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An Intent Prediction System for Wireless Fidelity (Wi-Fi) Sensor Data Using an Emerging Neural Machine Intelligence

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Abstract: This paper presents a User Intent (UI) mining scheme based on an emerging neural machine intelligence technique called the Neuronal Auditory Machine Intelligence (NeuroAMI) and considering a Wi-Fi sessions dataset containing about 8000 data points for intent prediction. The results of simulations considering graded increase in samples from 50samples to 999samples showed that substantial increases in accuracies are achievable. When compared to the Long Short-Term Memory (LSTM) method, the results showed that the NeuroAMI will outperform the LSTM by a factor of about 2 considering percentage accuracies.

Keywords: Data, Intent, Intelligence, Neural Network, Wi-Fi

I. INTRODUCTION

Machine learning techniques have been largely used to solve a wide range of problems ranging from the solution of first-order classification problems, regression fitting of data points such as to forecast consumer buy rate against some set of product specific parameters and in medical informatics. These techniques generally use some sort of intelligence inspired by neural operations in the mammalian cortex, insect behavior and foraging nature of various categories of animals. One very popular ML technique is broadly categorized as Deep Learning (DL) is basically an improvement of conventional neural networks and is well applied both in industry and academia. Intent prediction is an important problem area in machine learning (ML) field. It deals with the capability of a system or entity to decipher the likely actions that will be conducted by a human or machine device using an ML system observer as a reference.

User Intention (UI), a specific kind of intent prediction is particularly an emerging research study area that offers promises for a variety of commercial applications. Some important application areas include automated web opinion rating, incentivized product offerings, and automated search query service provisioning mechanisms and wireless sensor-oriented navigation and product identification systems.

In recent times, various attempts on UI mining have been conducted including the investigation on the feature representations of ad-oriented intent data (Im et al., 2019), public intelligence mining in social network platforms (Wu et al., 2019), and in self-driving models (Casas et al., 2018).

In this research paper, UI mining based on an emerging neural machine intelligence technique method and using an online learning paradigm with modifiable classifier algorithm is proposed for intent mining of wireless sensor device data suitable in the field of smart retailing. The potential and suitability of this technique is further validated via simulations-based approach and recommendations provided for future research in this emerging field.

II. RELATED STUDIES

In Lin & Xu (2019), joint prediction is performed by combining a softermax classifier with an LOF classifier through temperature scaling (Platt Scaling) in a Deep Long Short-Term Memory (LSTM) neural network and Convolutional Neural Network (CNN) machine learning (ML) system; both techniques were used to solve a single and multi-class prediction problem. Softer-max is a modification of the basic soft-max function used in a feed-forward artificial neural network to enable a more robust classification scheme. However, it requires careful optimization in order to be as efficient as the standard softmax classifier.

In one research direction, the use of Convolutional Neural Networks (CNN) for visual object count detection is accomplished for the prediction of intent and the automated schedule of traffic lights wirelessly (Ertler et al., 2018). Such techniques require proper siting of visual sensors (a geometric solution requirement) in order to enable accurate and precise intent predictions on the fly.

In Casas et al (2018), a deep CNN model is utilized for predicting an automobile driver maneuvering intent. Their proposed system used tensors as input to the CNN layer and the features represented as a multiclass problem. A binary focal loss (Lin et al., 2017; Liu et al., 2022) was used for evaluating performance and determination of ground truth estimates.
The use of Capsule Neural Networks (CaPSNET) is proposed for zero-shot user intent detection where in no labeled utterances are available or are missing. The authors have used LSTM, a sequential bi-directional neural network for encoding utterances into hidden states. A multi-head attention framework was also proposed to handle specific keywords in the learned utterances. Their proposed technique was applied to two real world datasets - a Natural Language Understanding (NLU) and a Commercial Voice Assistant (CVA) dataset. Baseline results on the datasets showed that the CAPSNET intent detection technique classifies better than several existing techniques (RNN, GRU, SVM).
Xu and Sarikaya (2013) used a Convolutional Neural Network (CNN) based on Conditional Random Fields (CRFs) for joint intent detection and slot-filling. In their proposed technique, the sequence labeling is described fully as a CRF (random embedding) model for multitask handling. They compared their model with Triangular-CRF (Tri-CRF). They reported an absolute F1-score gain of over 1.0% over the standard Tri-CRF technique and outperformed DBN with discriminative embedding, RNN with ATIS embedding and RNN with Wikipedia embedding for slot filling intent prediction tasks using the ATIS data corpus.
Young et al (2014a) proposed the use of Time History Information to support locomotive based Intent recognition for the disabled amputees. A majority voting scheme and a Deep Belief Network (DBN) based on dynamic Bayesian network classifier were employed.
Young et al (2014a) studied several classification strategies including Maximum Likelihood (ML) with Majority Voting (MV), Deep Belief Networks (DBN) and hybridized solutions including Sensor Time History Information (STHS) in DBN or MVs for gait cycle evolution studies in powered lower limb prosthesis. The ML with an assumed gaussian feature distribution with equal covariances was used as baseline strategy. Data from six transfemoral amputee subjects (5 males and 1 female) based on steady state locomotion and transitions and taken from 13 mechanical sensors located in the prosthesis and recorded at a signal frequency of 500Hz were utilized in the classification analysis. The results of their analysis showed that the incorporating STHS in the hybridized techniques lead to over half reductions in steady-state misclassifications during the intent recognition phase. In a related research, they employed the EMG and mechanical sensors to enhance the intent recognition accuracy (Young et al., 2014b).
Hussein and Granat (2002), proposed a Genetic Algorithm Gabor Matching Point (GAGMP) optimizer for patient intent feature parameters or atoms extraction and a neuro-fuzzy classifier as a detector. The GA part is specifically to minimize extensive computations by GMP by searching for best bases features. Subtractive clustering is used to determine the number of rules and type of input membership function needed for the fuzzy part. EMG signals obtained from a paraplegic subject were analyzed and the results reported for both sitting down and standing up tasks. The reported standing up and sitting down classification accuracies were 96.67% and 93.33% respectively with zero false positives.
In Ravichandar and Dani (2017), an Expectation-Maximization algorithm - a Bayesian-like learning algorithm trained with an Artificial Neural Network (ANN) is used to infer the intention of human actions where the intention estimates represent possible goal-location-oriented actions. Experimental studies were conducted on the basis of Human Robot Collaboration (HRC) and Human Assisted Robotics (HAR) and following a two-criterion intention success rule. Experimental results for the HRC tasks and based on several experiments showed percentage correctly predicted intentions of around 70% (Experiment 1), 40% (Experiment 2) and 30% (Experiment 3). The HAR experiments also involved three intent prediction control tasks - Pouring water in cup intent task, Handover medicine intent task and the Standup support intent task for Experiments 4, Experiments 5 and Experiments 6 respectively. For these classes of experiments, the authors report promising results using human arm gestures (hags).
Tran & Luong (2020) proposed a hybrid machine learning technique combining biLSTM and CNN for Vietnamese chatbot based retail intent detection. Simulation results showed CNN to give best AUC score when compared to the biLSTM and a baseline model. In Saleh et al (2018) a dual motion based intent prediction problem for pedestrian's road crossing (path prediction) was formulated. Their formulations included a high-to-fully automated vehicle scenario and a sequence data modelling scenario. Their machine learning model approach was based on a deep stacked LSTM-type RNN. Their proposed model was compared tò the Extended Kalman Filter (EKF), the interacting multiple model Kalman filter (IMMKF) and a Multilayered Layer Perceptron (MLP) for 70 and 50 steps ahead prediction window. Two popular datasets were analyzed. The first dataset, the Daimler dataset included 4 classes of activities: Bending in, Crossing, Starting, and Stopping. The second dataset was a context dataset including Crossing and Stopping. In the first dataset, their proposed LSTM-RNN outperformed the others for three of the activities with the EKF outperforming it for the Stopping activity. For the second dataset, the LSTM-RNN outperformed all other methods for crossing activity but was outperformed by IMM technique for stopping activity.

In Kyeong et al (2018), electromyographic (EMG) signalling is used to enhance the walking intentions prediction for various gait environments. Several sensors including kinematic, kinetic and EMG sensors were employed. Pre and Post Heal Contact (HC) and Toe-Off (TO) cases were analyzed using the Bayesian Linear Discriminant (BLD) classifier considering single and a mixture sensor types. For the Post-TO, the combination of EMG and Kinetic sensor types gave least error while all sensors combination gave least error for Pre-TO. For PostHC and PreHC, the aforementioned sensor configuration classification error situation is reversed.

A supervised real time control of powered lower limb prosthesis using intent recognition is proposed in Varol et al (2010). The control involves a three stage paradigm including intent recognition at the highest level, impedance control at middle level and torque control at lowest level. The intent recognition level employed a comparison strategy between states of prosthesis and activity-based probabilistic modelling based on the Gaussian Mixture Model. Activity modes analysed included standing, sitting and walking obtained from frame generated real time sensor feeds; this represents a tri-class problem. A majority voting scheme was also used to enhance the confidence during switching mode transitions while LDA and PCA were used for feature reduction. Results of analysis showed the LDA based intent recognizer to outperform the PCA type for the tri-class problem.

In Tang et al (2019) intent recognition of driving behavior during lane changes is implemented based on the hybrid adaptive neural network based fuzzy c-means clustering approach (FCMNN).

To determine the purchase intent of a customer, Srivatsan et al (2011) used a Fast Frequent Pattern Mining Algorithm based on Boolean vector and Relational AND operators to predict missing items in a shop. The idea is to use the principle of association rule mining and basic belief assignment (BBA) to predict with high support other shopping cart entries given a known subset of shopping cart entries. Their proposed algorithm gave very much reduced run times when compared to existing tree-based approach. Also in Jagdish and Sahini (2013), using association rule mining based on frequent item sets (Srivastan et al., 2011), they proposed a recommender system that predicts what else a customer is likely to add in a shopping cart.

Using domain transfer techniques, Stojanov et al (2019) studied the intent prediction mechanism in e-mail correspondences in an oil industry and IT sector. They investigated the email Commitment and Meeting intent task. Using an overlapping distribution criteria based on a CNN based encoder, they found out that positive intent words overlapped more in commitment than in meeting correspondences.

Kim and Lee (2018) proposed a machine learning framework based on the XGBoost technique for customer revisit intention prediction. The proposed model was used to analyze revisit data obtained from real world sensors positioned at about 12 strategic positions in a store. The idea was to predict the customer's revisit using their Wi-Fi ID and visited location or area in store as context. Accuracies of up to 74% were achieved for first time visitors and upto 80% for regular visitors (customers).

III. MATERIALS AND METHODS

A. Dataset Details

The dataset for experiments will be based on real world sensory data obtained from the research carried out in (Kim and Lee). This dataset contains customer revisit behaviors obtained from two stores in a Korean super-mart. The data was obtained using various Wi-Fi sensors installed at strategic positions (see Figure 1).

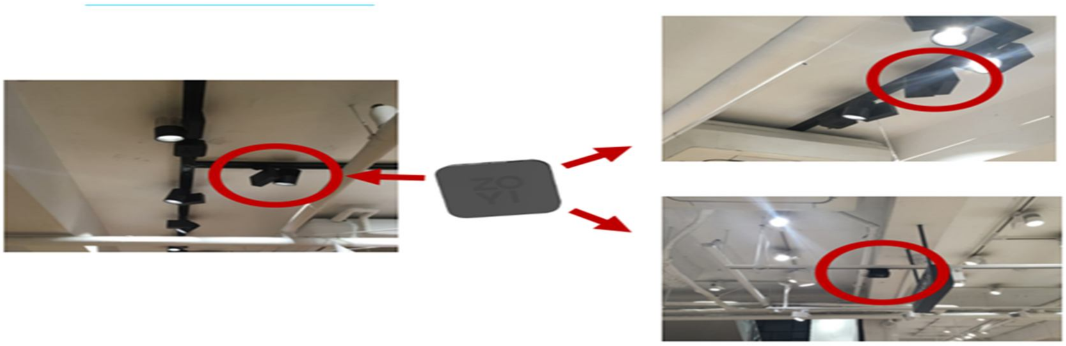

Figure 1: System of Wi-Fi In-Store Sensors for Revisit Intention Prediction; Source: Kim and Lee (2018).

The motive behind this approach was to capture the likelihood of a customer revisiting a particular place in a store. The customers are assumed to have a Wi-Fi enabled device; this device is expected to be turned on by the customer on entry into a store. The core Wi-Fi sessions dataset set contains about 8000 data points. A sample of this dataset is as shown in Table 1.

Table 1: Sample WiFi Session Data for Revisit Intention Prediction

index	wifi_id	ts	area	dwell_time
94	45809	1.48E+09	out	35
929	4108	1.48E+09	out	529
1319	45809	1.48E+09	out	1203
1366	45809	1.48E+09	in	1058
1367	45809	1.48E+09	1f	1058
1376	45809	1.48E+09	1f-d	575
1388	45809	1.48E+09	cafe	613
1389	45809	1.48E+09	b1	989
1397	45809	1.48E+09	2f	555
1411	45809	1.48E+09	2f-a	109
1420	45809	1.48E+09	2f-c	55
1495	45809	1.48E+09	1f-c	246
1513	4108	1.48E+09	out	46
1591	45809	1.48E+09	b1_only	372
1592	45809	1.48E+09	b1-a	8
1598	45809	1.48E+09	b1-b	239
1604	45809	1.48E+09	b1-c	33
3767	26007	1.48E+09	out	33
4582	10152	1.48E+09	out	1450

This dataset include the following key features: a Wi-Fi Device ID tag (wifi_id), a time stamp (ts), an in-store area location site tag (area), and a dwell time (dwell_time). The features are indexed at specific values as in Table 1.

In this research study, the features Wi-Fi Device ID and area location site tag are considered in a reduced feature set (see Table 2).

Table 2: Sample Reduced WiFi Session Data for Revisit Intention Prediction

wifi_id	area
45809	out
4108	out
45809	out
45809	in
45809	1f
45809	1f-d
45809	cafe
45809	b1
45809	2f
45809	2f-a
45809	2f-c
45809	1f-c
4108	out
45809	b1_only
45809	b1-a
45809	b1-b
45809	b1-c
26007	out
10152	out

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This reduction procedure makes it more challenging for ML algorithms. Also, an encoding rule program is developed to perform numeric encoding of the tags. In this way, comparisons of the proposed technique can be made with the existing conventional classifiers in terms of regular metrics such as accuracy, mean squared error, root-mean squared error etc. The obtained encodings from this program are shown in Table 3.

Table 3: Sample WiFi Session Data for Revisit Intention Prediction

Class	Numerical Encoding
out	1
in	2
café	3
b1	4
b1_only	5
b1-a	6
b1-b	7
b1-c	8
1f	9
1f-c	10
1f-d	11
1f-e	12
1f-f	13
2f	14
2f-a	15
2f-b	16
2f-c	17
2f-d	18
2f-e	19

Using the Table 3, the sample revised reduced feature data set is as shown in Table 4.

Table 4: Sample Reduced Wi-Fi Session Data with area class encoding labels

wifi_id	Class
45809	1
4108	1
45809	1
45809	2
45809	9
45809	11
45809	3
45809	4
45809	14
45809	15
45809	17
45809	10
4108	1
45809	5
45809	6
45809	7
45809	8
26007	1
10152	1

From the Table 4, the wifi_id then represents potential customers and Class represent their intended area of visit in-store.

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B. Proposed Method

The proposed intent mining system model architecture for the Wi-Fi sensor device data analysis is as shown in Figure 2. It is an extension of the system proposed earlier in (Kim & Lee, 2018) and is based on wireless embedded sensing devices for data acquisition. The motivation behind this second architecture model (Arch.2) is twofold:

1) It presents an important application area that can be found in the real world setting.
2) It provides data that are sensory based. By using such data, the data mining research expert is faced with a more tasking objective.

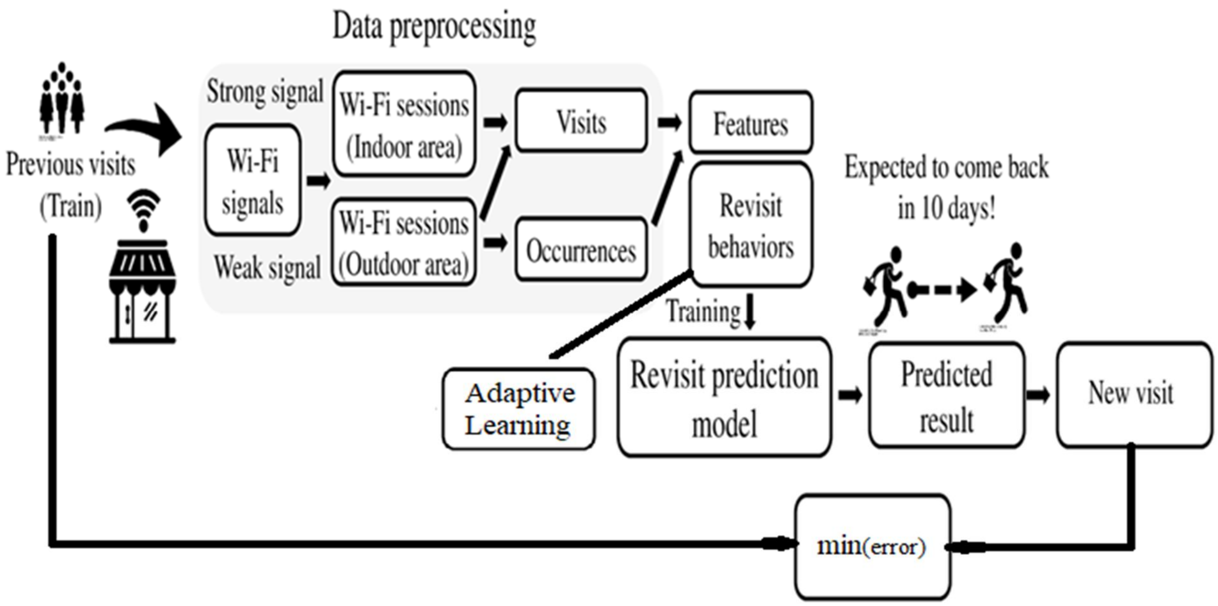

Figure 2: Proposed System Model for Revisit Intent Mining based on Wi-Fi Sensor Data (Adapted from Kim & Lee, 2018)

As can be seen from the proposed system, the end objective is to predict the possibility of new visit with reduced error. This can be achieved using an adaptive learning algorithm that will be described subsequently (see sub-section 3.2.1). Also as can be seen, there is no need for a test dataset as the system is designed to learn to predict during training. Thus, it is said to be an online learning model as data sequences or streams are predicted continually.

1) Adaptive learning algorithm

The proposed revisit intent mining system is based on a simple structured single adaptive learning algorithm earlier developed in (Osegi & Anireh, 2020) and more recently in (Osegi, 2023). This algorithm is a neural-like processing technique called the Neuronal Auditory Machine Intelligence (NeuroAMI) inspired by auditory sensations in the mammalian brain. There are basically two phases but the Phase-2 is seldom used. The key ideas in the proposed technique are as depicted in Algorithms 1 and 2 (for Phase-1 learning only):

Algorithm 1: NeuroAMI Processing Algorithm

Initialize S_{pred}, as prediction parameter, S_{stars}, as input sequences (standards) State, $S_{dev(mean)}$ as deviant mean, j as iteration counter.
for all s∈ $s.S_{stars}$, && $j > 1$, do
Compute $S_{deviant}$ and S_{stars} using equations (3) and (4)
$S_{dev} \leftarrow \|S_{deviant} - S_{stars}\|$ // deviations from standards
Compute $S_{dev(mean)}$ using equations (1)
Compute S_{pred} using equations (1) and (3)
Update $S_{dev(mean)}$ using Algorithm 2
end for

The procedure outlined in Algorithm 1 is described by the mathematical formulas defined as follows:

$$S_{dev(mean)} = \frac{\left(\left(\frac{\sum [S_{dev}]}{(n-1)}\right) + S_{deviant}\right) - 2}{n+1} \quad (1)$$

where,

n = number of data points in a temporal sequence

$S_{deviant}$ = the *(n-1)th* value of the temporal sequence

S_{dev} = the difference between $S_{deviant}$ and S_{stars}

S_{stars} = the *(n-2)th* values of the temporal sequence

S^{*} = sparse set of input sequences

In order to make a prediction with the AMI, the formula in (2) is used as:

$$S_{pred} = S_{deviant} + S_{dev(mean)} \quad (2)$$

where,

$$S_{deviant} = S_{n}^{*} - 1 \quad (3)$$

$$S_{stars} = S_{n}^{*} - 2 \quad (4)$$

Algorithm 2. NeuroAMI Learning Algorithm

1: Initialize S_{pred}, as prediction parameter, S_{stars}, as input sequences (standards) State, $S_{dev(mean)}$ as deviant mean, $S_{diff(1)}$ as difference between S_{pred}, $S_{deviant}$+1 and $S_{diff(2)}$ as difference between $S_{dev(mean)}$ and $|S_{diff(1)}|$, l_p as correction factor or bias.

2: *for* all s$\in$ $s.S_{stars}$ do

3: if $S_{diff(2)} > 0$

4: $S_{dev(mean)} \leftarrow S_{dev(mean)} - \left|S_{diff(1)}\right|$ // Weaken deviant mean by a factor, $|S_{diff(1)}|$

5: elseif $S_{diff(2)} < 0$

6: $S_{dev(mean)} \leftarrow S_{dev(mean)} + \left|S_{diff(1)}\right|$ // Reinforce deviant mean by a factor, $|S_{diff(1)}|$

7: else

8: $S_{dev(mean)} \leftarrow S_{dev(mean)} + l_p$

The AMI algorithm (Algorithm 1) is based on a simple Hebbian learning rule and described by the following reinforcement strategy. For a given AMI neuron,

1) if current prediction error is lower than zero, the prediction is improved by increasing its deviant weight value by the absolute prediction error difference at the current time step.
2) if current prediction error is greater than zero, the prediction is improved by decreasing its deviant weight value by the absolute prediction error difference at the current time step.
3) if exact matches occur, a small numerical value (laplacian correction) in small fractions of about a hundredth is added to the deviant weight updates.

Using these algorithms data mining software developers can build more robust online learning and prediction models for Wi-Fi sensor based intent mining systems.

IV. RESULTS AND DISCUSSIONS

The results generated in this research are simulations of the expected real world scenario. Two neural predictive techniques based on Auditory Machine Intelligence (AMI) and Recurrent Neural Network (RNN) based on the Long Short-Term Memory (LSTM) neural model. Sample snapshot of the running model interface system is given in Figure 3 and output capture snapshot in Figure 4. An automatic training and learning process as dictated by the designed algorithm is performed through time. This is achieved by presenting data sequences one at a time in a continual manner so that the algorithm is able to learn from past values prior to inference or decision making.

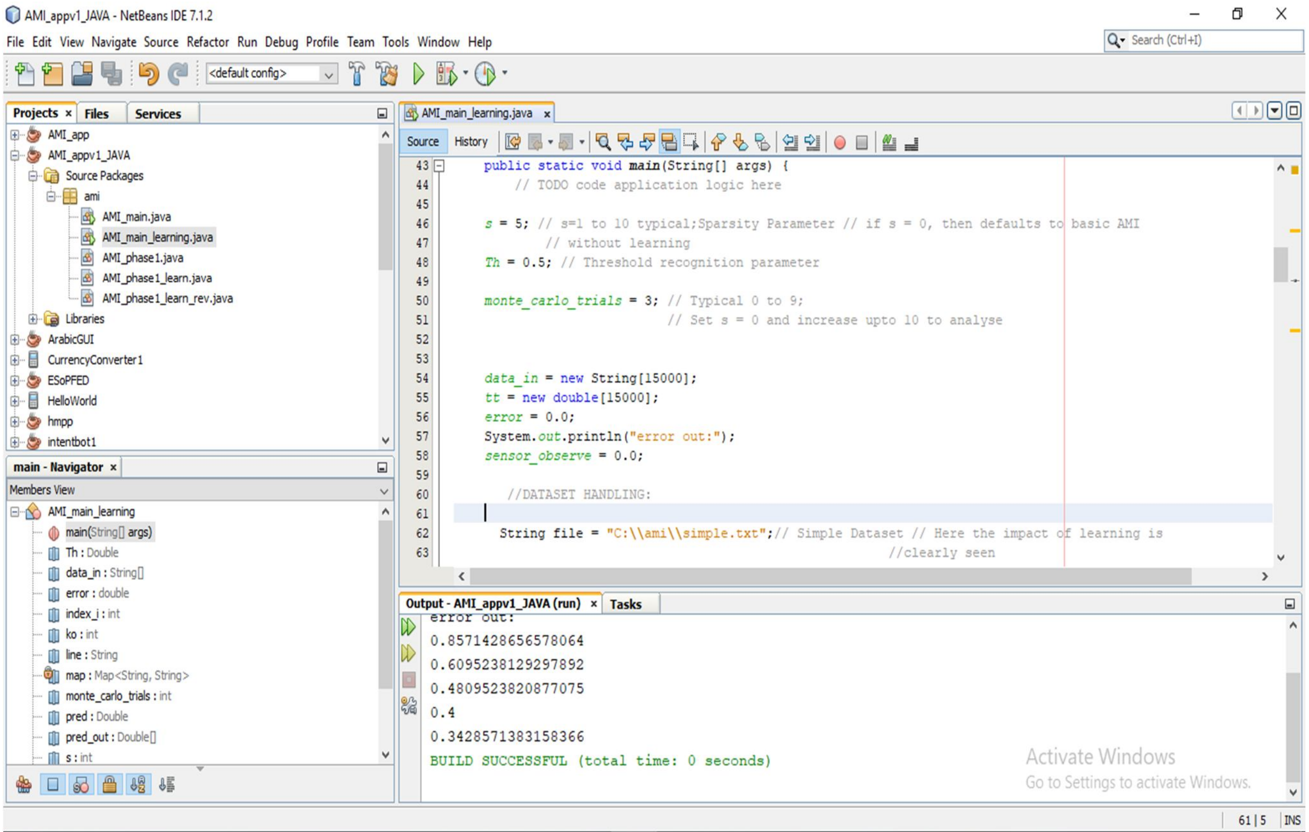

Figure 3: Program Interface in Java for running the model interface.

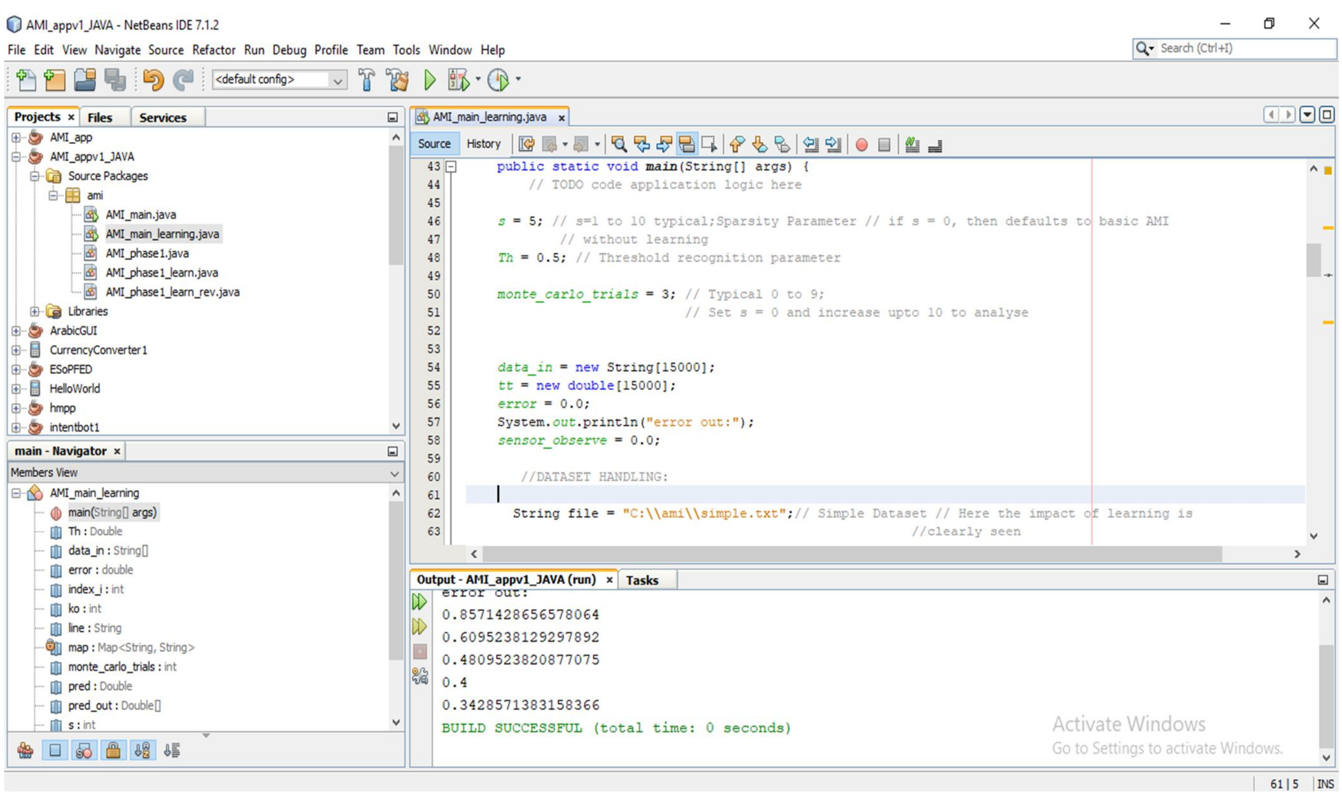

Figure 4: Program Simulation Interface in the MATLAB environment.

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A. Results using Revisit Intention Dataset with Proposed Method (50 samples)

The class accuracy response plot using the proposed neural prediction algorithm for 50 data samples is as shown in Figure 5.

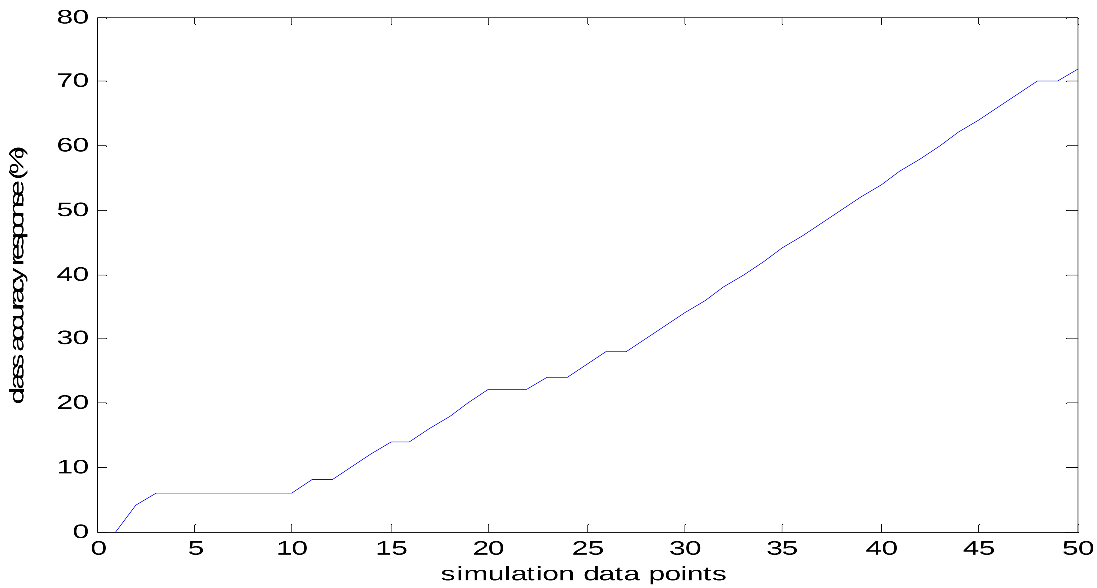

Figure 5: Neural Prediction algorithm class accuracy response for 50 data samples (s=5%).

This plot shows the process of predicting the area of visit by the proposed NeuroAMI algorithm in a continual learning manner. The neural predictive algorithm shows a staggered incremental response from data point 10 to about 25 as the data presented to it is increased; then there is a reasonable graded increase in accuracy for the remaining data points. A sample of the predicted versus actual values is also captured in Table 5.

Table 5: Sample result of Revisit Intention Prediction using NeuroAMI Neural Predictive Algorithm (part of 50 samples)

Prediction	Actual
1	1
1	1
1	2
1	9
1	11
1	3
1	4
1	14
1	15
17	17
1	10
1	1
5	5
6	6
1	7
8	8
1	1
1	1
14	14
1	2

Based on the result presented in Figure 5 as well as in Table 5, it is not sufficient to evaluate performance accuracy of a neural prediction model that learns; so several trial runs are needed. The results presenting the maximum class accuracy attainable for 10 trial runs is as shown in Table 6.

Table 6: Sample result of Revisit Intention Prediction using Neural Predictive Algorithm (10 trial runs, 50 samples)

Trial Run	Max Attainable Accuracy (%)
1	72
2	66
3	58
4	72
5	66
6	64
7	66
8	70
9	68
10	60
Average:	66.2

From the results in Table 6, the reported average of the proposed solution is 66.2%. This value is an estimate for 10 trial runs as stated.

B. Results using Revisit Intention Dataset with Proposed Method (999 samples)

The class accuracies of proposed solution when samples are extended to 999samples and for 10 trials are as shown in Table 7.

Table 7: Sample result of Revisit Intention Prediction using Neural Predictive Algorithm (10 trial runs, 999 samples)

Trial Run	Max Attainable Accuracy (%)
1	98.00
2	98.20
3	98.40
4	98.40
5	98.20
6	98.30
7	98.00
8	98.40
9	98.00
10	98.30
Average:	98.22

As shown in Table 7, the accuracy averages around 98% for the said trial runs which is an improvement of about 30% from the prediction results using 50 samples.

C. Results using Revisit Intention Dataset with Deep-LSTM Method (999 samples)

The Deep-LSTM network is validated using 100 and 1000 epochs respectively. The use of epochs as a variational parameter is due to LSTM sensitivity to it. The results are as presented in Table 8.

Table 8: RMSE using Deep-LSTM Neural Network (999 samples)

Epochs	Max Attainable Accuracy **(%)**
100	42.19
1000	43.74

As shown in the Table 8, there is a clear improvement in accuracy performance when a much higher epoch size is used. However, the accuracy is still much lower than the proposed NeuroAMI system.

V. CONCLUSION

In this research, an emerging machine intelligence approach is proposed for the online classification of wireless (Wi-Fi) sensor device data. The approach is based on an emerging neural approach (NeuroAMI) inspired by auditory sensations in the mammalian brain. The approach has shown promising results for both low Wi-Fi sensor training sample sizes and larger samples. The approach has also been compared to a state-of-the-art deep learning technique – the LSTM and showed superior performances.

With the proposed solution, it is possible to investigate other wireless sensor data domains particularly in the area of security and anomaly detection in case of privacy breaches. This remains an area for future studies.

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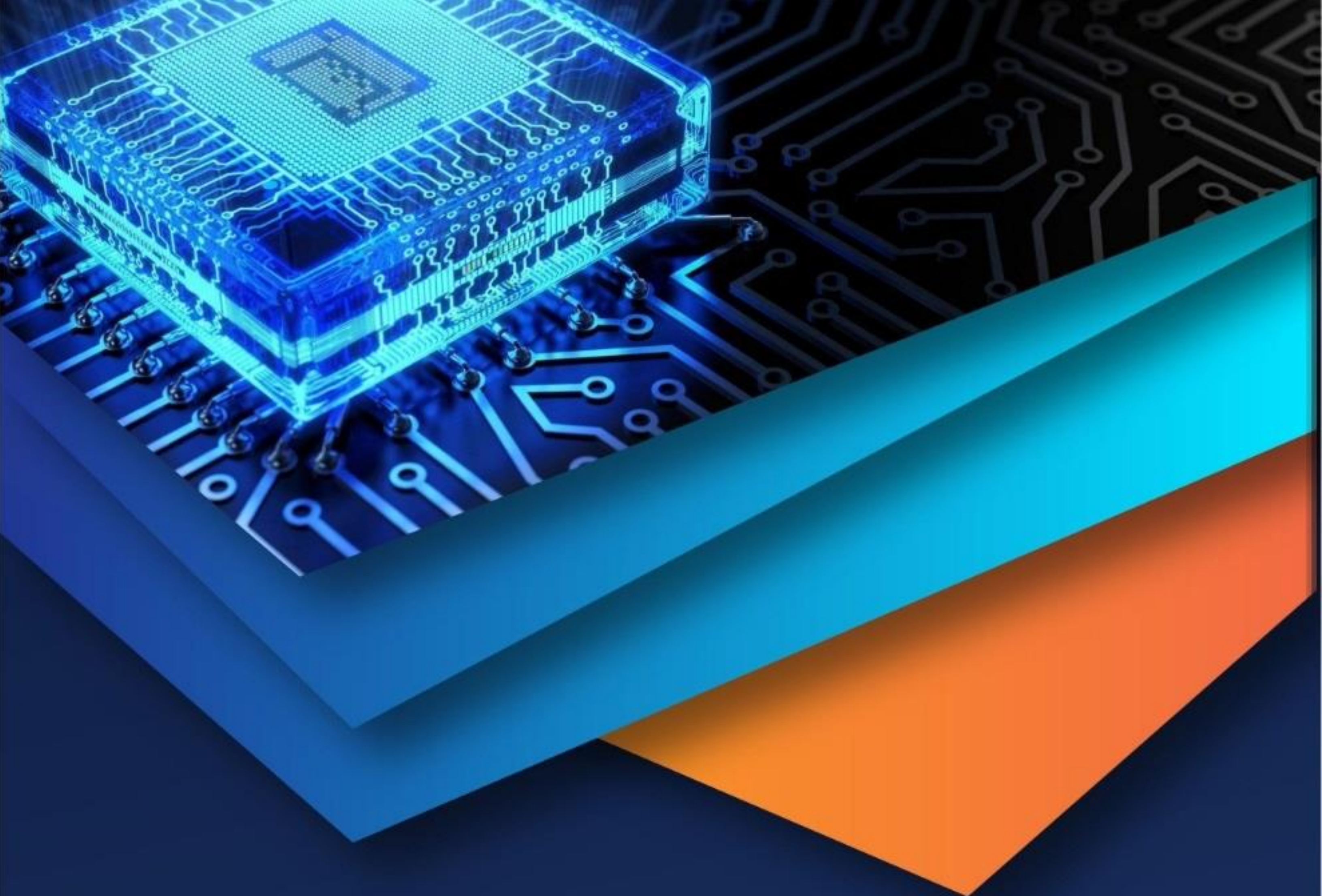

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