data from different areas of the body (Illicit Drug Use in Past Month n.d.). We have followed the standards and guidelines of public dataset named 'Illicit Drug Use in Past Month (Illicit Drug Use in Past Month n.d.)' to collect the data of 300 alcohol addicts from the province of Punjab (India). In the case study of alcohol addiction, we categorised the user based on the training data obtained from 300 alcohol addicts. A web service interface is used to collect user's data. The records of the users are made private as mentioned by them. A total of 110 females and 190 male alcohol addicts with mean age of 34 years have been collected. Among these 300 users, there are 125 users who are strictly addicted to alcohol. A dataset is divided in 80 by 20 ratio with 80% of 300 users i.e. 220 are used as

Table 3. Configuration details.

Sr. No.	Hardware/Software	Minimum Requirements
1.	Processor	Intel® Core™ i7 9700 k
2.	RAM	16 GB
3.	Hard Disk	256 GB SSD
4.	Operating System	Windows 10
5.	Programming Language	R (Rattle)
6.	Platform	R Studio

training dataset and remaining patients i.e. 80 are use as testing dataset. The statistical analysis of obtained data is shown in Table 4.

The distribution of the data collected is presented in Figures 4–12.

6.2. Baseline technique

As per existing survey, there is a no current framework, which deliberates data collection module for EHISs, three important ML models (KNN, Neural Networks and Bayesian Network) simultaneously and fog computing to improve computation during predictions, which validates the proposed framework IoTPulse using FogBus (Tuli et al. 2019a) i.e. real fog environment. Due to this, the current alcohol prediction systems become inefficient to respond in these situations. We have selected most relevant and recent baseline technique from literature i.e. SSDP system (Gutierrez et al. 2015) to validate IoTPulse in terms of energy, latency, network bandwidth and response time. SSDP predicts blood alcohol content. SSDP system gathers data sensed by smartwatch to find the level of drunkenness using Neural Networks-based approach. Further, it finds the user's intoxication level to find out the future

Table 4. Statistical analysis of the selected attributes.

Sr. No.	Features	Mean	Median	Standard Deviation	Minimum	Maximum
1.	Age in years	35	34	-	15	55
2.	Ratio of male with females (Gender ratio)	0.26	-	-	-	-
3.	Blood Pressure (Lower limit)	86	86	8.04	70	100
4.	Blood Pressure (Upper limit)	136.5	130	31.14	75	200
5.	Heart Rate (times/min)	75.42	71	15.84	51	109
6.	Blood Glucose level (mg/dL)	113.1	110	9.86	70	158
7.	ETG Score (ng/mL)	30.16	32	13.10	18	88
8.	FAEE Hair Alcohol Conc.(pg/mg)	744.2	738	101	469	899
9.	Daily Consumption (times)	2.12	2	1.44	0	6
10.	Blood Alcohol Level	144.1	120	25.59	9	400
11.	Testosterone (ng/dL)	222.2	270.5	86.15	205	890
12.	Target	0.8	111	-	-	-

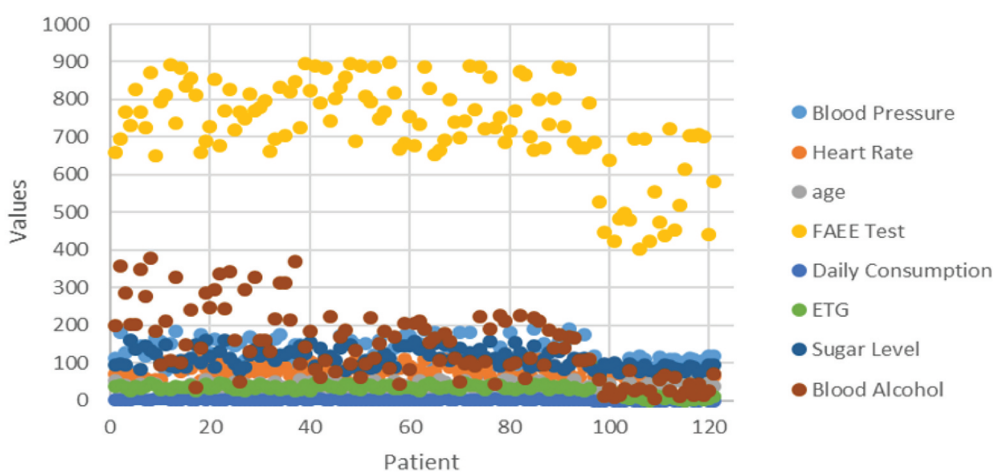

Figure 4. Distribution of various parameters selected.

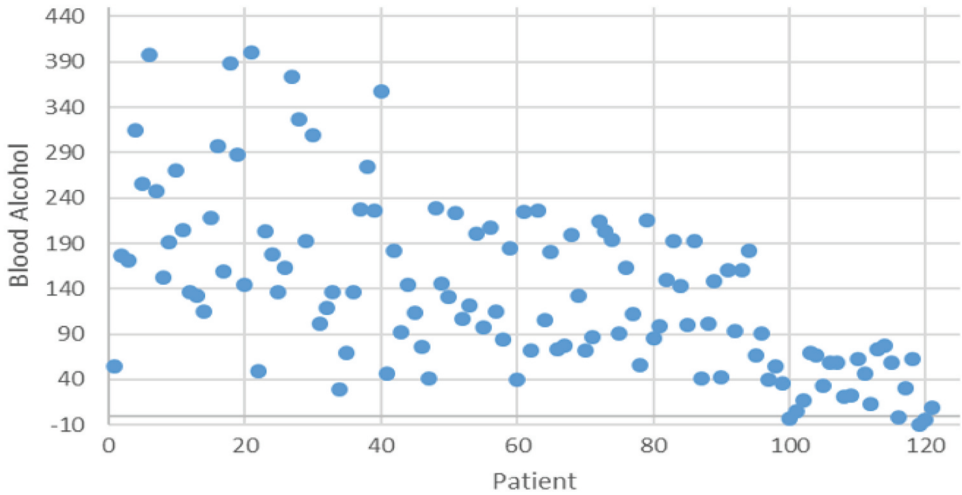

Figure 5. Blood alcohol distribution.

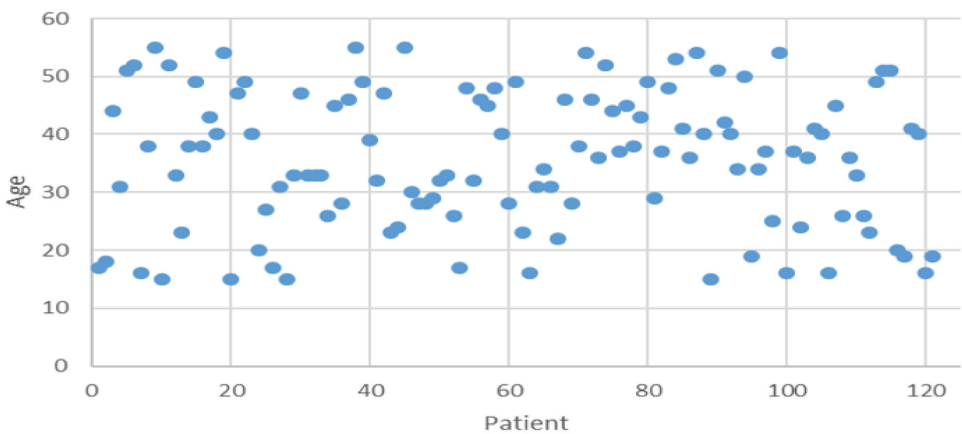

Figure 6. Age distribution.

consequences. SSDP system only uses Neural Networks and applied on stored data without collecting real time data using IoT sensors. There is no validation of proposed system against another ML algorithm. Further, there is no discussion about computing environment like fog or cloud to perform various computations at runtime for predictions, which causes latency.

6.3. Performance parameters

We have considered four performance parameters to test the efficiency of the proposed framework as described below. All parameters are extracted from prior works (Tuli et al. 2020a) and (Dhillon and Singh 2020).

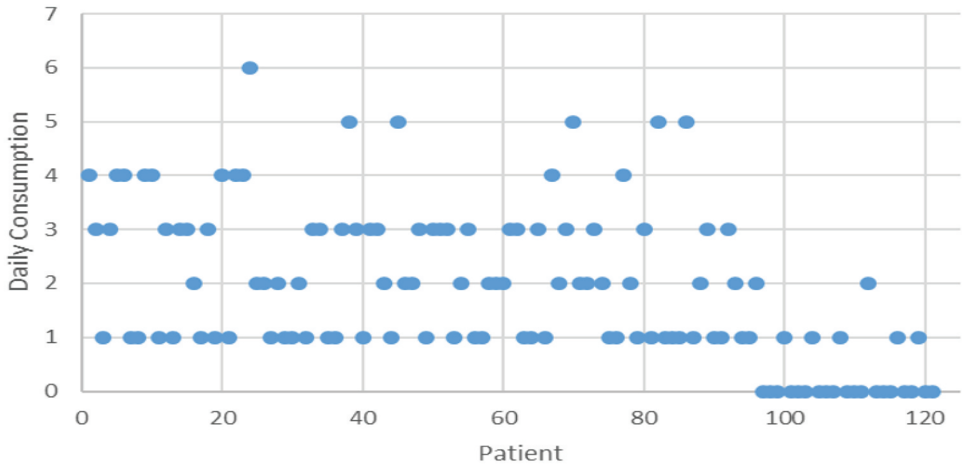

Figure 7. Daily alcohol consumption distribution.

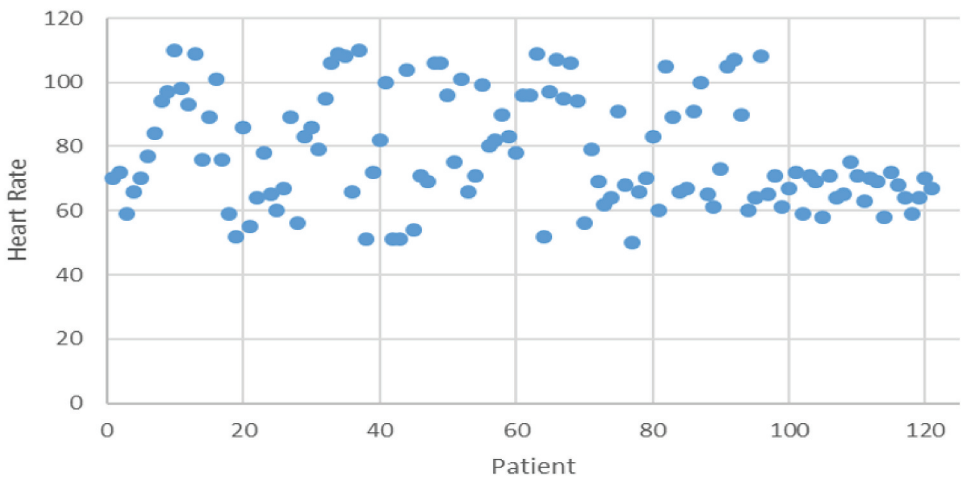

Figure 8. Heart rate distribution.

6.3.1. Sensitivity

The degree of total True Positive (TP) or positive cases that are predicted as true is known as sensitivity. It is also termed as recall and is given as:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{13}$$

where TP means patient having cancer is actually suffering from cancer and False Negative (FN) means person having no cancer are predicted as having cancer.

6.3.2. Specificity

Specificity is defined as the degree of actual negative value and is predictive as negative i.e.

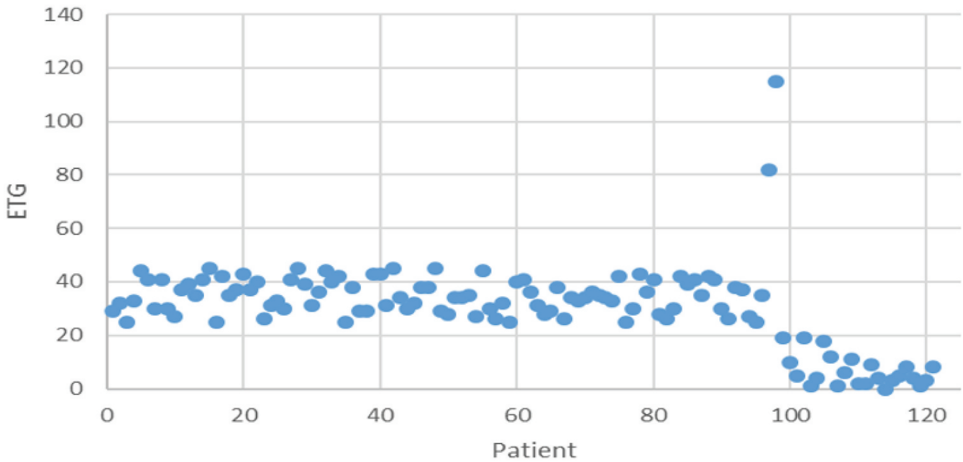

Figure 9. ETG distribution.

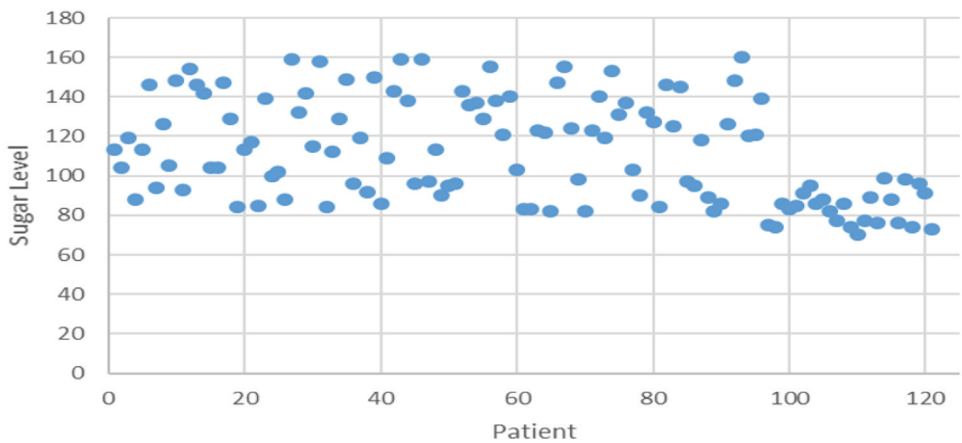

Figure 10. Blood sugar level distribution.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{14}$$

where True Negative (TN) means person not suffering from cancer has no cancer in actual. False Positive (FP) means the person predicted as having cancer has actual no cancer.

6.3.3. Precision

The percentage of actual results that are true or significant is known as precision and is given as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{15}$$

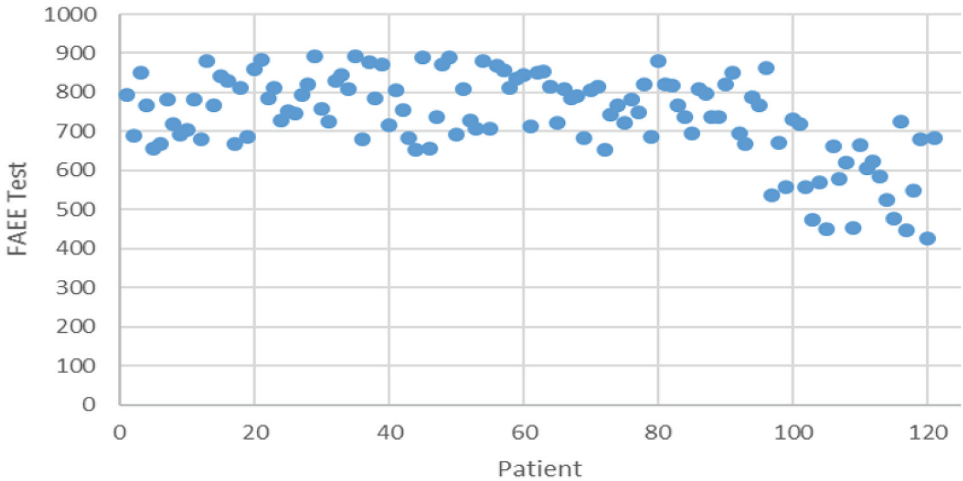

Figure 11. FAEE (Alcohol in Hair) distribution.

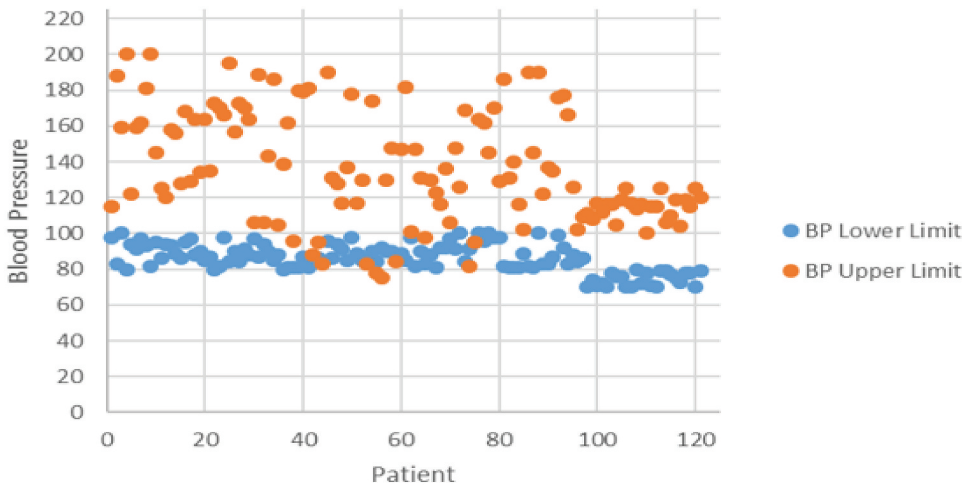

Figure 12. Lower and upper limit blood pressure distribution.

6.3.4. Accuracy

Accuracy is defined as the percentage of Predicted results which are predicted correctly with respect to actual values and is given by following.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{16}$$

6.4. Experimental results

Following the experiments, different observations of the confusion matrix are noted. Table 5 shows the results of alcohol addicts. Smartwatch Sensor Data-based Prediction

Table 5. summary of performance for iotpulse and ssdp.

	sensitivity		specificity		precision		accuracy	
model	IoTPulse	SSDP	IoTPulse	SSDP	IoTPulse	SSDP	IoTPulse	SSDP
Bayesian Networks	95.3	91.6	100	88.65	100	88.65	83.02	81.10
Neural Networks	99.8	95.2	85.7	82.6	95.9	85.77	96.72	89.65
KNN	88	81.45	100	87.6	100	92.46	88.89	82.78

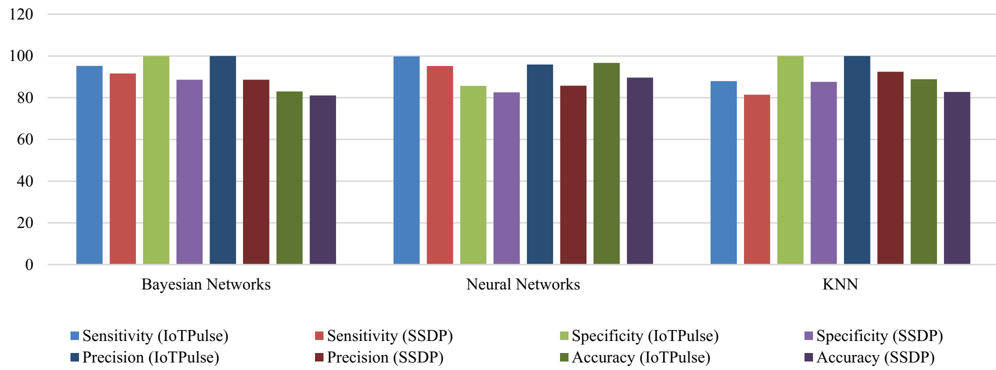

Figure 13. Performance comparison of various machine models for IoTPulse and SSDP.

(SSDP) system (Gutierrez et al. 2015) predicts blood alcohol content which is used to study the performance of IoTPulse in terms of performance parameters such as accuracy, recall, precision, sensitivity and specificity. SSDP system gathers sensor data from a smartwatch to find the drunkenness in using ML model.

Figure 13 demonstrates the comparison between the different evaluation parameters with regard to predictive models.

Further, we have compared various ML models (Bayesian Networks, Neural Networks and KNN) based on different performance parameters and identified that Neural Networks classifier has achieved 96.72% accuracy on the collected dataset for prediction of alcohol addiction for IoTPulse. Figure 13 shows IoTPulse performs better than SSDP in different types of performance parameters.

6.4.1. Energy efficiency

Power consumption is very important in IoT-based environments. If the device's power or battery drops within a limited time period then it will not an efficient system, because it would not be realistic to use. Therefore, the power consumed by various sensory devices in an IoT-based environment is estimated and is shown in Table 6.

The analysis indicates that the power usage of these systems differs considerably depending on the complexity of selected devices. It was also found that devices with wider screens use more power than smaller devices and the power usage depends on the sensor technologies used to gather data as well.

Table 6. Power consumed by different devices.

Sr. No.	Device Name	Power Used in Watts
i.	ETG Alcohol Test Dip Card	Not Accessible
ii.	Alco Screen 2 Saliva Alcohol Test	Not Accessible
iii.	Sphygmomanometer	2.5
iv.	Microcantilever sensor for liver monitoring	0.5
v.	Breath Alcohol Detector Test	2.5
vi.	Digital Breathalyser AlcoMate Prestige (Sensor equipped)	3
vii.	FAEE Hair Alcohol Abuse Test	150
viii.	Blood Glucose level monitor	2.5
ix.	Heart Rate Monitoring Sensor	0.3
x.	Bi-spectral monitor	180
xi.	Body Temperature Monitor e.g. Infrared Thermometer	3
xii.	Chem-Phys patch	2
xiii.	Testosterone Monitor	150
xiv.	Electrocardiogram (E.C.G.)	2.5

Table 7. The estimation of cost for various devices considered in IoTPulse.

S. No.	Device Name	Price in INR
i.	Sphygmomanometer	4000
ii.	Alco Screen 2 DOT Approved Saliva Alcohol Test	210
iii.	EtG Alcohol Test Dip Card	350
iv.	Microcantilever sensor for liver monitoring	7000
v.	Breath Alcohol Detector	2000
vi.	Digital Breathalyser AlcoMate Prestige (Sensor eqipped)	9000
vii.	FAEE Hair Alcohol Abuse Test	20000
viii.	Blood Glucose level monitor	1500
ix.	Body Temperature Monitor e.g. Infrared Thermometer	1400
x.	Heart Rate Monitoring Sensor	2000
xi.	Bi-spectral monitor	23000
xii.	Electrocardiogram (E.C.G.) Machine	8000
xiii.	Chem-Phys patch	8000
xiv.	Testosterone Monitor	20000

6.4.2. Cost evaluation

Table 7 shows the different cost estimations were made to determine the system's efficiency. It would be likely that systems with higher prices might provide additional functionality because we just used a simple system layout for cost evaluation.

7. Validation on real deployment using fogbus

FogBus (Tuli et al. 2019a) offers a mechanism to build and execute optimised Fog-Cloud systems with organised coordination and platform-independent application execution. FogBus links various sensors with gateway tools to transfer data and tasks to fog nodes that could involve edge devices or cloud servers. In the broker layer, the management of resources and initiation of tasks is performed on fog nodes. FogBus uses authentication blockchain, and encryption techniques to ensure privacy, data integrity, and protection which enhance the consistency, robustness and reliability of the fog system. FogBus uses HTTP RESTful APIs for collaboration, and uses Aneka tech framework to easily combine fog setup with Cloud (Vecchiola et al. 2012).

FogBus architecture enables service providers to increase the amount of active Fog nodes by system context. A computing node that is connected to the same Local Area

Network (LAN) will actually become a computing node by making itself available to the appropriate master node. The broker nodes later instal software components on the computing node to carry out the necessary operations. FogBus encourages multiple brokers coexistence in the broker layer such that gateway nodes may provide a range of choices for viewing the data streams for processing (Mancini et al. 2019). The workers are also shared among the brokers. In this situation, privacy and data confidentiality are not compromised, as each broker retains its own block chain and distinct employee database. Besides that, the software components working on the brokers allow Fog infrastructure to integrate simultaneously with multiple Cloud data centres. Furthermore, to allow practically deployable fault-tolerant solutions, FogBus can shift computing nodes to broker layer for managing other computing nodes in the vicinity.

In this work, we use FogBus for alcohol prediction by deploying the ML models on various brokers and manage the shared data on Blockchain platform as shown in Figure 14.

7.1. Experimental results

IoTPulse is validated against baseline technique i.e. SSDP (Gutierrez et al. 2015) (as discussed in Section 6.2) using four QoS parameters such as latency, response time, energy, and network bandwidth. Thus, IoTPulse uses a combined approach that leverages both ML models and integrated IoT and fog computing for optimum results. In our alcohol addiction framework, the consumer is classified on the basis of training data gathered from 300 alcohol addicts from Punjab Province (India). To effectively test the efficiency of IoTPulse and SSDP, we used the same Fog environment with FogBus (Tuli et al. 2019a) as mentioned above. All parameters are extracted from prior work (Naranjo et al. 2019; Gill, Garraghan, and Buyya 2019).

(1)**Network Bandwidth**:Figure 15(a) demonstrates the average network bandwidth of 1741 B/s and 2859.5 B/s for IoTPulse and SSDP, respectively. It is evident that IoTPulse uses

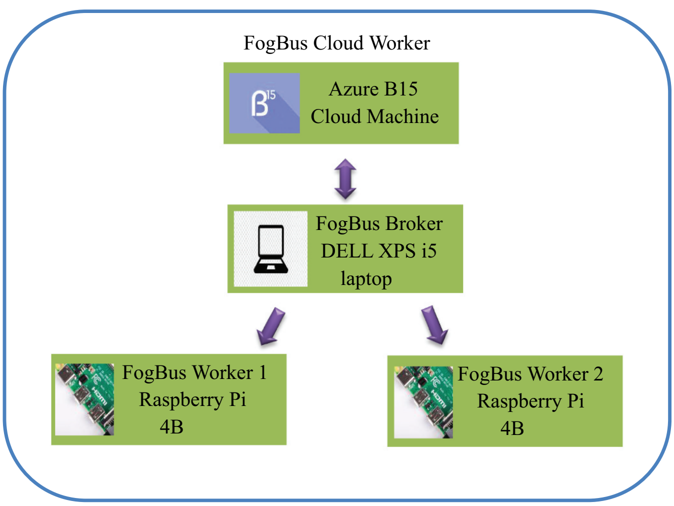

Figure 14. Evaluation testbed.

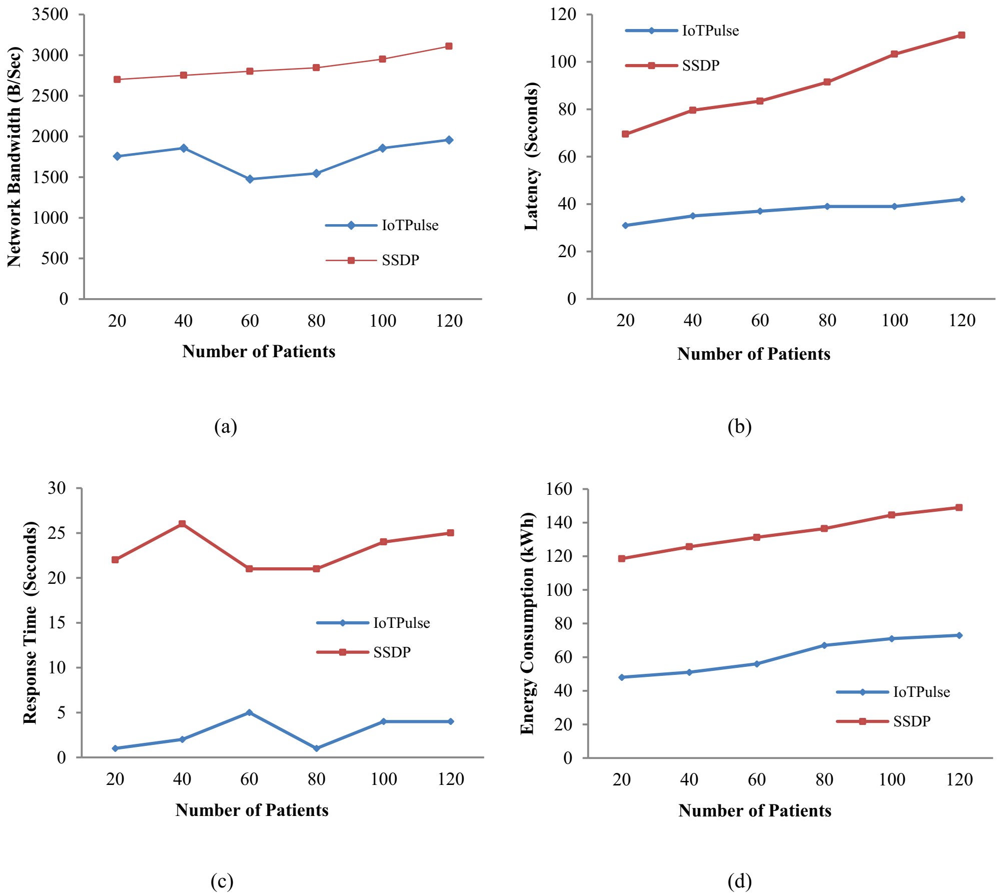

Figure 15. Evaluation results for IoTPulse and SSDP: (a) network bandwidth (b) latency, (c) response time, (d) energy consumption.

1741 B/s on average, that is 18.36% lower than SSDP because at runtime, IoTPulse processes IoT device data efficiently while meeting the QoS requirements.

(2)**Latency**: We analysed the latency of both IoTPulse and SSDP (i.e. the delay until the user requests for job processing are transferred). As the number of patient's increases, the latency value rises, which is presented in Figure 15(b). IoTPulse is found to have a lower latency in comparison to SSDP (as the number of patients rise). IoTPulse 's average latency value is 19.56% lower than SSDP. The explanation is that IoTPulse handles service requests on the Fog Data Server (FDS) instead of submitting job requests to the Cloud Data Server (CDS) which will contribute to a greater communication delay.

(3)**Response Time**:Figure 15(c) indicates the time taken for a device to respond to a request from the customer. Response time rises as the number of users increases. IoTPulse's average response time value is 21.56% lower than SSDP. The explanation behind the lower response time is the request handling mechanism which provides assets for job requests before actual resource scheduling. In addition, state of all the resources for each point is monitored by IoTPulse, allowing it to make an optimum decision than SSDP.

(4)**Energy Consumption**: That is the amount of energy absorbed by the CPU, switching devices, computing unit, network system and other elements such as fans, losses from conversion (Tuli et al. 2019a). The energy consumption value increases as the patients increases as displayed in Figure 15(d). IoTPulse's total energy usage value is 19.53% greater than SSDP. The average benefit of effective resource scheduling decreases substantial amount of network traffic, contributing to a decrease in the idle resources (switching equipment, processor, network system, storage unit) that minimise energy wastage.

7.2. Discussions

We used popular machine-learning models (Bayesian Network, Neural Networks and KNN) to predict the alcohol addiction using integrated IoT and fog computing environments. The performance of IoTPulse is compared against existing work i.e. SSDP system (Gutierrez et al. 2015) using various performance parameters comprising accuracy, sensitivity, specificity and precision which shows an improvement of 7%, 4%, 12% and 12%, respectively. Finally, IoTPulse is validated in FogBus-based real fog environment using QoS parameters including latency, network bandwidth, energy and response time which improves performance by 19.56%, 18.36%, 19.53% and 21.56%, respectively.

8. Conclusions and future work

With scientific developments in enterprise healthcare systems, IoT based systems with Machine analytics as a service have surfaced as the most effective candidate approaches for alcohol addiction prediction. These technologies have revolutionised the current view of healthcare facilities in smart cities and smart enterprises. In this research work, we have proposed an IoT based EHIS called IoTPulse for the prediction of alcohol addiction. Further, various ML models such as Bayesian Network, Neural Networks and k-Nearest Neighbour (KNN) have been implemented to predict alcohol addiction. The performance of three ML models is evaluated based on various performance parameters such as recall, accuracy, specificity and precision. In our alcohol addiction framework, the users are classified based on training dataset obtained from 300 alcohol consumers working in different enterprises in Punjab (India). Finally, IoTPulse is validated in real fog environment using FogBus to assess the performance of QoS parameters such as energy, response time, latency, and network bandwidth as compared to existing technique.

8.1. Future work

The proposed work can be extended in the following dimensions:

1.IoTPulse can be extended for prediction of any kind of illicit drug addiction, which has tremendous research and development opportunities. However, new threats will often arise with technical innovation. Real time dataset for illicit drug consumption can be collected using IoT-enabled devices and can be deployed as machine analytics as a service for EHISs as a smart enterprise concept.

2.As part of the future work, we propose to extend IoTPulse to allow cost-optimal execution given different QoS characteristics and fog-cloud cost models.

3.This present study is confined to Punjab (India) only. However, to extend the outcomes of this study, an extensive research can be carried out in different areas of the country or world for the prediction of alcohol addiction.

4.More intelligent ensemble models can be deployed for further improving the accuracy, recall, specificity and precision.

5.Further, IoTPulse can be extended to incorporate other fog computing applications such as agriculture, healthcare, weather forecasting, traffic management and smart city.

6.IoTPulse can also be extended towards other important domains of healthcare such as diabetes, cancer and hepatitis for prediction, which can provide efficient services to corresponding patients.

7.Technologies like IoT and fog computing will surface as a foundation for effective alcohol addiction and its prediction for future studies.

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