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Artificial Intelligence Powered Iomt Framework For Monitoring Elderly Health

K.Aruna Anushia[1], Dr. S. Arumuga Perumal [2]

[1]Reg.No:19223152172008 ,Research Scholar, Department Computer Science (Research Centre) , S.T.Hindu College ,Nagercoil, Tamilnadu-,629 002 India, Affiliation of Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli 627012,Tamilnadu, India.

[2]Assosciate Professor & Head, Department of Computer Science, S.T.Hindu College Nagercoil, Tamilnadu-629 002 India.

ABSTRACT

Real time remote health monitoring is the most promising technology to helping the elderly people in their daily lives. The increase in the elderly population has increased the demand for health care services. Internet of Medical Things (IoMT) and wearable sensors have been adopted for health care services for fast monitoring, prediction, and diagnosis. Nevertheless, there have been difficulties that need to be solved by the use of Artificial Intelligence (AI). This paper intends to design an AI powered- IoMT framework for monitoring elderly people health.Five vital signs include heart rate, respiration rate, blood oxygen saturation, temperature, and blood pressure are collected from the elderly using wearable sensors and the data are transmitted via Wi-Fi and are stored in IoMT cloud. The stored data are preprocessed to refine the collected data. The prediction of normal/abnormal data is made by Wavelet Artificial Neural Network (WANN) and then decision is made whether to send alert to physician /caretaker or not. Performance analysis is carried out to validate the efficiency of the proposed system and compared with well-known methods. Results prove that monitoring of health in the elderly using AI system is a feasible way for remote health monitoring systems.

Keywords: health status prediction, vital signs, WANN, IoMT, elderly monitoring system

1. INTRODUCTION

The growing numbers of elderly population and increasing life expectancy have brought enormous challenges to many aspects of human life, especially in health. According to the united nations report, in 2019, the percentage of elderly population is 12.3%, which is projected to projected to rise as 16.2% in projected to projected to rise as 16.2% in 2050 [1]. Elderly people have many health problems like falling easily, memory problem, and fainting etc. [2]. These problems to cause the elderly people to need monitoring by a caretaker. In current social conditions, most caretakers leave the house for a carrier. They are unable to monitor constantly care for the elderly people, and the elderly without care remains a problem. Therefore, advanced technologies can be applied to make a system for continuously monitoring elderly people.

Internet of Medical Things (IoMT) devices can be of big help in elderly health monitoring. IoMT is a system of interconnected medical devices, software, healthcare devices and services that exchange real time data by means of network technologies. IoMT effectively contribute to provide Health Monitoring System (HMS) for elderly people especially when they may have some valid reasons to independently live alone [3]. Several health care systems have been developed by using IoMT and modern sensors.For instance, Al-khafajiy et al. [4] suggested a system for monitoring health status of elderly via wearable sensors. This system uses wearable sensors to collect vital signs and pass the information to clouds for analyzing and storage.

A majority of research investigations have focused on prediction of diseases like Alzheimer’s, Diabetes, and Parkinson [5]. However, besides monitoring particular signs other vital signs involve of activity forms of the elderlies are also indispensable for decision making system. These limitations motivate us to build an Elderly Healthcare Monitoring System (EHMS) in an IoMT platform that tracks vital signs. The contributions of this paper are summarized as follows:

- Design an Artificial Intelligence (AI) powered IoMT platform named Elderly Health Monitoring System (EHMS) for monitoring health status of elderly.
- Predicting elderly’s health status via continuously monitoring vital signs such as Heart Rate (HR), Respiration Rate (RR), Blood Pressure (BP), Temperature (T), and blood oxygen saturation (SPO_2)
- Assessing the biological signal changes via Wavelet Artificial Neural Network (WANN) in order to predict elderly healthy status and compare the results with earlier approaches.

The rest of this paper is framed as follows. Section 2 presents a review on earlier works. Section 3 explains the proposed EHMS. Section 4 discusses the experimental results of the EHMS. Section 5 concludes the paper.

2. LITERATURE REVIEW

Numerous methods have been presented in Internet of Things (IoT) based health care system. Al-khafajiy et al. [4] presented a remote monitoring system for tracking health condition of elderly people through wearable sensors. Elderly’s vital signs values are collected and sent to a cloud data center for storing and analysing process to detect possible abnormal changes in health status. The obtained result from simulation revealed that the proposed systems with gaining low latency and low packets-lost can be a cost-effective solution for healthcare systems.

Kaur et al. [6] used machine learning techniques including K-NN, Support Vector Machine (SVM), Decision Trees, Random Forest (RF), and Multi-Layer Perceptron (MLP) besides healthcare datasets stored in the cloud space for improving the interaction between doctors and patients based on IoT infrastructures, which makes remote health monitoring possible.

Hamim et al. [7] designed an android application based on IoT which consists sensor of a heart pulse, body temperature sensor and sensor of galvanic skin response. All the data obtained from the sensors stored and transferred to cloud space to remote health monitoring.

Ani et al. [8] suggested a remote health monitoring method by combining IoT and Random Forest (RF). Wearble sensors were used to gather data from patient. By this method of monitoring, future recurrence could be minimized by providing alert to the physicians.

Jeyaraj and Nadar [9] focused on framework of novel IoT application oriented physiological signal monitoring system for e-healthcare system. Deep neural network-based system was employed for accurate signal prediction and used estimation algorithm in addition. Signal measurement was accomplished by intelligent sensor. he model was validated for four physiological signal accuracies with two users.

Dudakiya et al. [10] used Arduino as a gated way connected to sensors to get vital data.The obtained signals were analysed by using ada boosting and Naïve Bayes (NB) for predicting health condition. In this study, Arduino is attached to the patient’s body and connected to Wi-Fi for data transformation. This cannot be the best practice interim of Arduino hardware size and accuracy in kept detached to patient body and connected to the Wi-Fi.

In this research, wearable sensors are used to measure vital signs and send all values to smart phone via Bluetooth device. The mobile will act as a gateway to transmit all data to cloud for data processing, analysis and storage.

3. PROPOSED AI POWERED IOMT FRAMEWORK

The proposed EHMS make use of wearable sensors and smart phone to monitor elderly people health in real time. The main task for the EHMS is to monitor biological signals collected from person’s wearable sensors and then data stored in the cloud. The stored data can be assessed by authorized physicians and caretaker at anytime from anywhere. The key layers of the suggested EHMS are depicted in Figure.1. The system encompasses four layers including:

1. Perception layer
2. Communication layer
3. Cloud center and
4. Monitoring platforms

3.1 Perception Layer

To monitor the elderly’s health status, the physiological data to be collected using wearable sensors. The wearable sensors measure some vital signs such as T, RR, HR, BP, SPO_2 without interruption. The data are transmitted to smart phone via Bluetooth and then to a cloud database. The main elderly's health vital sign indicators and normal range is given in Table.1.

Table. 1 The main vital signs and their normal range

Sl.No.	Vital signs	Acronym	Normal range	Unit
1	Heart rate	HR	60-100	Beats per minute
2	Respiration rate	RR	8-12	Breaths per minute
3	Blood oxygen saturation	SPO2	>96%	Percentage
4	Temperature	T	336.5-38	^{o}C
5	Blood pressure	BP	120/80	mmHg

3.2 Communication layer

Communication layer is responsible for interacting with sensory data. The gathered vital signs are passed to smart phone via Bluetooth and then to a cloud data center.

3.3 Cloud center

Cloud is the place where the sensed data is processed and stored. It receives elderly's vital signs from their phone via internet. The proposed system uses Amazon web services [11] as cloud platform. All data processing and analysis will be done in the cloud for any

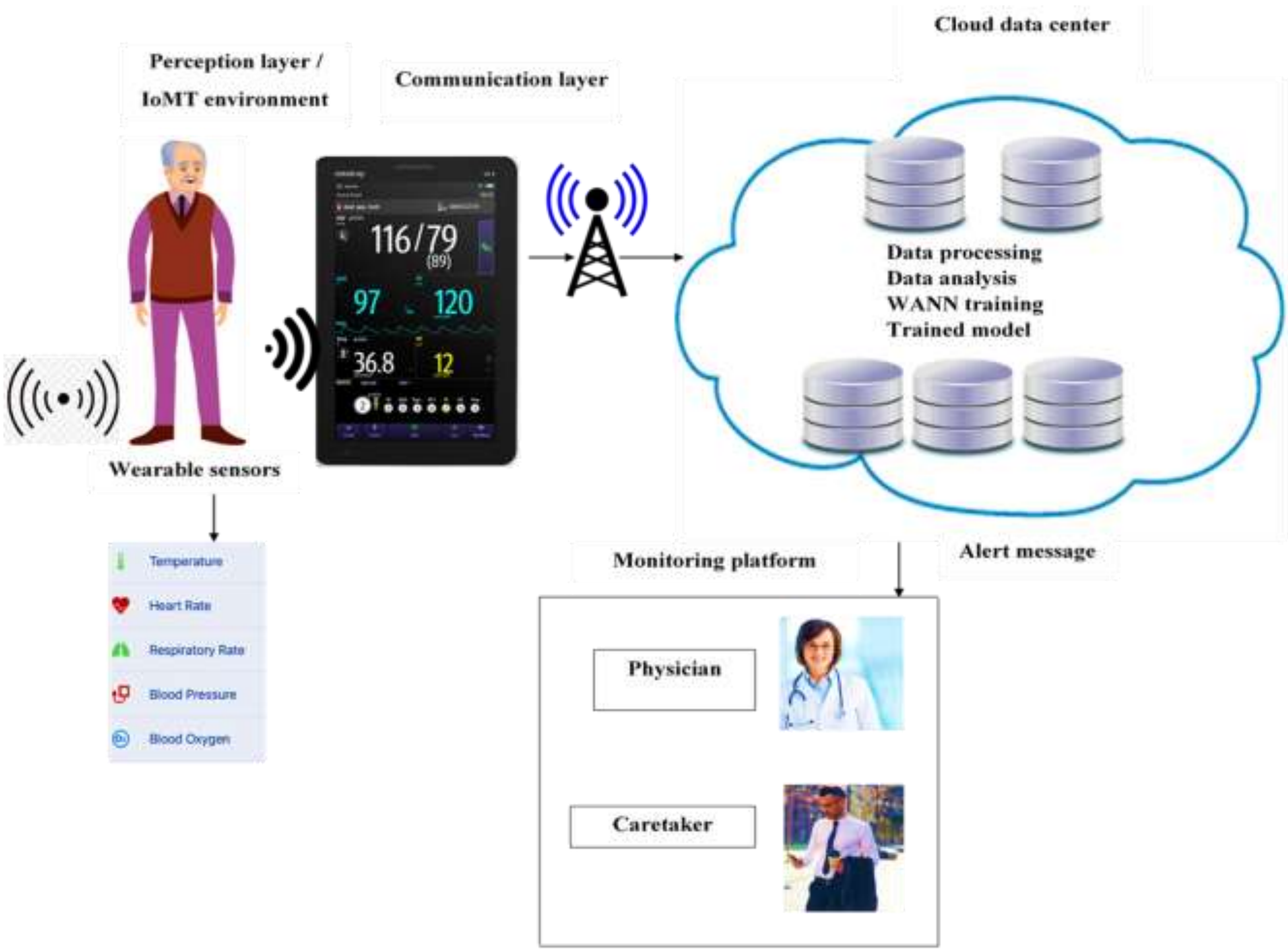

Figure.1 AI powered IOMT for monitoring elderly health

abnormal detection in elderly's health. The resulted data will be sent either to caretaker or physician or both depend on elderly health status. Data are preprocessed using min-max technique to limit the range [0,1] for further analysis.

$$y_{\text{norm}} = \frac{y - y_{\text{min}}}{y_{\text{max}} - y_{\text{min}}} \tag{1}$$

Where, y- input value, ynorm-normalized value, min –minimum value, and max-maximum value. The normalized values are fed as input to the WANN to perform classification. Structure of the developed WANN is shown in Figure.2. AWNN has 3 layers: an input layer, hidden layer and an output layer. Input layer is responsible for receiving input signals or feature vectors from the source. The hidden layer has hidden neurons similar to neurons in standard Neural Network (NN). In standard NNs, sigmoidal activation function is utilized at the hidden layer. Wavelets are used as activation function in hidden layer of WANN. Finally, the output layer corresponding to the linear combination of wavelet basis function.

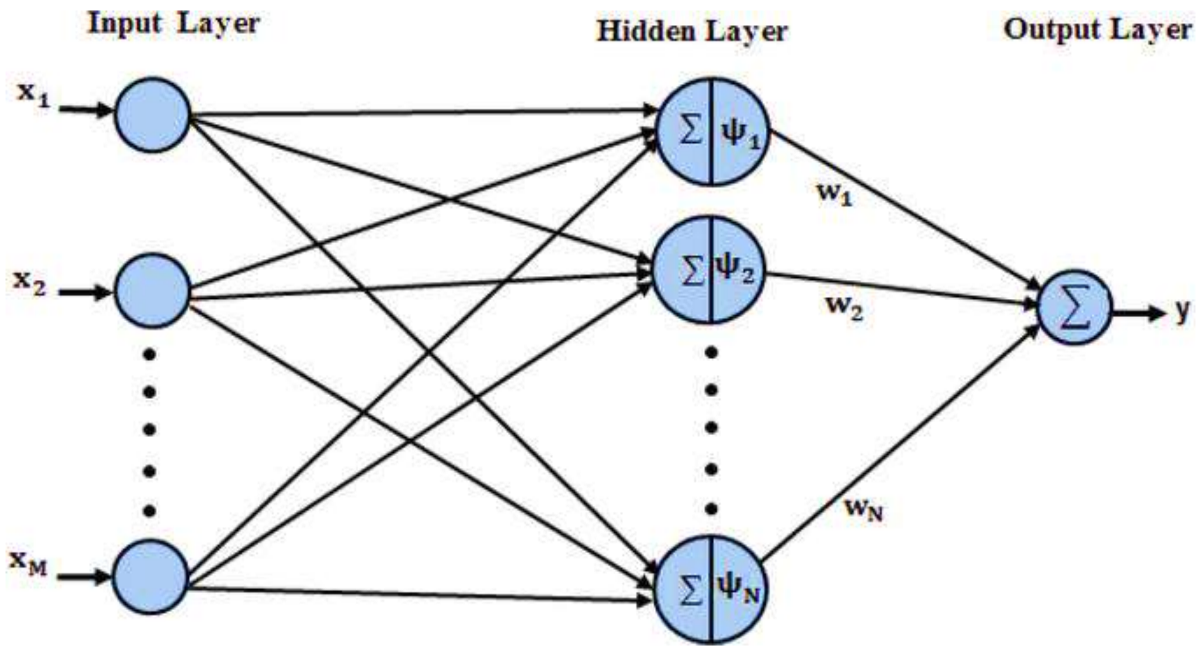

Figure.2 Designed WANN

The hidden layer output can be expressed as,

$$h(j) = \psi_j \left[\frac{\sum_{i=1}^{M} x_i w_{ij} - b_j}{a_j}\right] \tag{2}$$

$$\Psi(t) = \cos(1.75t)\exp\left(-\frac{t^2}{2}\right) \tag{3}$$

The output layer can be defined as,

$$y = \sum_{j=1}^{M} w_j h(j) \tag{4}$$

Where, x-input, y-output, wij-weight between input and hidden layers, wj-weight between hidden and output layer,b-shift factor, and a-stretch parameter

3.4 Monitoring platform

This platform includes physician and caregiver's details. The server will analyze the output of WANN. If something abnormal happens, it will send alert message to both physician and caregivers. With this predictive monitoring system alert messages are given which helps to take emergency action immediately as the abnormality is detected. This can save elderly life and guarantee a great personalized monitoring system.

4. EMPIRICAL STUDY

In this investigation, five vital signs given in Table. 1 have been adopted for EHMS, however earlier methods were not considered in other studied papers. For assessing the effectiveness of the proposed EHMS, a dataset with 5937 samples were collected from volunteers. These samples have all the vital signs listed in table. 1.

For evaluating the efficacy of EHMS, eight key parameters are computed. Table. 2 lists the evaluation parameters and their equations. Confusion matrix is commonly utilized for measuring performance of ML classifier [12]. It holds the samples which has four variables namely True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)[13].

Table.2 Evaluation metrics

Measures	**Equation**
Classification accuracy	$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$
Specificity	$\mathrm{SPC} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} = \frac{\mathrm{TN}}{\mathrm{N}}$
Recall	$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$
NPV	$\mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FN}}$
MCC	$\mathrm{MCC} = \frac{\mathrm{TP.TN} - \mathrm{FP.FN}}{\sqrt{(\mathrm{TP} + \mathrm{FP})(\mathrm{TP} + \mathrm{FN})(\mathrm{TN} + \mathrm{FP})(\mathrm{TN} + \mathrm{FN})}}$
Precision	$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$
Balanced classification rate	$\mathrm{BCR} = \sqrt{\mathrm{SEN\ X\ SPC}}$
Miss rate	$\mathrm{MR} = 1 - \mathrm{ACC}$

For validation, data division approach is used wherein the whole data is partitioned into training and test samples. 70% of the samples are used for training and 30% of the samples are used for testing. Figure. 3 and Figure. 4 depicts the performance of the EHMS in terms of confusion matrices for training and testing samples respectively. In this study, abnormal condition is defined as TP whereas normal condition as TN. As shown in Figure. 3, 2201 samples are correctly identified as abnormal which corresponds to 53% of all training samples. Similarly, 1903 samples are identified as normal. This corresponds to 45.8% of all training data. 28 of the normal data are incorrectly identified as abnormal and this corresponds to 0.7% of all training data. 24 of the abnormal samples are wrongly identified as normal which corresponds to 0.6% of all training samples.

For validation, a total of 1781 data are used which includes 893 abnormal and 763 normal data. As shown in Figure. 4, 903sample are accurately classified as abnormal and this corresponds to 50.8% of all test samples. Similarly, 799 sample are correctly classified as normal and this corresponds to 44.9 % of all test data. 49 of the abnormal data are wrongly classified as normal data are wrongly classified as normal and 28 of the normal data are incorrectly classified as abnormal. Consequently, TP, FN, TN and FP are 50.1%, 2.8 %, 42.8% and 1.6% respectively. This outcome shows accuracy of 95.7%.

Figure. 3 Training Performance of the proposed EHMS

Figure. 4 Testing Performance of the proposed EHMS

Table 3 delineates the outcomes of the proposed EHMS. During training, the attained accuracy, SPE, R, P, BCR, NPV, MCC and MR are 0.987, 0.985, 0.989, 0.987, 0.987, 0987, 0.974, and 0.012 respectively. During training, the EHSC gave an accuracy of 0.0.957, SPE of 0.966, R of 0.949, P of 0.970, BCR of 0.957, NPV of .942, MCC of 0.913 and MR of 0.043.Graphical representation of Table.3 is illustrated in Figure.4.

Table.3 Efficiency of the proposed system

Data	ACC	SPE	R	P	BCR	NPV	MCC	MR
Training data	0.987	0.985	0.989	0.987	0.987	0.988	0.974	0.013
Test data	0.957	0.966	0.949	0.970	0.957	0.942	0.913	0.043

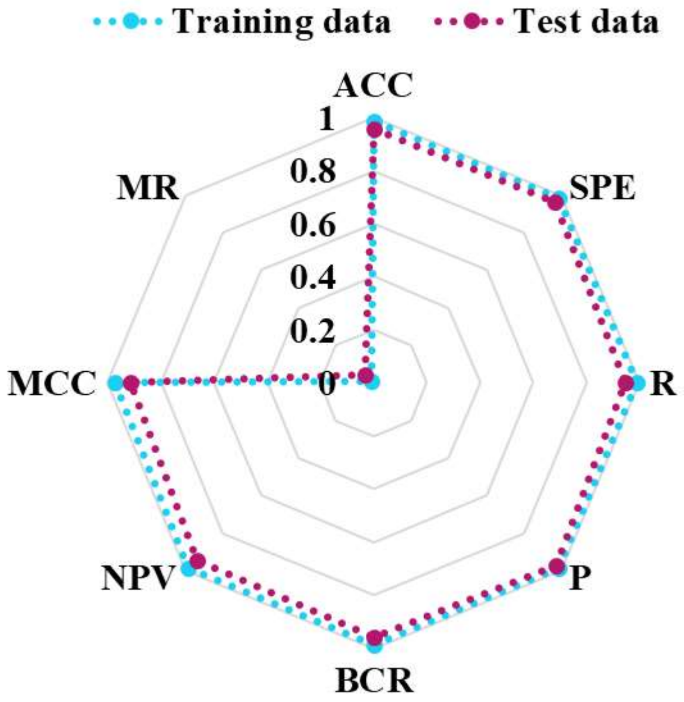

Figure.4 Proposed EHMS's performance

Performance of the proposed EHMS is compared with other well-known methods such as Random Forest (RF) [6], KNN [14], XG Boost (XGB) [15], and Resent [16] in order to prove its power. The obtained results from different methods are tabulated in Table.4 that shows the performance comparison in light of ACC and MR. As in Table.4, The proposed system achieved the highest ACC of 0.957 in comparison to the RF method with 0.811, KNN method with 0.873,XG method with 0.892, and 3D Resnet with 0.83. Further to this, with respect to MR, Table 4 reveals that the proposed EHMS has gotten lowest MR value of 0.043 comparing to RF with 0.189, KNN with 0.127, XG with 0.108, and 3D Resnet with 0.17

Table.4 Comparison with earlier approaches

Researchers	Method	ACC	MR
Kaur et al. [6]	RF	0.811	0.189
Ahmed [14]	KNN	0.873	0.127
Tang et al. [15]	XG	0.892	0.108
Lu et al. [16]	3D Resnet	0.83	0.17
Proposed	WANN	0.957	0.043

Also, as illustrated in Figutre.5, the RF has been performed with highest time of 69.3 ms among other methods.The KNN, XG and 3D Resnet have been executed in 45.7 ms, 52.5ms, and 62.9 ms respectively. It is observed that the proposed WANN has been performed with lowest time of 33.8ms over the same data.

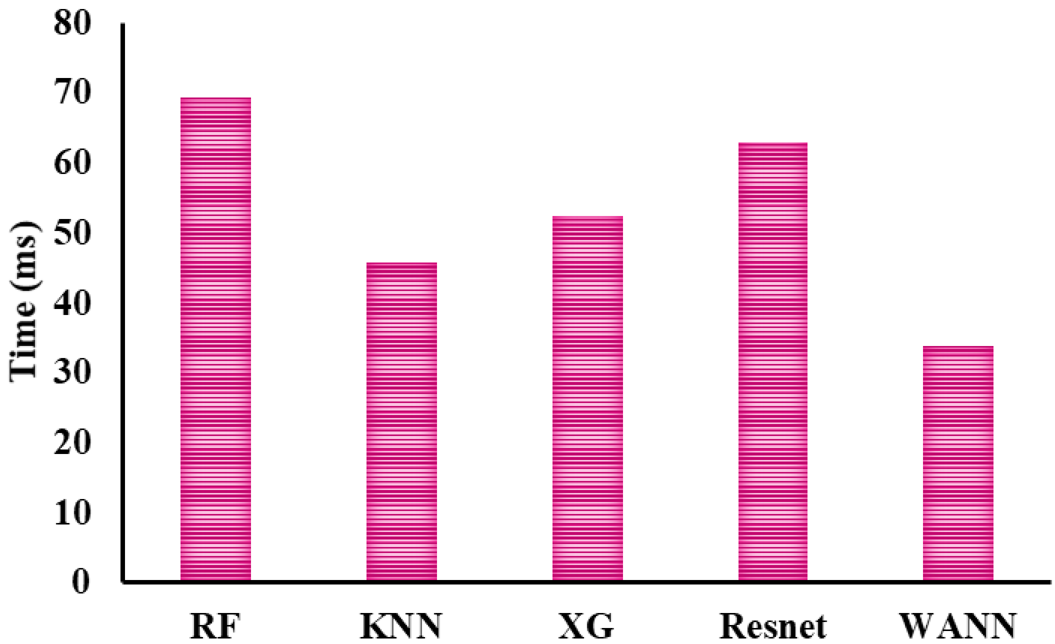

Figure.5 Comparison of execution time

5. CONCLUSION

This paper introduced a remote health monitoring system for elderly in home based application scenarios. In this system, IoMT and AI technique were used to meet the automated development requirement of the system. Vital signs werecollected from the aged people using wearable sensors and the data were passed through Bluetooth and then stored in IoMT cloud. The data were preprocessed with min-max technique. The normalized data were subjected to WANN to perform classification task. The decision making system decides whether to send alert or not based on the output of the trained WANN. If abnormal is detected, alert will be send to both physician and caretaker. Effectiveness of the system was assessed in terms of ACC, P, R, SPE, BCR, NPV, MCC, MR, and execution time. From the analysis, it is noted that the proposed system works well compared to other methods. In future, this work can be extended by implementing video based system.

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