A Cloud Based Machine Intelligent Human Activity Recognition System Using Internet of Things to Support Elderly Healthcare

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ABSTRACT

Purpose: *Human activity recognition is now a major concern in elderly healthcare perspective. Regular monitoring of daily activities is strongly needed for the elderly or old age persons at home. Therefore, the Internet of Things (IoTs) can be a solution to this problem.*

Design/Methodology/Approach: *In this paper, a cloud-based machine intelligent human activity recognition (HAR) system using IoT is proposed to recognize the regular activity of old person at home. In this system, the IoT device or wearable device connected to the body is embedded with activity recognition sensors those sense the physical activity and send the readings to the device. The device then sends the readings to the cloud using the Internet for classifying the actual activity of the person. The cloud is installed with a machine intelligent model which accurately classifies the activities. For the selection of this model, in this work we considered many standards supervised machine intelligence models.*

Findings/Result: *Simulation is done using Orange 3.26 python-based tool by considering Kaggle activity recognition data. Results state that NN shows better performance than other models in classifying the activities of the elderly person.*

Originality/Value: *A new cloud-based machine intelligent HAR system for smart home using IoTs is proposed to monitor the regular activity of the old person.*

Paper Type: *Methodology Paper.*

Keywords: IoT, Cloud, HAR, Elderly Healthcare, Machine Intelligence, CA

1. INTRODUCTION :

Currently, IoT is a widely accepted technology and a booming area of research field with wireless/wired infrastructure, where any smart device/hardware can be connected to provide on-demand service to the connected users [1]. IoT network mainly depends on the standard communication protocols [1] such as AMQT (advanced message queuing protocol), Bluetooth, cellular, MQTT, Wi-Fi, Zigbee, Z-Wave, CAP (constrained application protocol), DDS (data distribution service), EMPP (extensible messaging and presence protocol), LoRa, LoRaWAN, etc. The infrastructure of IoT mainly focuses on OSI seven layers architecture for performing the communication function, however multilayer architecture can also be used [1].

IoT has a wide variety of applications [1] in many areas such as smart homes, smart city, self-driving cars, farming, agriculture, IoT retail shops, wearables, smart grid, industrial IoT, smart supply chain management, waste management, pollution monitoring, traffic management, telehealth, smart health, healthcare technology, disaster management, robotics technology, defense, education, etc. From this study, we can say that IoT can make the people's life easier with its automotive nature. IoT now uses many new technologies and models to reduce the load on the device itself by offloading the computation and processing of tasks in other devices such as local servers or fog or cloud. Also, to solve or process new and complex problems, IoT is now using AI (artificial intelligence) which mainly uses the machine learning (ML) models or deep learning models by taking the previous records or results of data and predicting the next result or event or data. AI can solve many types of problems such as classification, clustering, decision making, etc. One such type of classification problem in IoT is HAR, where the IoT device connected to the body of the elderly person will continuously record the activity readings using the relevant sensors and analyze the readings to classify the activity [2-5]. The activity can be sitting, walking, laying, etc. These activities must be correctly identified or classified for recognition of activities when considering elderly person activity monitoring. So, in this work, we have designed a cloud-based system to monitor the elderly person's activity at home using an IoT device.

The contributions done in this work are shown below:

1. In this paper, a cloud-based machine intelligent HAR system using IoT is proposed to monitor the activity of the elderly person at home.
2. In this system, the IoT device or wearable device is connected to the body which is embedded with activity recognition sensors those sense the physical activity and send the readings to the device. The device then sends the readings to the cloud using the Internet for classifying the actual activity of the person.
3. The cloud is installed with a machine intelligent model which accurately classifies the activities. For the selection of this model, in this work we considered NN, kNN, RF, SVM, Tree, NB, AB, and LR supervised machine intelligence models.
4. An activity recognition dataset has been collected from the Kaggle data repository [6] for training and testing and finding a suitable model for the system that shows high CA. The best supervised machine intelligence model is installed at the local server to classify the activities.
5. Simulation is done using Orange 3.26 tool. Results show that NN performs better than kNN, RF, SVM, Tree, NB, AB, and LR in terms of CA. ROC analysis is also performed to assess the model performance. From observation, it is found that NN will be a better model at cloud for the classification of elderly activities.

   The rest of the work is presented as follows. Section 2 to Section 9 presents the related work, research gap, research agenda, objective, methodology, simulation and result discussion, conclusion, and recommendation.

2. RELATED WORK :

Many research work is conducted in this area for identification of human activities using a ML approach. Some research papers are discussed as follows. Ziyan et al. [7] used ML to identify human activity. Subasi et al. [8] found an approach to recognize human activity in a smart healthcare environment using ML methods. Khan et al. [9] proposed a deep learning method for HAR. Tan et al. [10] proposed an ensemble learning method to recognize human activity using sensor data from smartphones. Mittal et al. [11] proposed a HAR model using IoT device and smart sensors based on a ML approach. Zhang et al. [12] used deep learning technique to recognize the activity using the wearable device. Wan et al. [13] proposed deep learning-based real-time HAR model using smartphone data. Souza Junior et al. [14] found an approach using ML to identify human activities. Table 1 discusses about these above related research works.

Table 1: Review of articles related to HAR Source: [7-14]

S. No.	Field of Research	Focus	Outcome	Reference
1	HAR	The authors recognized activity of human using ML techniques.	The activities of the humans are detected well.	Ziyan et al. (2021) [7]
2	HAR	The authors proposed an approach to recognize activity of human in smart healthcare environment using ML methods.	The activities of the human in smart healthcare is recognized well.	Subasi et al. (2020) [8]
3	HAR	The authors proposed a deep learning based HAR.	The deep learning based human	Khan et al. (2022) [9]

			activity recognizes the activities well.	
4	HAR	The authors proposed an ensemble learning method to recognize activity of human using sensor data from smartphone.	The human activities using smartphone sensor data are recognized well.	Tan et al. (2022) [10]
5	HAR	The authors proposed a HAR model using IoT devices and smart sensors based on a ML approach.	The HAR model recognizes activity well using smart sensors.	Mittal et al. (2022) [11]
6	HAR	The authors proposed a deep learning model to recognize the activity using the wearable device.	The activities are recognized well using the wearable device.	Zhang et al. (2022) [12]
7	HAR	The authors proposed deep learning based real time HAR model using smartphone data.	The smartphone data is used well in deep learning model for recognition of activity.	Wan et al. (2020) [13]
8	HAR	The authors found an approach to recognize human activity using ML.	The human activity is recognized well using the ML approach.	Souza Junior et al. (2016) [14]

3. RESEARCH GAP :

From the above study, many research papers focus on the identification of human activities only using ML approach. As per our knowledge, very less work is done in the area of cloud-based machine intelligent framework for detection of HAR. So, in this work, a cloud-based framework is designed to identify the activities of an elderly person at home continuously using a supervised machine intelligence model.

4. RESEARCH AGENDA :

The main agenda of research is based on the design of a framework for categorizing the individual IoT devices using ML approach that is connected to a network. The research agenda is presented as follows. Section 5 defines the objective of the work. Section 6 presents the method of the whole work. The simulation and result of the work is presented in section 7. The conclusion of the whole work is presented in section 8. The recommendation of the work is shown in section 9. Then at last the references related to the work is presented.

5. OBJECTIVES :

The objectives related to this paper are presented as follows:

(1) To design a cloud-based machine intelligent HAR system using IoT for monitoring the activity of the elderly person at home.

(2) To select the best supervised machine intelligent model for the cloud for activity recognition more accurately.

(3) To simulate the machine intelligence part using python-based Orange 3.26 data analytics tool using an activity recognition dataset for measuring the performance of the models based on CA and ROC.

6. METHODOLOGY :

The methodology mainly describes the system architecture framework and process flow of the whole model. The system architecture mainly consists of two layers as device layer and the cloud layer as sown in Fig. 1. Device layer consists of an IoT device that is connected to the body of the elderly person. The IoT device is embedded with activity recognition sensors such as Gyroscope, Accelerometer, etc. The sensors sense the readings and transfer them to the main control unit of the IoT device. The IoT device then sends the readings continuously to the cloud server using 5G/4G/LTE/3G/Wi-Max technology. Here, we assume that the IoT device is already authenticated with the cloud. The cloud layer consists of a cloud device that gives services to the users who want to access the current activity of their elderly persons. Here, the cloud device is installed with a supervised machine intelligence model. That model is selected based on the highest classification accuracy after training and testing each model. Then the new readings received at the cloud can be classified and updated the cloud. The user or relative of the elderly person can access the cloud for activity recognition.

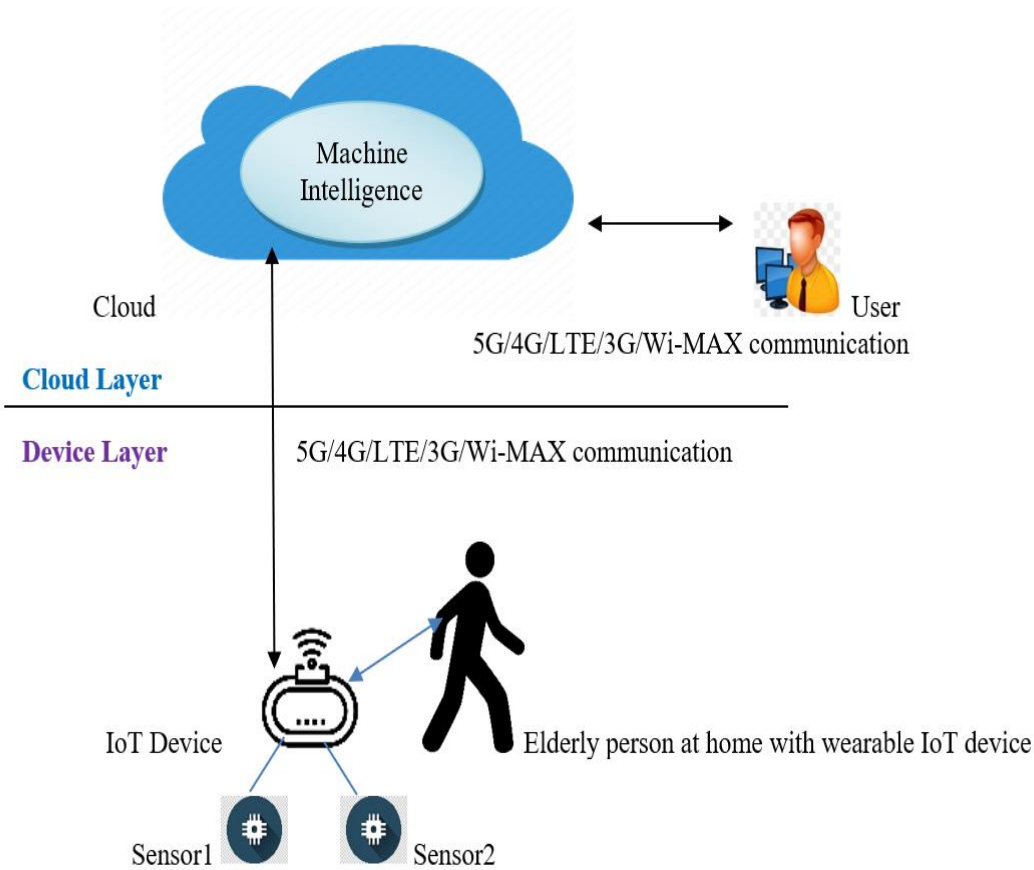

Fig. 1: System architecture framework Source: Author

The process flow of our work is discussed in Fig. 2 as follows. The process starts with a connection of activity monitoring sensors with the wearable IoT device of the elderly person. Then, the standard activity recognition dataset is fed into the machine intelligence models in the cloud. Training and testing in the cloud are performed for the selection of the best model in the cloud. Then, we select the best model with high accuracy and install that model in the cloud for the classification of activities more accurately. Afterward, when the system starts, new sensor readings are continuously sent to the cloud from the IoT device for the classification of accurate activity. Cloud receives the readings from IoT devices and predicts the actual activity. Then cloud updates the activity continues in the database. The user or relative can access the activity of the elderly person by accessing the cloud activity results.

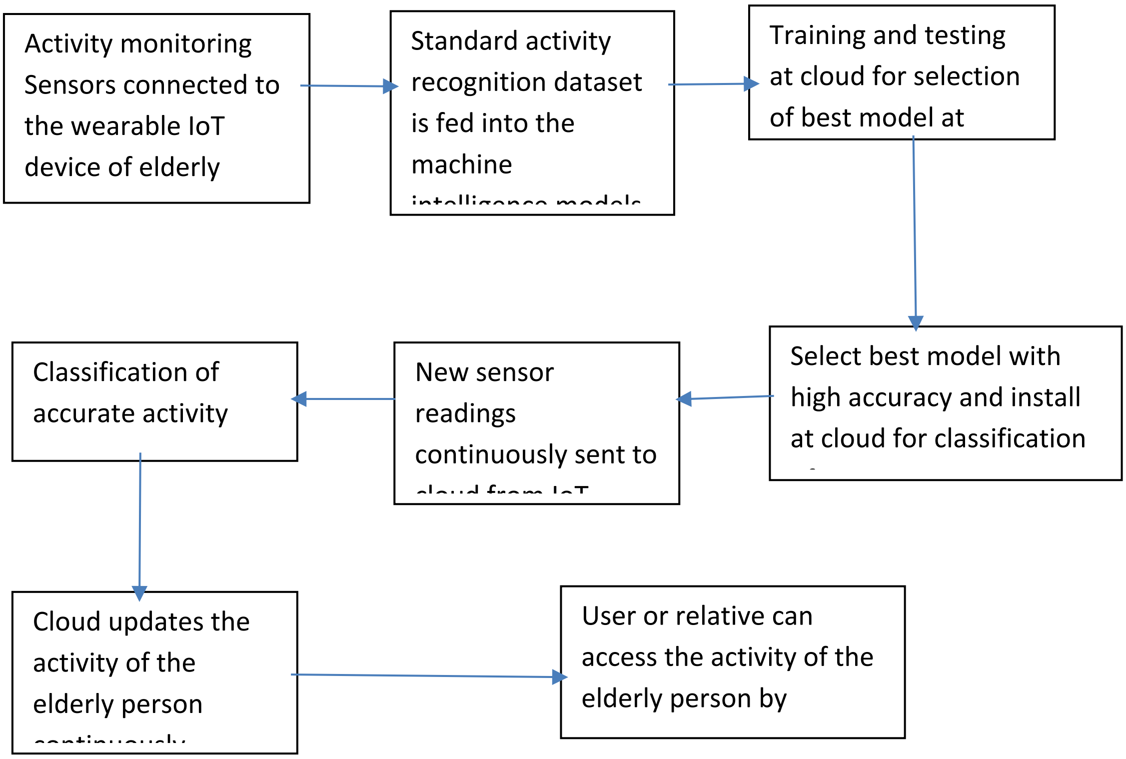

Fig. 2: Process flow diagram of the proposed elderly activity recognition system Source: Author

Algorithm 1: Device identification in smart home cloud infrastructure
Input: Training and Testing Dataset
Output: Activity Type

1. Connect sensors to wearable IoT device
2. Training and testing at cloud using supervised ML models
3. Best Model = maximum(CA1, CA2, CA3,…,CAn) //classification accuracies of n different models
4. Start IoT device to send new readings continuously
5. Activity is recognized in the cloud using best machine intelligence model
6. Cloud updates the activity of the elderly person in the database
7. User or relative can access the activity for monitoring

7. RESULTS :

The performance of the model is assessed in Orange tool [15] that is installed in a machine with 64 bit OS, 2.4 GHz processor speed, and 8 Gb ram. The supervised models considered for this simulation are RF, kNN, NN, SVM, Tree, NB, AB, and LR [16-31] for the selection of the best model using the performance metrics like AUC, CA, F1, precision (PR) and recall. The description of performance metrics can be referred from [16-31]. CA is mainly considered to classify the activity accurately.
The dataset considered for this is collected from Kaggle data repository [6]. The dataset has 6 activity categories and 7353 instances or rows and there are 563 attributes or columns such as accelerometer and gyroscope readings. The 6 activity categories are LAYING, SITTING, STANDING, WALKING, WALKING UPSTAIRS, and WALKING DOWNSTAIRS. The number of instances for these activities are 1408, 1286, 1374, 1226, 986, and 1073 respectively. We assume that this dataset can be considered as the activities of the elderly at home.
The simulation setup is done as per Fig. 3 where supervised ML models are taken with the dataset file given for training and testing. Here the sampling used for training and testing is k-fold, where k is set to 10. The default parameters setup of individual models can also be referred from [15]. Then the results can be found using the test and score as represented in Fig. 3. The results are shown in Table 2.
From Table 2, it is found that NN show better performance than other models with a CA of 98.80%.

Therefore, it will be better if we prefer NN as the model for installing in the cloud for classifying the activities with higher accuracy. Other performance metric results are also shown in Table 2 like AUC, F1, precision and recall, however, we mainly focus on CA as per the above discussion.

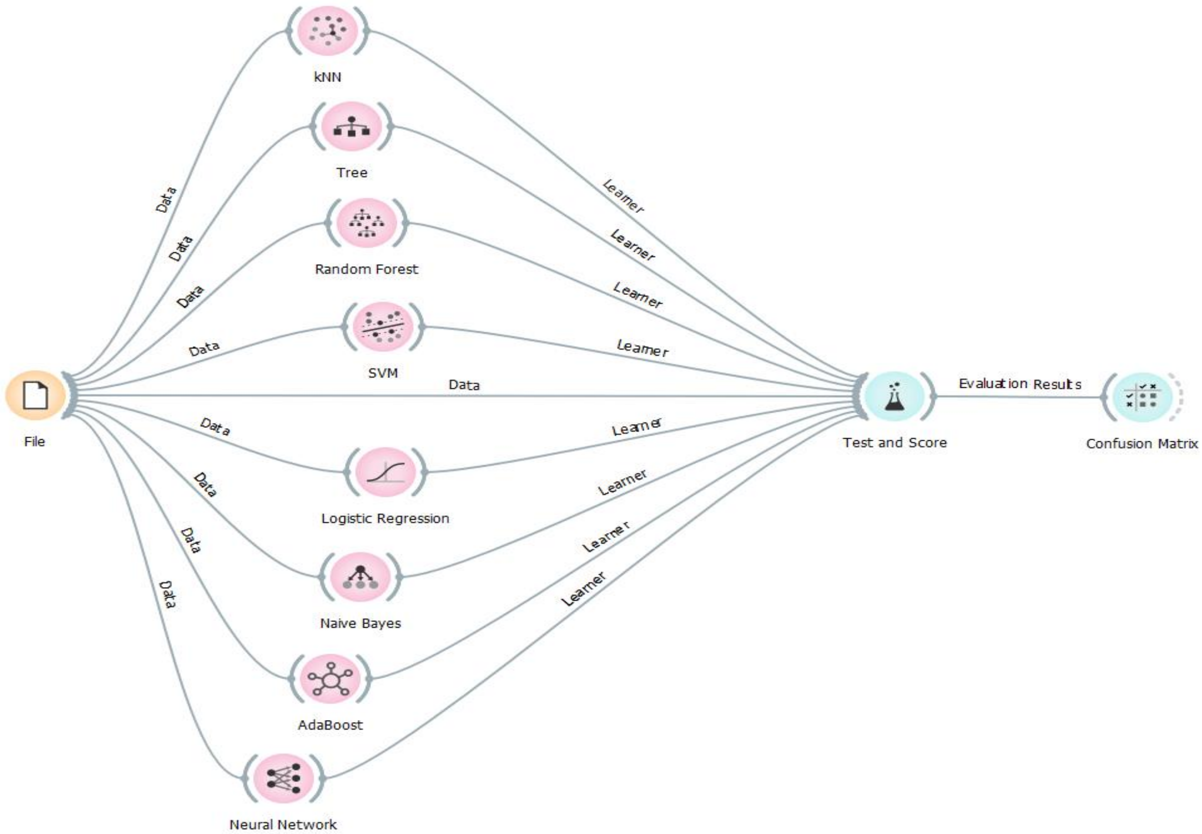

Fig. 3: Orange workflow setup for training and testing of models for selection of best model. Source: Author

Table 2: Comparison of different supervised machine intelligence models Source: Author

Models	**AUC**	**CA**	**F1**	**PR**	**Recall**
kNN	0.998	0.975	0.975	0.975	0.975
Tree	0.980	0.950	0.950	0.950	0.950
SVM	0.993	0.901	0.894	0.920	0.901
RF	0.999	0.972	0.972	0.972	0.972
NN	1.000	**0.988**	0.988	0.988	0.988
NB	0.947	0.711	0.716	0.744	0.711
LR	0.999	0.981	0.981	0.981	0.981
AB	0.968	0.946	0.946	0.946	0.946

The confusion matrix (CM) of all 8 models is represented in Fig. 4 - Fig. 11. From this CM from diagonal elements, it can be observed how many actuals are correctly predicted. The ROC analysis is also performed to show the individual activity category classification using true positive rate (TPR) vs false positive rate (FPR). From, the results are found that NN is closer to 1 and it indicates it shows accurate results. Fig. 12 shows the CA graph of the above 8 models. The ROC analysis is completely shown in Fig. 13 - Fig. 18 for different activities of human. From these ROC results, it is found that NN is closer to the y-axis and has higher accuracy than other models.

Predicted

Actual	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	∑
LAYING	1406	1	0	0	0	0	**1407**
SITTING	0	1165	120	0	0	1	**1286**
STANDING	0	50	1324	0	0	0	**1374**
WALKING	0	0	0	1225	0	1	**1226**
WALKING_DOWNSTAIRS	0	0	0	6	976	4	**986**
WALKING_UPSTAIRS	0	0	0	1	0	1072	**1073**
∑	**1406**	**1216**	**1444**	**1232**	**976**	**1078**	**7352**

Fig. 4: CM of kNN Source: Author

Predicted

Actual	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	∑
LAYING	1400	3	0	0	2	2	**1407**
SITTING	0	1213	72	1	0	0	**1286**
STANDING	0	69	1305	0	0	0	**1374**
WALKING	0	0	0	1161	29	36	**1226**
WALKING_DOWNSTAIRS	0	0	0	34	922	30	**986**
WALKING_UPSTAIRS	1	0	1	46	40	985	**1073**
∑	**1401**	**1285**	**1378**	**1242**	**993**	**1053**	**7352**

Fig. 5: CM of Tree Source: Author

Predicted

Actual	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	∑
LAYING	1404	0	0	0	3	0	**1407**
SITTING	1	628	656	0	0	1	**1286**
STANDING	0	61	1313	0	0	0	**1374**
WALKING	0	0	0	1222	2	2	**1226**
WALKING_DOWNSTAIRS	0	0	0	1	983	2	**986**
WALKING_UPSTAIRS	0	0	0	2	0	1071	**1073**
∑	**1405**	**689**	**1969**	**1225**	**988**	**1076**	**7352**

Fig. 6: CM of SVM Source: Author

Actual \ Predicted	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	Σ
LAYING	1405	2	0	0	0	0	1407
SITTING	0	1227	58	0	0	1	1286
STANDING	0	77	1297	0	0	0	1374
WALKING	0	0	0	1207	8	11	1226
WALKING_DOWNSTAIRS	0	0	0	13	962	11	986
WALKING_UPSTAIRS	0	0	0	12	16	1045	1073
Σ	1405	1306	1355	1232	986	1068	7352

Fig. 7: CM of RF Source: Author

Actual \ Predicted	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	Σ
LAYING	1404	0	0	0	2	1	1407
SITTING	2	1223	60	0	0	1	1286
STANDING	0	58	1315	1	0	0	1374
WALKING	0	0	0	1223	0	3	1226
WALKING_DOWNSTAIRS	0	0	0	0	980	6	986
WALKING_UPSTAIRS	0	0	0	7	0	1066	1073
Σ	1406	1281	1375	1231	982	1077	7352

Fig. 8: CM of LR Source: Author

Actual \ Predicted	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	Σ
LAYING	1027	297	10	0	0	73	1407
SITTING	100	829	330	0	0	27	1286
STANDING	1	478	845	2	0	48	1374
WALKING	0	0	0	818	235	173	1226
WALKING_DOWNSTAIRS	0	0	0	12	848	126	986
WALKING_UPSTAIRS	0	0	0	12	203	858	1073
Σ	1128	1604	1185	844	1286	1305	7352

Fig. 9: CM of NB Source: Author

Predicted

Actual	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	∑
LAYING	1405	1	1	0	0	0	1407
SITTING	0	1187	97	0	0	2	1286
STANDING	0	87	1286	0	0	1	1374
WALKING	0	1	1	1158	29	37	1226
WALKING_DOWNSTAIRS	0	0	0	26	926	34	986
WALKING_UPSTAIRS	0	0	0	45	33	995	1073
∑	1405	1276	1385	1229	988	1069	7352

Fig. 10: CM of AB Source: Author

Predicted

Actual	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS	∑
LAYING	1405	1	1	0	0	0	1407
SITTING	0	1247	38	0	0	1	1286
STANDING	0	43	1330	0	0	1	1374
WALKING	0	0	0	1224	1	1	1226
WALKING_DOWNSTAIRS	0	0	0	1	985	0	986
WALKING_UPSTAIRS	0	0	0	1	1	1071	1073
∑	1405	1291	1369	1226	987	1074	7352

Fig. 11: CM of NN Source: Author

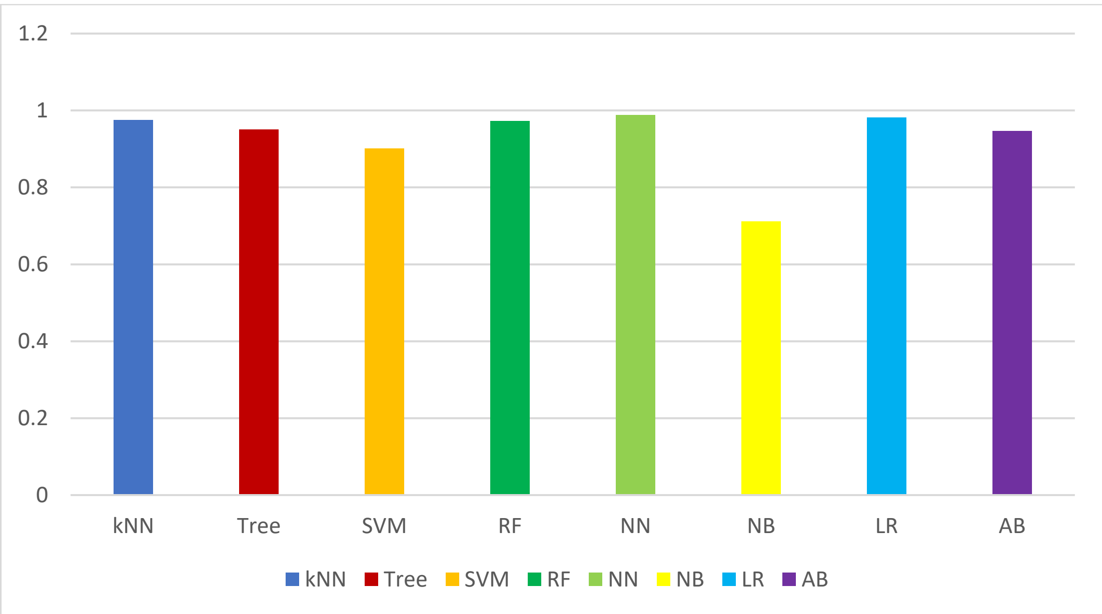

Fig. 12: CA of different supervised machine intelligence models Source: Author

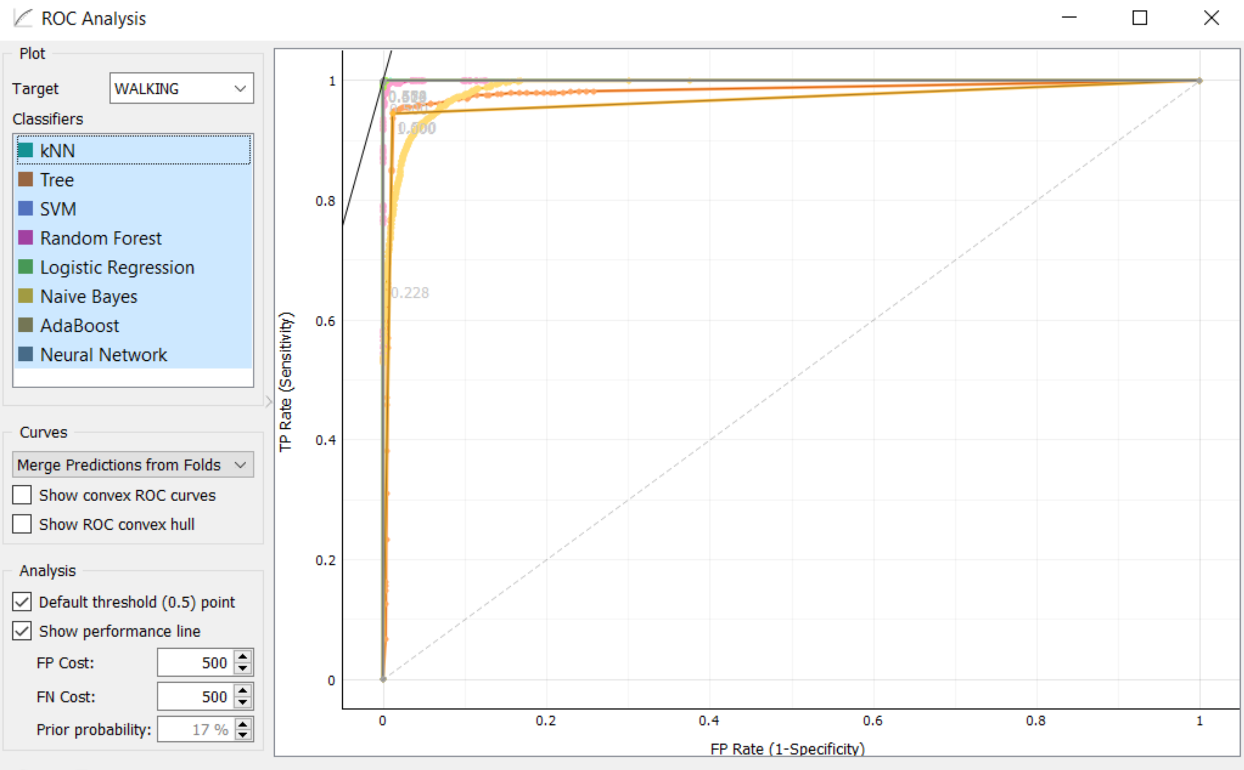

Fig. 13: ROC analysis to show TPR vs FPR to show WALKING Source: Author

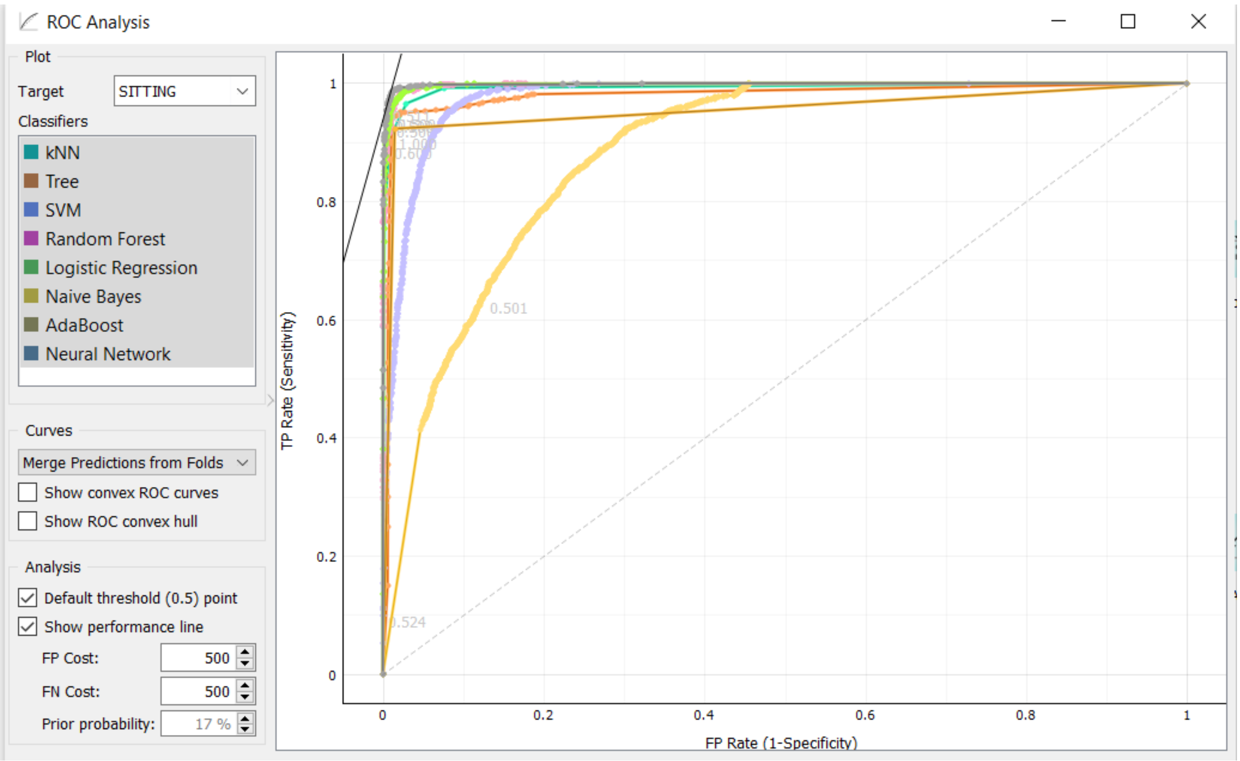

Fig. 14: ROC analysis to show TPR vs FPR to show SITTING Source: Author

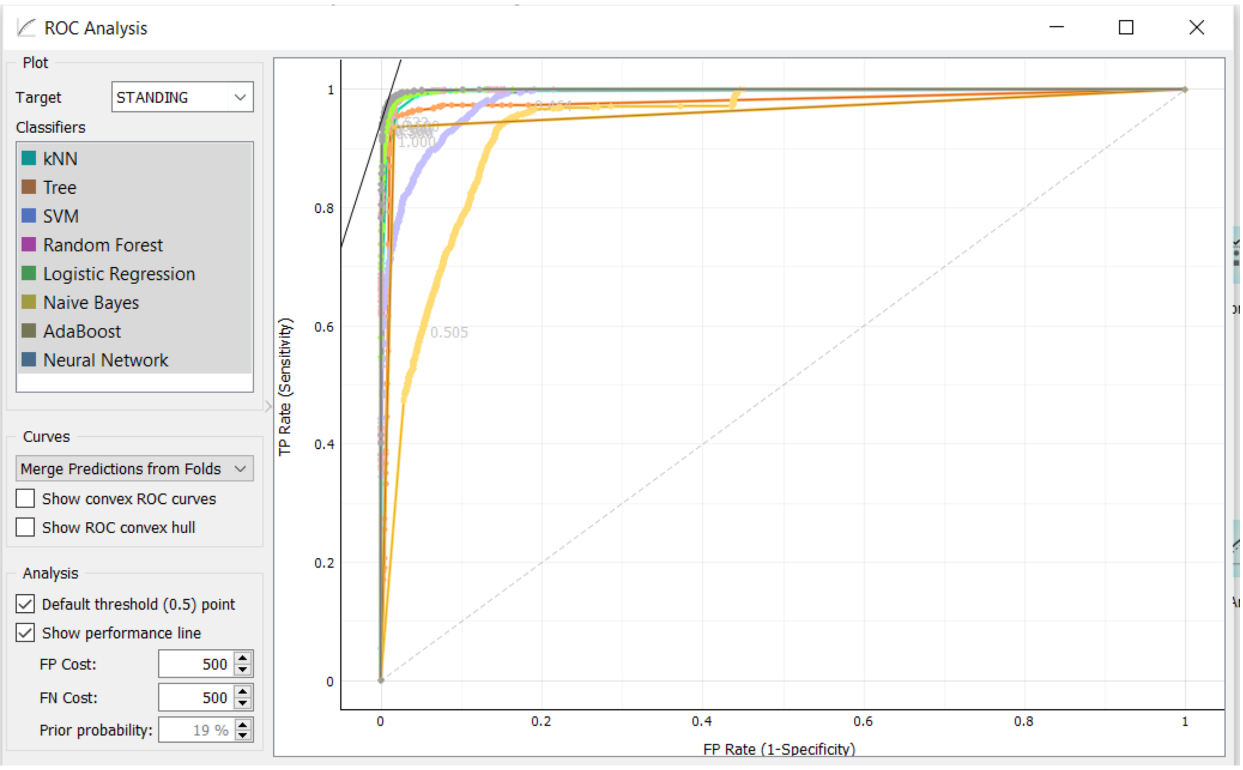

Fig. 15: ROC analysis to show TPR vs FPR to show STANDING Source: Author

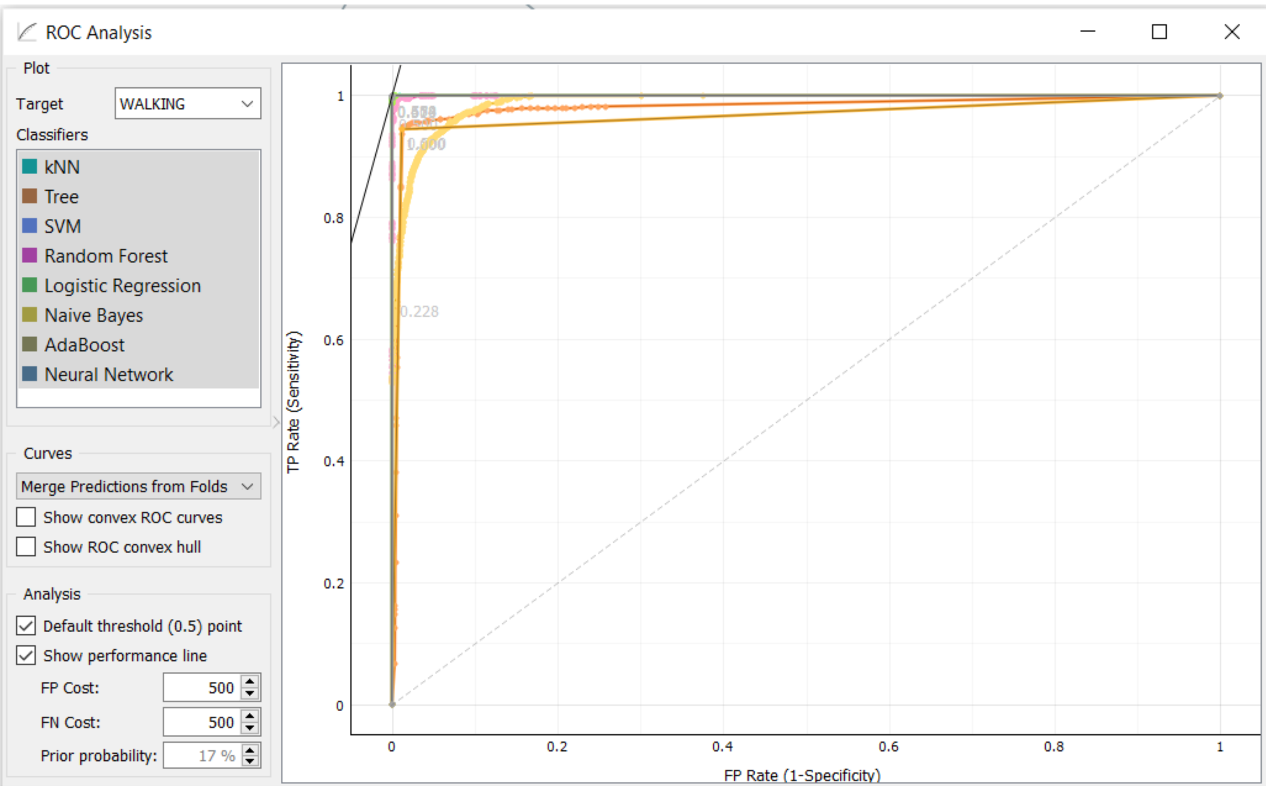

Fig. 16: ROC analysis to show TPR vs FPR to show LAYING Source: Author

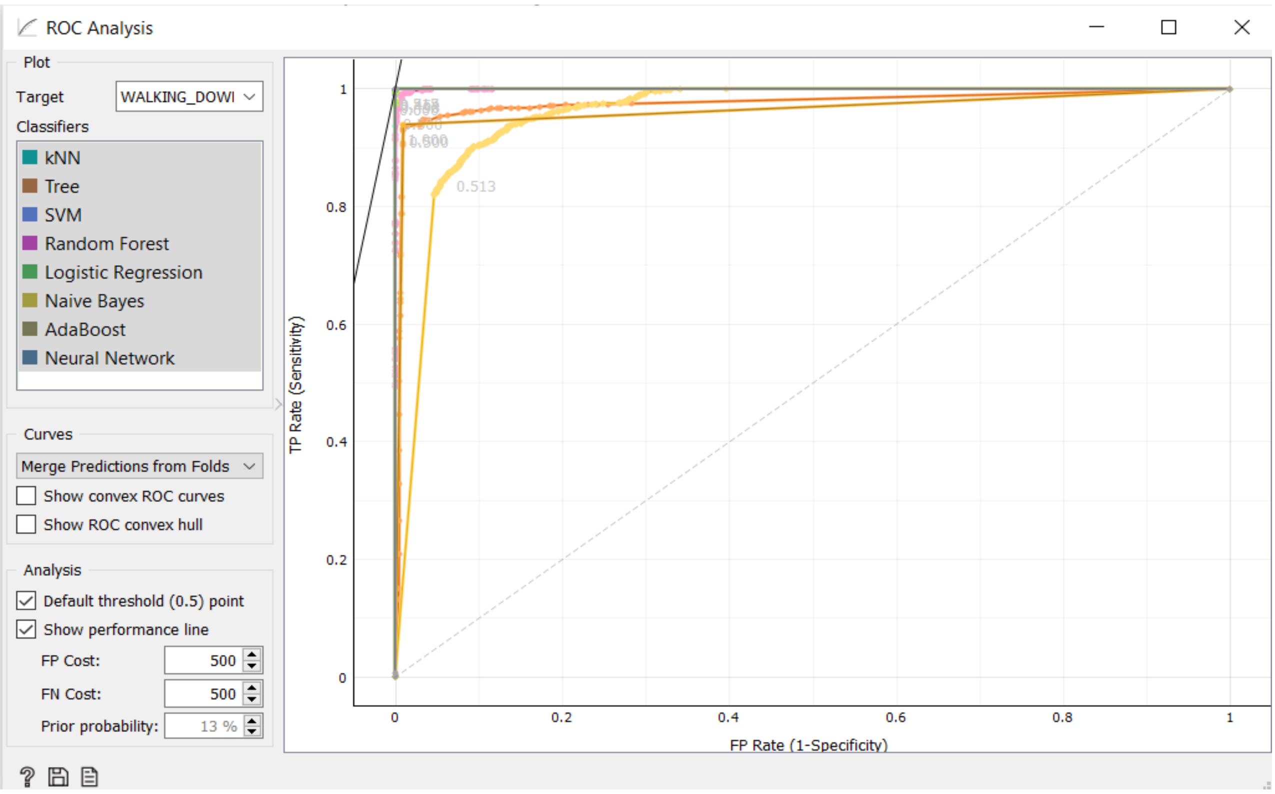

Fig. 17: ROC analysis to show TPR vs FPR to show WALKING_DOWNSTAIRS Source: Author

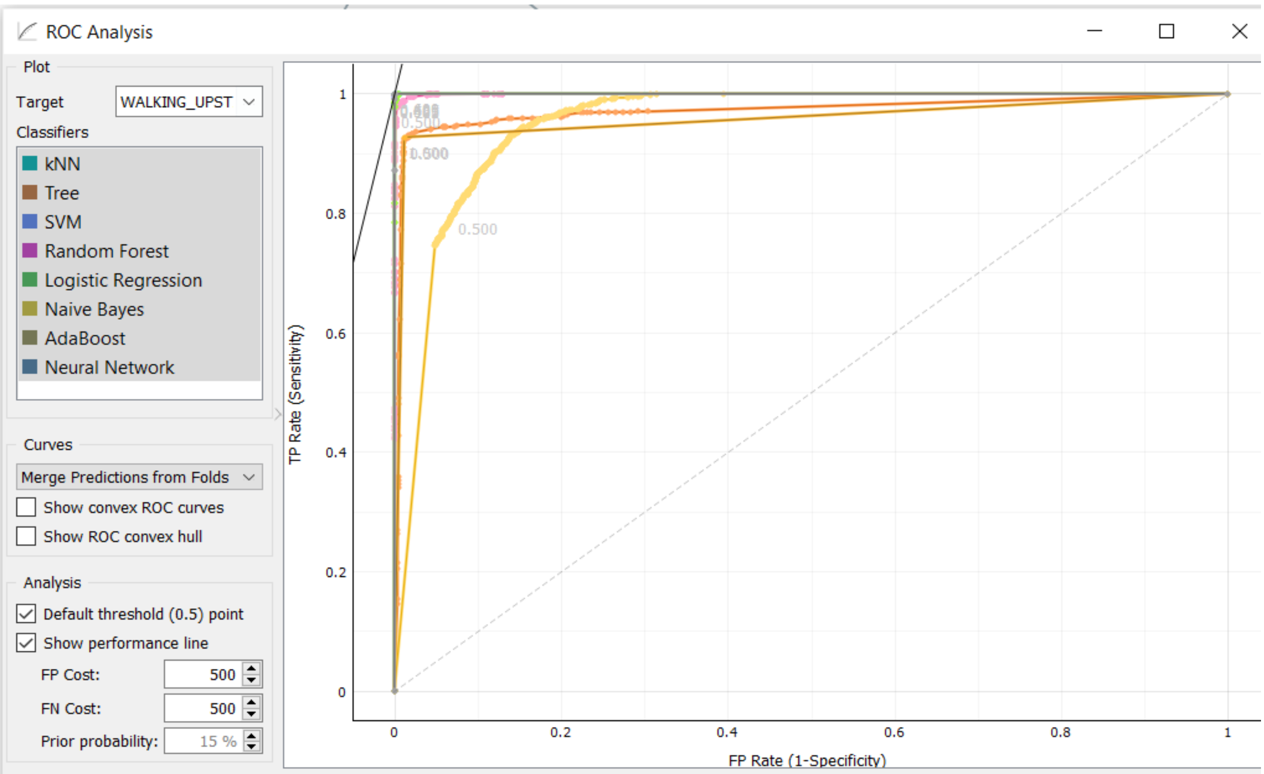

Fig. 18: ROC analysis to show TPR vs FPR to show WALKING_UPSTAIRS Source: Author

8. CONCLUSION :

In this work, a cloud-based machine intelligent HAR system using IoT principles [32] is proposed to identify the activity of the old person at home. It is observed from the result that NN show better performance than other models with a classification accuracy of 98.80%. Therefore, it will be better if we prefer NN as the model for installing in the cloud for classifying the activities more accurately. The CM of all 8 models is also represented above. The ROC analysis is also shown where NN is found to be better in classifying the activities. In future, we will consider a larger dataset for increasing the CA of the model. Also, hybridization of the models in future will be better approach to enhance the CA.

9. RECOMMENDATION :

Future work on this system can be focused on the new machine intelligent models or hybrid models, to improve the classification accuracy. In the system, new experimental settings can be performed to evaluate the performance.

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