International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Improving Data Transmission by Efficient Communication Protocol to Control Wearable Sensors with Risk Level Analysis in Smart E-Health

[1]D. Hareesha, Dr. Charan Singh Tejavath[2] , Dr. K. Vinay Kumar[3] and Gouthami Velakanti[4]

Submitted: 26/04/2023 **Revised**: 24/06/2023 **Accepted**: 04/07/2023

Abstract: A single paragraph of about 200 words maximum. For research articles, abstracts should give a pertinent overview of the work. We strongly encourage authors to use the following style of structured abstracts, but without headings: (1) Background: Place the question addressed in a broad context and highlight the purpose of the study; (2) Methods: briefly describe the main methods or treatments applied; (3) Results: summarize the article's main findings; (4) Conclusions: indicate the main conclusions or interpretations. The abstract should be an objective representation of the article and it must not contain results that are not presented and substantiated in the main text and should not exaggerate the main conclusions. Wearable biosensors are attracting much attention in the medical and physiological therapeutic disciplines due to their ability to offer patients time-sensitive data, non-intrusive assessments of biochemical markers dispersed across the body in the bloodstream, and real-time diagnostic devices. These types of sensors are a new option for evaluating human health and take advantage of some technology that needs to be put in hospitals. Wearable sensors have come a long way, but there are still numerous potentials and problems in substances, sensing efficiency, and practical application. Therefore, we still have a ways to go before human health metrics are continuously monitored over an extended period. This is achievable by using the right methods of communication and patient risk-level decision-making techniques. Since MQTT is an effective communication protocol for data transmission, Smart E-Health (SEH) is designed in this study. In addition, Fuzzy-based Back Propagation Neural Network (FuzzBPNN) is made to determine the risk level of a patient's health state based on the results of their vital signs. A risk variable with a value range of 0 to 1 is a proxy for the risk level. A patient's health is more critically ill and requires more medical care, the higher the risk value. The MIMIC II dataset is taken and compared with the state-of-the-art methods for experimental analysis. It is found that Smart_FuzzBPNN achieves a 98.4% of detection rate, 11% of packet drop rate, 94% of risk level analysis detection, and 97.5% of energy efficiency in 12.5ms.

Keywords: *wearable sensor; smart healthcare; message queuing telemetry transport; decision making; risk priority.*

1. Introduction

Due to substantial advancements in healthcare and medicine and greater public awareness of the need for personal and environmental hygiene, life expectancy has been rising globally [1]. Additionally, throughout the past few decades, there has been a rise in interest in family planning, which has helped to lower birth rates worldwide. The World Health Organization (WHO) predicts that by 2017, more people will be 65 and older than children under the age of five [2]. In terms of social services and medical needs, this massive ageing population would tremendously impact society's socioeconomic makeup. In addition, the cost of hospitalization, pharmaceuticals, and healthcare supplies continues to rise, which drives up the cost of medical services [3]. In order to offer superior medical care to the ageing population or those living in areas that have restricted access to medical care while guaranteeing the maximum level of convenience, autonomy, and engagement between individuals, novel approaches and technology must be developed and put into practice. Instead of paying for expensive medical services like hospitals or retirement communities, continuous health surveillance enables individuals to keep living at home. Thus, it offers a viable substitute for on-site medical surveillance that is less expensive [4]. These devices, which come with integrated sensors that are non-invasive and discreet, may serve as useful diagnostic instruments for medical staff when

1Assistant Professor, Dept.of ECE, P V P Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh,520007. hareeshashyam@gmail.com

2Associate Professor & HoD, Department of CSE, Sri Indu College of Engineering&Technology (A), Sheriguda, Hyderabad, Telangana-501 510.charan.sicet@gmail.com

3Department of CSE,Kakatiya Institute of Technology and Science, Warangal, kotte.vinaykumar@gmail.com.com

4Assistant Professor,Department of CSE, Kakatiya Institute of Technology and Science Warangal

gautami.velakanti@gmail.com

tracking vital signs of wellness and patient movements in real time from a different facility [5]. It makes sense that wearable sensors are essential to these monitoring systems, which in recent years have drawn the interest of several researchers, businesspeople, and tech titans. Wearable technology can track and save real-time information about a person's physiological state and mobility activities [6]. Systems for monitoring a person's health using wearable sensors may include various flexible sensors in clothing, elastic bands, and textile fibres [7, 8]. These physiological indicators can be measured by the sensors, including the electrocardiogram (ECG), electromyogram (EMG), heart rate (HR), body temperature, electrodermal activity (EDA), arterial oxygen saturation (SpO2), blood pressure (BP), and respiration rate (RR) [9,10].

Additionally, activity-related signals are frequently measured using micro-electro-mechanical system (MEMS) based small motion sensors, including accelerometers, gyroscopes, and magnetic field sensors [11]. Analysing signals from the body continuously could aid in the early detection and diagnosis of several cardiovascular, neurological, and pulmonary illnesses.

Real-time tracking of a person's mobility activities can also help with sleep evaluation, gait pattern analysis, and fall detection. Wearable health monitoring systems typically include a range of electrical and MEMS instruments, actuators, wireless communication modules, and signal processing units. An appropriate protocol for communicating [14], ideally a low-power and primary wireless media, such as Bluetooth connectivity [15], ZigBee, or Near Field Communications (NFC), is utilized for transmitting measurements collected from each sensor linked in a Wireless Body Sensor Network (BSN) [12,13]. The computational node executes sophisticated data processing, analysis, and selection methods and can save and present the outcomes to the user. It might be a Personal Digital Assistant (PDA), cell phone, machine, or a specially made analysing section that uses a microcontroller or a Field Programmable Gate Array (FPGA). It serves as a doorway to foreign healthcare institutions by sending the measured data to the medical staff over the Internet. Given that, the following are the outcomes made by this work:

- The ability to utilize fuzzy-based back propagation neural networks as an instrument for decision-making and the gradual alteration of understanding towards knowledge. Consider the suggested IoT environment with the advantages of a smart structure and the application of wearable sensor technologies to track patient health data.
- Choosing the best communications standard, particularly the MQTT protocol, is important for enhancing power and storage optimization to support a dependable data transfer range.
- An instrument for decision-making helps identifies events and crisis period recognition to boost wearable sensor operational efficiency.
- By calculating an overall risk, the structure establishes the individual's risk level under observation. It builds models using historical data and data mining techniques and analyses the acquired vital sign measures in real-time.
- We determine the rating of a vital sign employing its previous and present ratings, consequently evaluating its current state based on how it has changed over time; the degree of severity is expressed by a danger variable varying from 0 to 1. The greater the risk worth, the more serious essential the condition of the individual is, and the greater the needed treatment.

The structure of the current document is as follows: A relevant collection of research for wearable sensors in smart healthcare is provided in section 2. In section 3 suggested decision-making model with communication protocol is given. In part 4, the performance of the suggested model is shown along with benchmark methods. The fifth section presents the general conclusion for the suggested method.

2. Related Works

This part overviews various ML and DL methods for intelligent medical monitoring through wearable sensors. As an outcome, the research considers the outcomes of different strategies. The author in [16] developed a new wearables-assisted smart health monitoring for sleep quality prediction utilizing the best deep learning model (WSHMSQP-ODL), allowing the devices to collect information regarding sleep-related activity originally. The information is then put through pre-processing to create an established format. The extended seagull optimization (ESGO) technique is employed for hyperparameter values adjustment to improve the DBN model's ability to forecast the amount of rest. A wearable smart sock device was employed in the [17] investigation to monitor the foot-ankle biomechanics throughout gait activity. To calculate the articulation degrees in the horizontal and lateral lines determined with a camera-based motion-capturing structure, two artificial intelligence models—long short-term memory (LSTM) and convolutional neural networks—as well as multivariate linear regression models were developed. Strolling rates were varied to evaluate the prototype's capacity for recording motions at different strolling rates and develop general frameworks for calculating joint angles in the horizontal and anterior planes.

The aim of [18]'s scheduled study will be to accurately classify common human behaviours using gyroscope and magnetometer sensor information after converting them into spectroscopy representations. Following that, the pre-trained weights of two well-known and effective transferred learning convolutional neural network models are used to extract features. The most effective feature subset has been chosen using a wrapper-based feature selection technique, shortening learning duration and enhancing classification performance. [19] described modelling and design of a patient monitoring (PM) system based on artificial intelligence for assessing crucial indicators for the prognosis of diabetic mellitus. The study briefly analyzed diabetes and an artificial intelligence (AI) model based on the Fully Connected Neural Network (FNN) machine learning method. According to wearable sensor health metrics, [20] categorizes epilepsy conditions using a hybrid technique combining machine learning and a fuzzy logic inference system. Using ensemble bagging and ensemble boosting regression, the ensemble machine learning classifiers are utilized to forecast epilepsy occurrences.

The aim of [21] is to use machine learning algorithms to forecast a potential occurrence of cardiac disease. The wearable biomedical prototype's incorporated ECG sensor provides electrocardiogram (ECG) patterns. ECG pattern variations are tracked. The R-to-R method is used to calculate heart rate from ECG patterns. The Cleveland data set, which consists of 13 qualities, is employed. These attributes include ECG-related ones such as resting ECG findings, depression in the ST segment caused by exercise relative to rest, and slope of the peak exercise segment. According to data [22] gathered from wearables, elderly people purchase them. The various purchasing segments were identified by trial supervisors (TS) in the information gathered. They used three machine learning algorithms such as k-Nearest Neighbors (k-NN), Random Forest (RF), and Support Vector Machines (SVM). For the autonomous hospital bed transfer (AHBT) usage, the use of a polynomial regression (PR) artificial intelligence (ML) Memory approach based on a Dreyfusian descriptor was suggested in [23]. The E-Healthcare Monitoring System (EHMS) is merged with machine learning (ML) techniques in the [24] paper to create an advanced automation system. This system will allow for connections, monitoring, and decision-making for accurate diagnosis.

By present systems, interactions are additionally essential for an effective healthcare system. according to many present-day designs, keeping consultations and data organized and up to date requires much human labour and a period while under a smart healthcare system, doing so would require rigid planning and record-keeping. The earlier method did not advise administrators of the accessibility of nurses, physicians, and others. One of the numerous benefits of smart health surveillance is that many contemporary researchers have identified a chance for machine learning and cloud-based computing as an answer for medicine. In several studies, which include cancer diagnosis, controlling diabetes, and recovery, ML medical facilities were developed for specialized purposes. These systems were developed for various purposes, but they are all connected using similar enabling technology.

3. Methodology

3.1 Problem Formulation for Decision Making

Think of a person making a series of choices to get the desired result. We research situations in which choices made today will have an impact tomorrow. For instance, if a person decides to estimate risk and make a choice at the current time step, they cannot make a mistake. The necessity to consider how present actions may affect judgements in the future makes these situations exceptionally difficult for decision-making, which makes them the perfect candidates for utilizing strategies to enhance human performance. The tip prediction challenge is formalized first in this step. We simulate our situation as a typical, undiscounted Markov Decision Process $M = (S, A, R, P)$ with a limited time T, with individuals striving to maximize reward. S stands for state space, A for action space, R for reward function, and P for transition function. A state $s \epsilon S$ intuitively encapsulates the system's current configuration and an action $a \epsilon A$ is a person's choice. By mapping states to actions π_H, we describe humans as a decision-making policy. The human examines the present scenario s_t at each time step $t \epsilon \{1,2, \ldots T\}$ and chooses a course of action $a_t$in accordance with the probability distribution $(a_t|s_t) = \pi_H(s_t, a_t)$. The framework then moves to the next state, s_{t+1}, that consists of a variable that is selected at random with a distribution of probability of $p(s_{t+1}|s_t, a_t) = P(s_t, a_t, s_{t+1})$, and the process is repeated until $t = T$.. At that point, they are rewarded with $r_t = R(s_t, a_t)$. A rollout is a series of state-action-reward triples sampled using this method, indicated by the symbol $\rho = (s_1, a_1, r_1), \ldots (s_t, a_t, r_t))$. We calculate the accumulated anticipated reward of a particular policy π with

$$J(\pi) = E_{D(x)} \sum_{t=1}^{T} r_t \quad (1)$$

$D^{(x)}$ is the distribution of rollouts brought on by applying policy x, where. We designate the human policy as πH, which can be inferred from historical trail data while not being directly witnessed. Determining the ideal strategy, $x *= argmax\ J(\pi)$, which maximizes cumulative reward, will also be helpful.

3.2 Construction of Wearable Sensors Network Model

The Smart E-Health (SEH) is modelled in this work as an experimental analysis carried out by attaching 5 bio-medical sensors (ECG, EMG, SkEl, ECG, Th, and StGa) to the skin of four patients, as shown in Figure 1. The patients are monitored for their temperature, brain function, pulse, heart rate, and blood sugar level. The patients' ages range from 20, 35, 45, 55, and 65. Using a mobile app, a handheld smartphone communicates with a healthcare facility three kilometres from the patient. The access point is set up as a receiving station in the experimental analysis, 3 km from the subject's home.

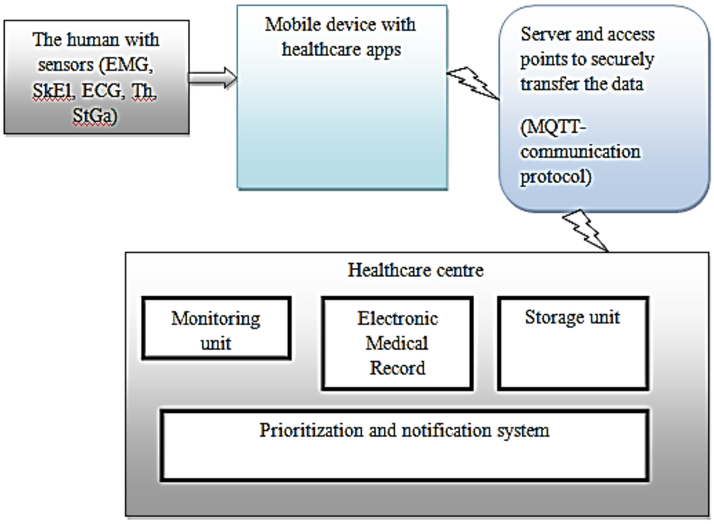

Fig 1. Construction of Wearable sensors network model

Various periods for observing the sensor results are used based on the movement. Standing, sleeping, walking, and eating are considered while evaluating activities. The sensing requirements (present, missing) for the activities indicated above for the installed sensors are listed in Table 1.

Table 1. Activity of each sensor in patient's body

Activity	**EMG**	**SkEl**	**ECG**	**Th**	**StGa**
standing	present	present	present	Absent	present
sleeping	present	Absent	present	present	present
walking	present	Absent	present	present	Absent
eating	present	present	present	Absent	present

3.3 Sensing and Monitoring Process

The wearable sensor may communicate with mobile devices through a radio transmitter. Additionally, it has a short-term memory for processing detected signals. The five tuples $(Sen,\ Sen_2,\ Sen_3,\ Sen_4\ and\ Sen_5)$ that make up the sensed information $SenInf$ correspond to the values of the EMG, SkEl, ECG, Th, and StGa sensors. $SenInf$ is broadcast regularly. The sensing time of the device and the human body affects how frequently the tuples repeat. The sensing time of the gadget and the human body affects how frequently the tuples repeat. The $SenInf$ is updated and sent to the mobile device, which has display, notification, and relaying capabilities, following the conclusion of each session. This information is embedded in the mobile device with the integration of hardware and software functions. Two forms of sensing—periodic (based on operation time) and event detection—are adapted during the sessions. Following a clear pattern, which is detailed below, the periodic sensing and monitoring procedure is as follows:

The sessions for a tuple should be $\{ses_1, ses_2, \dots ses_n\}$ such that its average ses_{avg} equals$\sum_{j=1}^{n}\frac{ses_j}{n}$. Depending on how much operational time each $Sen,\ Sen_2,\ Sen_3,\ Sen_4\ and\ Sen_5$ has, this is fixed separately for each. As a result, the maximum number of updates a mobile device can get in a 24-hour day is called a " max $\{ses_{avg}(i)\}$ update," which is transmitted to the medical centre at regular intervals. Instead, the modification interval of ses_i and ses_{avg} does not hold if the sensor delivers an aberrant value. An occurrence is identified if the data sensed is outside of the sensors' typical operating range. An urgent situation is indicated if the readings measured by the wearable gadget exceed or deviate from the typical range. This interval to identify events, eve_{det}, is calculated using.

$$eve_{det} = [\frac{|ses_j|}{|ses_j| - ses_{avg}} + 1] \quad (2)$$

In this section, $ses_j < eve_{ses} \leq ses_{j+1}$ denotes that "eve_{ses} happens after an occasional interval and at the same time. If if $ses_{avg} > |ses_j|$ the baseline position wherein continuous surveillance and treatment are required is predicted.

3.4 Activation of MQTT Protocol

Following the sensing process, the MQTT protocol runs in the server to facilitate effective communication. As seen in Figure 2, the MQTT primary processes are divided into various parts components.

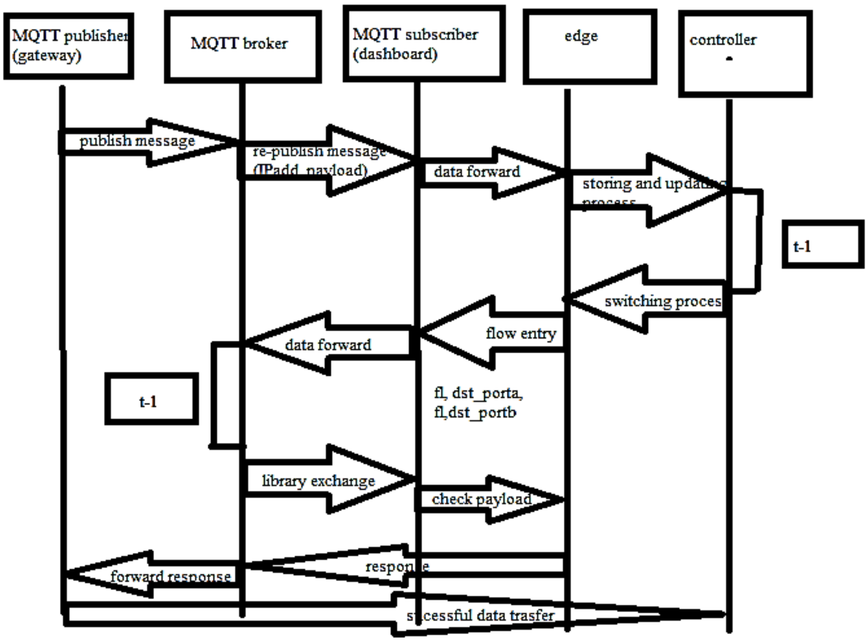

Fig 2. MQTT communication protocol for efficient data transfer

One component is a multicast group query of MQTT publishers that takes place in the sensing layer and is a gateway. A multiplex grouping inquiry of MQTT subscribers on the dashboard is an additional component. The other portion handles the creation of an MQTT broker that transmits MQTT messages. Furthermore, gateway When an MQTT publisher creates a published message, the multicast group that handles the search of the publishers kicks in. The payload for delivering the information to the dashboard is included in the publisher connecting messages, along with specifications for the publishing's IP address. To an edge switch, this message is transmitted. The communication includes the OpenFlow protocol and is forwarded to the controller if the edge switch does not already have a flow entry. The controller decompresses the OpenFlow protocol and analyses the message to store the broadcast tree's publisher metadata. When the subscriber's message is sent, the multicast group query of the MQTT subscriber is activated. The subscribe messages include the payload and subscriber IP address. Except for saving the member information, the procedure is the same as the MQTT publisher's multicast group query procedure. Multicast trees are created by referring to the IP addresses of publishers, subscribers, topics, and the status of the network link.

The flow entry for the switches is (fl, dst_{portA}) and (fl, dst_{portb}). fl stands for a port in an inbound packet, and * is a wildcard that denotes the entirety of an IP address. The dst_{port} argument allows MQTT messages to be categorized according to their port number. A refers to a multicast group address. The broker's address is B. The edge switches set up the flow entry (fl, dst_{portb}), and perform two operations, changing the MQTT packet's IP destination field and forwarding it to a port for transmission from publisher to subscriber. The switches only function to forward a multicast MQTT packet through $(fl, dst_{porta}$of the flow entry, except for the edge switches.

3.5 Decision-Making Model and Prioritizing of Packets

Complex decision-making is revisited in the Smart E-Health (SEH) to improve smart healthcare applications' profit. The classified tuples are independently stored in EMR. This forms the basic elements of the EMR, upon which the other decisions are imposed. We proposed the decision model of the fuzzy neural network-attached $Smart$ computing layer, in which the backpropagation (BP) algorithm was applied to train a neural network. The environment series $Env(t)$ and the system's output $Sys\_out(t)$ are constantly measured and assessed according to the connecting $Smart$ operation layer's guiding concept. The control decision centre uses a network called $Smart\_FuzzBPNN$, which includes the fuzzy layer, smart layer, impact evaluation layer, BP input layer, implied layer, and output layer. The complete description is listed below:

- Fuzzy layer: The series of ambient quantities received by the input system produces an undefined vector of $\mu\,(\mathrm{E(t)})$ by the set fuzzy membership function.
- Smart layer: After a predetermined sampling interval, the decision centre receives a time series of the system's dynamic constant ΔD and sends the $\mathrm{Cont(t)}$ control signal at time t. The atmospheric time-lapse $\mathrm{EnvTime\,(t)}$and condition sequence $\mathrm{StaSeq\,(t)}$ are gathered at a fixed monitoring interval, and the smart layer operation $\mathrm{H(StaSeq\,, EnvTime\,)}$ generates the evaluation coefficient $\mathrm{H(StaSeq\,, EnvTime\,)}$ for the management system.
- Impact assessment layer: In the consequences assessment layer, $\mathrm{Imp(t)}$ is calculated by multiplying the fuzzy generalization of the sensory period series $\mathrm{E(t)}$ by $\mathrm{H(StaSeq\,, EnvTime\,)}$, as in the following equation:
- $\mathrm{Imp(t) = H(StaSeq\,, EnvTime\,) * \mu(E(t))}$
- Following an array of $\mathrm{Imp(t)}$ computations, the BP layer is output straight to the implied layer.

The final control signal $\mathrm{Cont(t)}$. is in the output layer.

The classic fuzzy BP neural network has an extra layer of computing called H that is used to compute gain coefficient $H(StaSeq, EnvTime\,)$ immediately and to assess gain coefficient $H(StaSeq, EnvTime\,)$ in real-time. The association evaluation of numerous environment-perceived factors and state variables in H operation uses the grey correlations research theory. As a result, the number of changes for the training sample and the variation of sample data difference results in fewer judgment mistakes, which enhances the system's reliability.

3.6 Score Aggregation Layer

Health professionals and physicians use the patient's recorded vital signs' overall score to evaluate a patient's health. This overall score represents the preliminary warning score. It enables them to decide on the appropriate intervention strategy and the degree of urgency of the patient's condition. In our procedure, the aggregate score is employed as a parameter in the FIS to obtain the individual's risk level as an output. The formula is as the following:

$$AS = \sum_{i=1}^{Q} Cons\_score \tag{3}$$

Q is the total amount of observed vital signs, and $Cons\_score$ is the most recent score for the i-th vital sign throughout a round R. The input is first fuzzified using the Low, Medium, and High fuzzy member functions. After then, a series of fuzzy logic rules are used to determine the patient's risk level. The following definitions apply to the aggregate score fuzzy membership functions f $fuzz1_{(u)}[low], fuzz2_{(u)}[medium]\ and\ fuzz3_{(u)}[high]$:

$$fuzz1_{(x)} = \begin{cases} 1, & u \le 1 \\ \frac{1}{1-Q}u + \frac{Q}{Q-1} & ,1 \le u \le Q \\ 0, & otherwise \end{cases} \tag{4}$$

$$fuzz2_{(u)} = \begin{cases} \frac{1}{Q-1}(u-1), & 1 \le u \le Q \\ \frac{1}{1-Q}(u+1-2*Q), & Q \le u \le 2Q-1, \\ 0, & otherwise \end{cases} \tag{5}$$

$$fuzz3_{(u)} = \begin{cases} 2\left(\frac{u}{Q}-1\right), & Q \le u \le \frac{3}{2}Q \\ 1, & u \ge \frac{3}{2}Q \\ 0, & otherwise \end{cases} \tag{6}$$

Q is the total number of recorded vital signs, and u is the overall score AS. Low if AS is between 0 and 6, Medium if AS is between 1 and 10, and High if AS is greater than 6.

3.7 Risk Level Prediction Layer

A person's level of risk Rk is quantified as a variable with a possible range of 0 to 1. It is an indicator of how seriously ill the individual in question is. The more severe/critical the patient's health condition is, the greater the risk value. The following fuzzy membership functions are defined to assess the risk level: Low-, Medium-, and High-Risk categories. $0 < Rk < 0.5$ indicates low risk, $0.2 < Rk < 0.8$ indicates medium risk, and $0.5 < Rk < 1$indicates high risk for a patient. The patient's risk level is calculated using data from the five tuples (ft) of biosensors in order to reach a judgment. The last type is some prognostic or corrective information offered to the patient and may catalyze a certain activity. The aggregate score AS of the $ft's$ monitored vital indicators serves as the FIS's input.

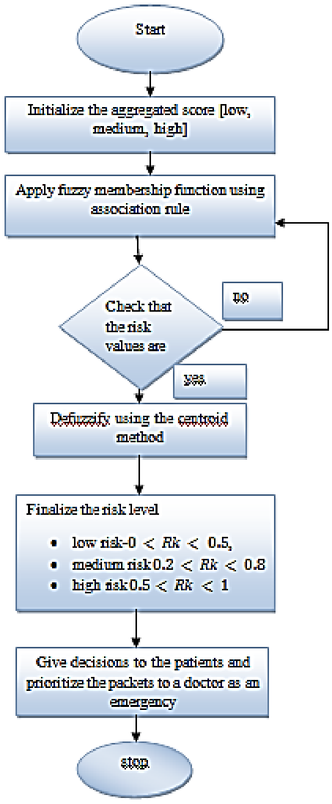

Fig 3. Flow chart for risk analysis and decision support

The patient's risk level is its output. It uses the fuzzy membership functions and fuzzy rule base provided by medical professionals or experts to map the input to the output. This is how the fuzzy rule basis is explained: Rule 1 states that the patient's risk level is Low-Risk if the overall score is Low. A crisp patient's risk level RK is then obtained by de-fuzzing the risk level using the centroid approach. Given the significance of RK, a conclusion, piece of advice, or even a course of action is chosen. It is chosen from a table that shows how the patient's risk ratings and the decisions are related. Health professionals set such a table 2. According to the cause's level, the choices or suggestions can be to rest, take medication, consult a doctor, etc. For instance, if $0 \leq RK < 0.22$, decision 1 is made. The entire process is given in Figure 3.

Table 2. Decision and risk values based on association rule

Decisions	**Risk value range**
decision 1	RK < 0.22
decision 2	0.22 ≤ RK < 0.3
decision 3	0.3 ≤ RK < 0.7
decision 4	0.7 ≤ RK < 0.9
decision 5	RK ≥ 0.9

The person in charge receives these prioritized packets. The patient receives counsel or a decision based on the value of RK. The coordinator sends the medical centre the information gathered and the decisions made. The coordinator works in rounds where $RD = ft \times TP$, where ft is five tuples, and TP is the common period for all biosensors. Let $RD(n) = (rd_1, rd_2, rd_3, rd_4, rd_5)$ represent the vector of the initial readings from the five biological sensors at the start of every cycle.

Let $st = (st1, st2, st3, st4, st5)$ be the resulting vector of the current scores at moment t, and $SC(n) = (SC1, SC2, SC3, SC4, SC5)$ be the column of the calculated scores corresponding to $RD(n)$. The coordinator computes $SC(n)$, reads $RD(n)$, and sets $S0 = SC0$ at the start of each round. The coordinator recognizes the sending biosensor foot each time it receives a measurement to compute score i and update SCt. The next step is to determine whether SCi differs from zero. It recognizes an emergency and queries the other biosensors to obtain their measurements when this occurs. The coordinator computes SCt and determines the overall score AS after receiving them. The latter serves as the FIS's input. Lastly, a choice is made based on the patient's risk level as generated from the FIS. After every round, the AS is determined, and a choice is made based on the information provided by the FIS.

4. Performance Analysis

The performance of our proposed Smart_FuzzBPNN is compared with existing methods such as wearables-assisted smart health monitoring for sleep quality prediction using optimal deep learning (WSHMSQP-ODL) model [16], Fully connected Neural Network (FNN) [19] and polynomial regression machine learning (PRML) is carried out using parameters such as accuracy, precision, recall, F1-score. These parameters are analysed for below dataset mentioned.

4.1 Dataset Description

A portion of the Multi-parameter Intelligent Monitoring for Critical Care (MIMIC) II database was used for this study. Every entry matches a grown-up patient's stay in the intensive care unit (ICU). It contains minute-by-minute time series of the patient's heart rate (HR), systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial blood pressure (MAP).

4.2 Comparative Analysis

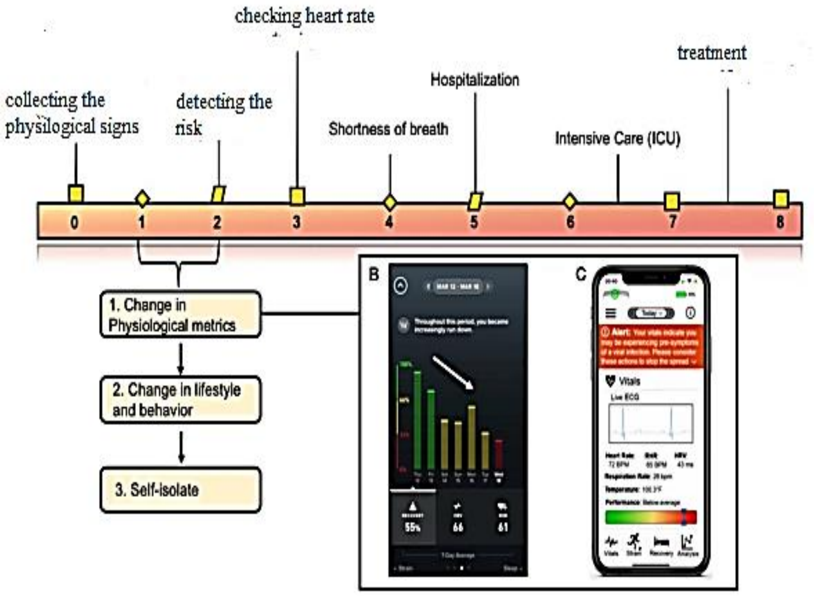

Fig 4. Collecting of signals

Figure 4 shows a Schematic detailing an example of an iPhone application collecting physiological data from a wearable sensor and translating those metrics to alert an individual on his/her overall health status

Table 3. Comparison of detection rate

patient	WSHMSQP-ODL	FNN	PRML	Smart_FuzzBPNN
0	0	0	0	0
P1	87	90	84.7	97.4
P2	88.5	90.5	85	98
P3	89	89.9	85.7	98.3
P4	85.7	89	86	98.4
P5	88	91	85	97.9

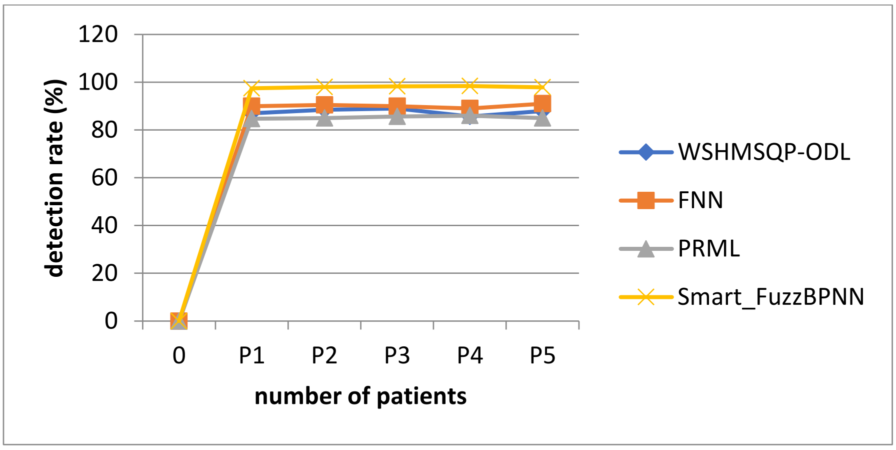

Fig 5. Comparison of detection rate

The suggested Smart_FuzzBPNN technique and the existing methods are compared in Figure 5, where the X-axis indicates the number of patients (1-5) and the Y-axis displays the detection rate achieved in %. When analyzing figure-3, the existing WSHMSQP-ODL, FNN and PRML achieve 89%, 91% and 85%of detection rates, whereas the suggested Smart_FuzzBPNN achieves 98.4%, which is 9.4%, 7% and 13.4% better than WSHMSQP-ODL, FNN and PRML. Table 3 shows Comparison of detection rate

Table 4. Comparison of end-to-end delay (ms)

patient	WSHMSQP-ODL	FNN	PRML	Smart_FuzzBPNN
0	0	0	0	0
P1	33	44	23	12
P2	34.1	44.9	23.7	11.9
P3	34	45	23	12.4
P4	33.9	45.3	24.6	12
P5	33	45.1	24	12.7

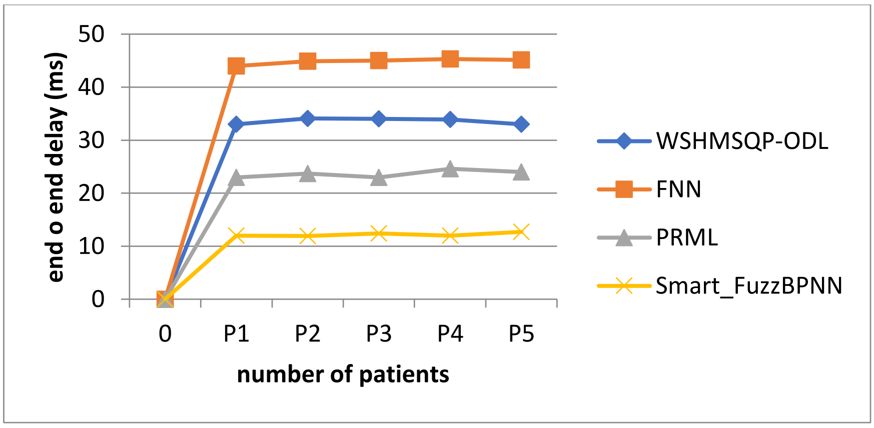

Figure 6. Comparison of end-to-end delay

The suggested Smart_FuzzBPNN technique and the existing methods for an end-to-end delay are compared in Figure 6, where the X-axis indicates the number of patients (1-5) and the Y-axis displays the for an end-to-end delay achieved in ms. When analyzing the existing WSHMSQP-ODL, FNN and PRML achieve 34.2ms, 45.1ms and 24.9ms of end-to-end delay, where the suggested Smart_FuzzBPNN achieves 12.5ms which is 22ms,32ms and 12ms WSHMSQP-ODL, FNN and PRML. Table 4 defines Comparison of end-to-end delay (ms)

Table 5. Comparison of packet dropped rate (%)

patient	WSHMSQP-ODL	FNN	PRML	Smart_FuzzBPNN
0	0	0	0	0
P1	77	53	35	10
P2	77.9	54.6	36	10.9
P3	78	55	37	11
P4	78.4	54.3	38	11.4
P5	78.3	56	39	11.9

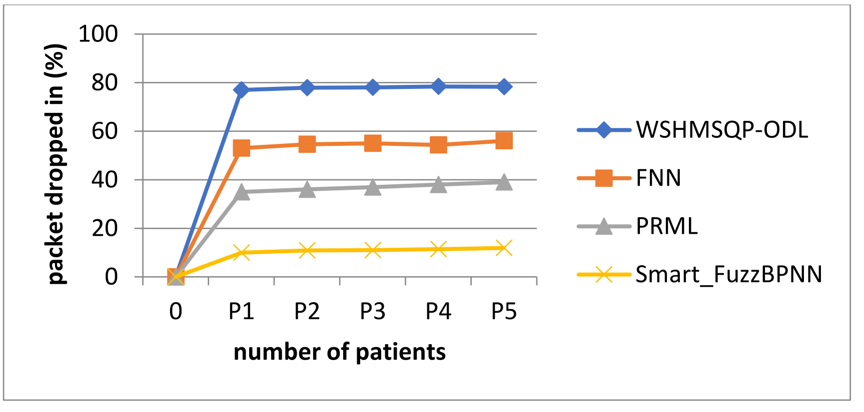

Fig 7. Comparison of packet dropped the rate

The suggested Smart_FuzzBPNN technique and the existing methods are compared in Figure 7, where the X-axis indicates the number of patients (1-5) and the Y-axis displays the packet dropped rate achieved in %. When analyzing the existing WSHMSQP-ODL, FNN and PRML achieve 78%, 54% and 38%of packet dropped rate, whereas the suggested Smart_FuzzBPNN achieves 11% is 67%, 41% and 21% better than WSHMSQP-ODL, FNN and PRML. Table 5 shows comparison of packet dropped rate (%)

Table 6. Comparison of risk level analysis

patient	WSHMSQP-ODL	FNN	PRML	Smart_FuzzBPNN
0	0	0	0	0
P1	78	87	89	93
P2	77.9	86.4	86.4	93.4
P3	77	84	89	94
P4	76.3	86.3	86.3	94.2
P5	75.2	87	87	95

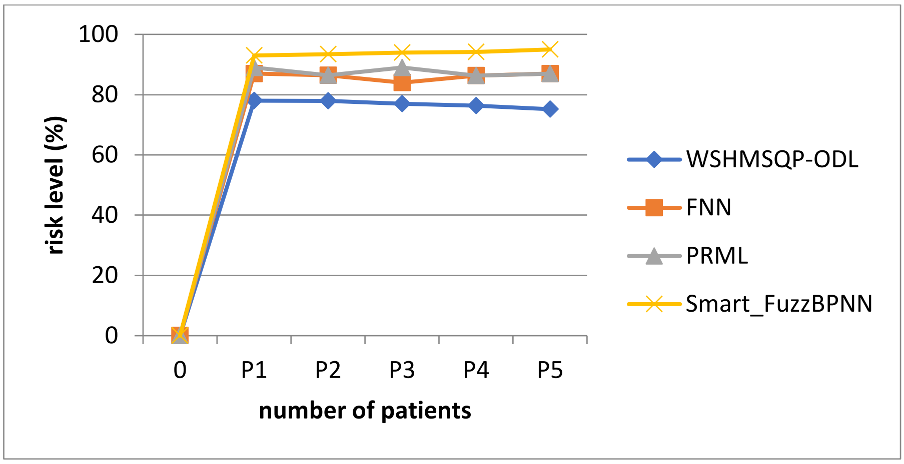

Fig 8. Comparison of risk level

The suggested Smart_FuzzBPNN technique and the existing methods are compared in Figure 8 where the X-axis indicates the number of patients (1-5) and the Y-axis displays the risk level achieved in %. When analyzing the existing WSHMSQP-ODL, FNN and PRML achieves 78%, 86% and 89%of risk level detection, where, the suggested Smart_FuzzBPNN achieves 94% which is 16%, 8% and 5% better than WSHMSQP-ODL, FNN and PRML. Table 6 shows comparison of risk level analysis

Table7. Comparison of energy efficiency

patient	WSHMSQP-ODL	FNN	PRML	Smart_FuzzBPNN
0	0	0	0	0
P1	86	76	79	97
P2	87.4	77.8	78.9	97.6
P3	8.9	77	79.9	98
P4	87	77.9	79.4	98.9
P5	87.3	7.9	79	97

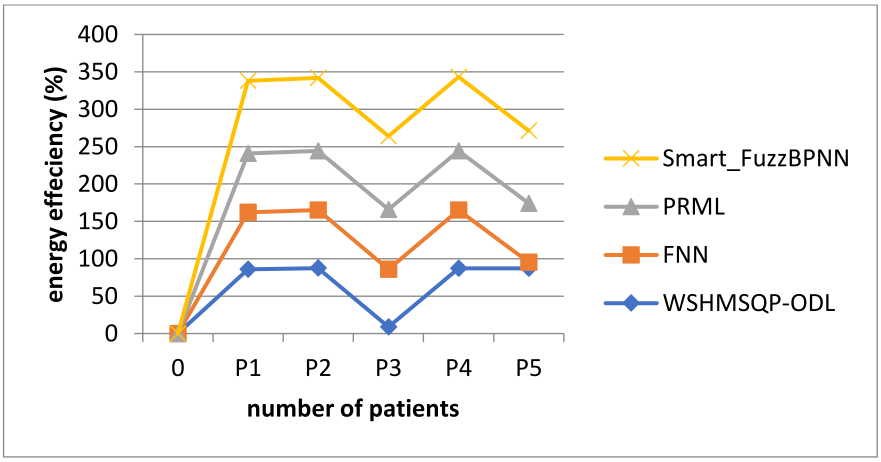

Fig 9. comparison of energy efficiency

The suggested Smart_FuzzBPNN technique and the existing methods are compared in Figure 9 where the X-axis indicates the number of patients (1-5) and the Y-axis displays the energy efficiency achieved in %. When analyzing the existing WSHMSQP-ODL, FNN and PRML achieves 87.3%, 76.5% and 79%of energy efficiency, where, the suggested Smart_FuzzBPNN achieves 97.5% which is 10.2%, 22% and 17% better than WSHMSQP-ODL, FNN and PRML. Table 7 shows comparison of energy efficiency and Table 8 shows overall comparative analysis

Table 8. Overall comparative analysis

parameters	WSHMSQP-ODL	FNN	PRML	Smart_FuzzBPNN
Detection rate (%)	89	91	85	98.4
end to end delay (ms)	34.2	45.1	24.9	12.5
Packet dropped rate (%)	78	54	38	11
Risk level analysis (%)	78	86	89	94
Energy efficiency (%)	87.3	76.5	79	97.5

5. Conclusions

In order to address the difficulties of providing home-based health surveillance and preventing hospitalization, the Smart_FuzzBPNN smart healthcare surveillance system has been suggested in this article. According to the research, there exists a significant need for creating a system of healthcare that can monitor senior citizens in real-time and at home. By constantly tracking their health, Smart_FuzzBPNN may significantly help to the provision of an enjoyable and secure setting for elderly and disabled persons, enabling individuals to continue living autonomously beyond the worry of an unforeseen or catastrophic medical condition. In a nutshell, Smart_FuzzBPNN collects biological information from patients using wearable sensors and sends it to the server for processing and analysis. As a result, any abnormality found in the patient's data will be communicated to their physicians via the hospital platform. With a fixable design that is simple to adapt and grow, Smart_FuzzBPNN offers a dependable and affordable system for remote patient monitoring. Additionally, the findings demonstrate that by utilising the perfect Smart_FuzzBPNN system, which is able to remotely and in real-time monitor patient symptoms, the system could effectively assist in improving healthcare facilities. The Smart_FuzzBPNN will continue to develop and be improved in the future. For example, the procedure can be expanded to apply optimisation techniques to aid in the early prediction of life-threatening diseases. Additionally, the system has a significant quantity of healthcare information that will be used to create a framework for suggestions that can offer advice on diets and lifestyle choices for improved health.

References

[1] Centers for Disease Control and Prevention. The State of Aging and Health in America 2013. *Centers for Disease Control and Prevention*, US Department of Health and Human Services; Atlanta, GA, USA: 2013.

[2] Global Age Watch Index 2015. [(accessed on 20 June 2016)].

[3] World Health Organization Family Planning/Contraception. 2015. [(accessed on 20 June 2016)].

[4] World Health Organization Are You Ready? What You Need to Know about Ageing. World Health Day. 2012. [(accessed on 20 June 2016)].

[5] U.S. Health Care Costs Rise Faster Than Inflation. [(accessed on 20 June 2016)].

[6] Deen M.J. Information and communications technologies for elderly ubiquitous healthcare in a smart home. *Pers. Ubiquitous Comput.* **2015** ,*19*, 573–599.

[7] Agoulmine N.; Deen M.; Lee J.-S.; Meyyappan M. U-Health Smart Home. *IEEE Nanotechnol. Mag*. **2011,** *5*, 6–11.

[8] Wang H.; Choi H.-S.; Agoulmine N.; Deen M.J.; Hong J.W.-K. Information-based sensor tasking wireless body area networks in U-health systems. *Proceedings of the 2010 International Conference on Network and Service Management*; Niagara Falls, ON, Canada. 2010; pp. 517–522.

[9] Pantelopoulos A.; Bourbakis N. A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis. *IEEE Trans. Syst. Man Cybern. C*. **2010,** *40*, 1–12.

[10] Nemati E.; Deen M.; Mondal T. A wireless wearable ECG sensor for long-term applications. *IEEE Commun. Mag*. **2012,** *50*, 36–43.

[11] Hong Y., Kim I., Ahn S., Kim H. Mobile health monitoring system based on activity recognition using accelerometer. *Simul. Model. Pract. Theory*. **2010 ,***18*, 446–455.

[12] Ullah S.; Higgins H.; Braem B.; Latre B.; Blondia C.; Moerman I.; Saleem S.; Rahman Z.; Kwak K. A Comprehensive Survey of Wireless Body Area Networks. *J. Med. Syst.* **2012** ,*36*, 1065–1094.

[13] Al Ameen M.; Liu J.; Kwak K. Security and Privacy Issues in Wireless Sensor Networks for Healthcare Applications. *J. Med. Syst.* **2012,** *36*, 93–101.

[14] Castillejo P.; Martinez J.; Rodriguez-Molina J.; Cuerva A. Integration of wearable devices in a wireless sensor network for an E-health application. *IEEE Wirel. Commun*. **2013,** *20* ,38–49.

[15] Dementyev A.; Hodges S.; Taylor S.; Smith J. Power consumption analysis of Bluetooth Low Energy, ZigBee and ANT sensor nodes in a cyclic sleep scenario; *Proceedings of the 2013 IEEE International Wireless Symposium (IWS)*; Beijing, China. April 2013; pp. 1–4.

[16] Hamza, M. A.; Abdalla Hashim, A. H.; Alsolai, H.; Gaddah, A.; Othman, M.; Yaseen, I.; ... & Zamani, A. S. Wearables-Assisted Smart Health Monitoring for Sleep Quality Prediction Using Optimal Deep Learning. *Sustainability*, **2023,***15(2)*, 1084.

[17] Davarzani, S.; Saucier, D.; Talegaonkar, P.; Parker, E.; Turner, A.; Middleton, C.; ... & Freeman, C. Closing the Wearable Gap: Foot–ankle kinematic modeling via deep learning models based on a smart sock wearable. *Wearable Technologies*, **2023,** *4*, e4.

[18] Sahoo, K. K.; Ghosh, R.; Mallik, S.; Roy, A.; Singh, P. K.; Zhao, Z. Wrapper-based deep feature optimization for activity recognition in the wearable sensor networks of healthcare systems. *Scientific Reports*, **2023,** *13(1)*, 965.

[19] Achebe, P. N.; Akpado, K. A.; Obioma, P. C. Modelling and Design of Artificial Intelligent based Patient Monitoring System for Measuring Vital Parameters for Diabetes Mellitus Prognosis. *International Journal of Research Publication and Reviews*, **2023,** *14(1)* 467-479.

[20] Kadu, A.; Singh, M.; Ogudo, K. A Novel Scheme for Classification of Epilepsy Using Machine Learning and a Fuzzy Inference System Based on Wearable-Sensor Health Parameters. *Sustainability*, **2022,** *14(22)*, 15079.

[21] Jansi Rani, S. V.; Chandran, K. S.; Ranganathan, A.; Chandrasekharan, M.; Janani, B.; Deepsheka, G. Smart wearable model for predicting heart disease using machine learning: Wearable to predict heart risk. *Journal of Ambient Intelligence and Humanized Computing*, **2022,** *13(9)*, 4321-4332.

[22] Garcia-Moreno, F. M.; Bermudez-Edo, M.; Rodríguez-García, E.; Pérez-Mármol, J. M.; Garrido, J. L.; Rodríguez-Fórtiz, M. J. A machine learning approach for semi-automatic assessment of IADL dependence in older adults with wearable sensors. *International journal of medical informatics*, **2022,** *157*, 104625.

[23] Tan, Y. H.; Liao, Y.; Tan, Z.; Li, K. H. H. Application of a Machine Learning Algorithms in a Wrist-Wearable Sensor for Patient Health Monitoring during Autonomous Hospital Bed Transport. *Sensors*, **2021,** *21(17)*, 5711.

[24] Godi, B.; Viswanadham, S.; Muttipati, A. S.; Samantray, O. P.; Gadiraju, S. R. E-healthcare monitoring system using IoT with machine learning approaches. *In 2020 international conference on computer science, engineering and applications (ICCSEA)*, 2020, March pp. 1-5.

[25] Vinston Raja, R., Ashok Kumar, K. ., & Gokula Krishnan, V. . (2023). Condition based Ensemble Deep Learning and Machine Learning Classification Technique for Integrated Potential Fishing Zone Future Forecasting. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2), 75–85. https://doi.org/10.17762/ijritcc.v11i2.6131

[26] Flores, A., Silva, A., López, L., Rodriguez, A., & María, K. Machine Learning-Enabled Early Warning Systems for Engineering Student Retention. Kuwait Journal of Machine Learning, 1(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/106