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Intelligent Embedded Advanced Machine Learning Approach for Smartphone Movement Identification using Stacked Auto-Encoders

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***Abstract*—Nowadays, the embedded system technology is emerging and being used in every area, especially for monitoring applications using the cloud and IoT. The subfield of machine learning (ML) that deals with embedded systems are denoted as embedded ML (EML) or Tiny ML. Using and deploying ML on devices with embedded systems has significant advantages. In this research, a smartphone was connected to a computer device through embedded technology for gathering information about the movements of the cell, such as clockwise and counter-clockwise rotations, up and down, left and right, idle movements, and wave or snake motions. The data of the motion of the cell was in a three-dimensional array (X, Y, and Z axes) over time. Every data sample was loaded within 10 seconds, and the data size was 3X625. We split the data into 80:20 for training and testing and applied stacked auto-encoders for feature extraction. In the first step, we got the output features1 from auto-encoder 1, which was the input of the second auto-encoder. The softmax classifier classified the features2 generated by autoencoder2 and got more extreme results than other applied models like MLP and SVM. The model stacked auto-encoders performed highly with 0.998 accuracies and a value of 1 for AUC for the testing dataset, without any over fitting problem. This analysis is very useful for tracking smartphone movements easily. As per the motion of the cell, we can analyze the carrying smartphone human motions using apps and tools.**

***Index Terms*— Smartphone, Stacked Auto-encoder, Embedded Systems, Embedded Machine Learning.**

I. INTRODUCTION

An embedded system (ES) is designed to partially complete or complete its task without human intervention. It is a system, created specifically to execute a few tasks most effectively. A method of working, organizing, and accomplishing single or multiple jobs by following a set of rules is referred to as an ES. A combination of

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computer software and hardware is another definition of ES. The ES communicates with the physical components of our environment, such as controlling a motor, sensing temperature, and performing other functions [1]. Some of most application are shown figure 1.

Embeded ML (EML) or TinyML (TML) models are significant for processing electronic devices like smart phones, watches, and others. Electronic systems can learn from the data automatically and use the knowledge they acquire to make assessments, predictions, and decisions through machine learning (ML). These kinds of applications use a lot of computing power, so they are run on personal computers and cloud servers. EML can be performed directly on the devices that are utilized for effectiveness and efficiency [2]. Embedded IoT systems are crucial for the huge amount of data collection with exponential sensors[3]. For this reason, we will apply ML models on embedded systems.

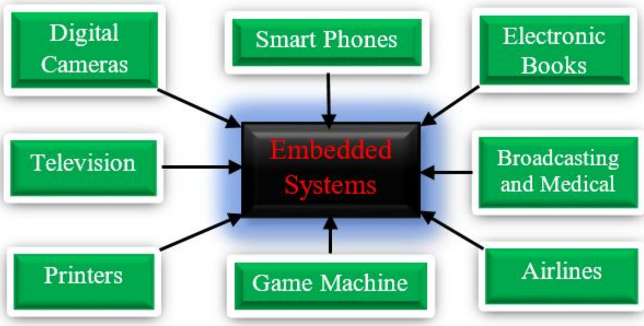


Figure 1 : Applications of Embedded Systems

The movement of smartphones connected through embedded ML systems is one of the significant research areas. In this research, we gather the motion of the cell using cloud systems in 3-dimensional wave formats and apply advanced ML models like stacked auto-encoders, one-dimensional CNN, and so on, for classification and predicting the movement of smartphones. The remaining sections of the paper is presented as,

- Section 2: literature review projects background research works related to embedded and embedded ML connected with motions and wave forms.
- Section 3: The proposed model and materials represent the working process of the smart phone movement's identification through novel approaches and models. Mainly focused on the construction, description of the dataset, and description of stacked auto encoder approaches with a softmax approach, also described are performance parameters and a confusion matrix for classification analysis.
- Section 4: results analysis depicts the analysis of the dataset with stacked auto encoders.
- Section 5: conclusion reports and describes the limitations of the research and future works related to the recognition of smartphone movement identification.

II. Literature Survey

Smartphones have become an essential component of everyday life. In this modern era machine learning is evolving, and its techniques are brilliant in solving real-world problems. It is developing in every field of study. Liu et al. (2018) [4] analyzed human activities. Smartphone sensors are for the identification of activities. They categorized them as motion-based and phone movement based. Machine learning classification models were used for activity recognition, and their performance is analyzed using Convolutional Neural Network (CNN) model. Ali et al. (2020) [5] have developed an organized model that was capable of ensuring neurological health and is utilized for long-term health monitoring systems. They started the evolving stage of Human activity recognition in security, health care, surveillance, virtual reality, control systems, and automation. They observed the daily-living activities of the user, such as walking, sitting, jogging, etc., for several days and arranged them based on exhibited movement into stationery. They achieved an accuracy of around 70% for each activity, particularly for the stationary position.Yu et al. (2019) [6] researched vibration signals using Novel Morphological filters. In this, their aim is fault feature extraction. The MF is called EDMF. It is very effective for preserving efficient impulse components and depressing noise with four morphological operators. Wan et al.(2019) [7] constructed a model using a stacked auto-encoder for Outlier detection of monitoring data. They conveyed that stacked auto-encoders are impeccable at Data mining, monitoring, and feature extraction. They used encoding and decoding parameter mapping to reduce the errors using cluster outliers. The threshold method is used to identify the faults of reconstruction by following the PauTa measure criterion and Grubbs criterion.

Yen et al. (2020) [8] propounded some deep learning algorithms associated with sensors that recognize mainly six human activities such as walking, sitting, walking upstairs, standing, walking downstairs, and lying. They stated that the commons wearable devices such as watches and wristbands are non-suited for patients, so they proposed a waistband. The feature extraction done by the one-dimensional convolutional NNs and their testing samples obtained an accuracy of 98.93%.

Alperovich et al. (2018) [9] proposed a deep encoder-decoder network model. It is made with a convolutional auto-encoder. It reduces the dimensions of a light field by taking the epipolar plane images in both horizontal and vertical directions. The encoder and decoder paths are trained using unsupervised and supervised learning severally. They have obtained good results on a new real-world dataset. Abuhamad et al. (2020) [10] proposed a model for better security in preventing unauthorized access to smartphones. He used a deep learning-based approach called Autosense for identifying distinct behaviors done by users while accessing their information through smartphones. They obtained an accuracy of 98% in the F1 score and worked efficiently on the real-world dataset. Botter et al.(2001) [11] used a traditional approach i.e., a basic neural network model with functions on a non-symmetry basis for extracting features from ECG(Electrocardiograph) signals. Pei et al. (2018) [12] researched stacked encoders which are used in understanding the movements of the upper limb body part, and a motion tracker is used to observe the arm's endpoint. They developed an accuracy score of 88% with stacked autoencoders in offline analysis. Aleesandrini et al. (2021) [13] reconsidered the general technique of photoplethysmography to observe human activities using wearable devices. They developed a way to fix the fault of motion artifacts in PPG (Photoplethysmography) signals. They added the PPG signals to the RNN network in detecting human activity as their first step. They acquired an accuracy rate of 95%.

Mahamoodabadi et al. (2006) [14] developed a method to extract features for ECG signals based on the multi-resolution wavelet transform. They used a noise cancellation technique in their first step. They achieved an accuracy score of 98%. Yan et al. (2020) [15] researched the network traffic that has been intruding on the net nowadays. In a large-scale industry, it is often hard to list the features in that dynamic network. They used deep learning methods based on the auto-encoder to extract the features and different structures and also achieved a 92% accuracy score in one of their models. Park et al. (2017) [16] proposed embedded inertial sensors to navigate smartphones because of the limited vision of GPS. He observed step detection using an accelerometer and used machine learning techniques to calculate the peaks of the signal. Finally, they predicted the smartphone gestures like texting, trousers front and back conditions, and handheld. Liu et al. (2018) [17] used stacked auto-encoders, which was a deep learning approach to identify the faults in machinery like gearboxes etc. They considered the deep learning approach to extract the features. They used a small training dataset to avoid the over-fitting of the model. Chandra et al. (2018) [18] researched extracting features from ECG signals and also provide a noise-free signal using MODWT (maximal overlap discrete wavelet transform). Many other wave features like P, Q, S, and T are extracted. This model predicts the new input with an accuracy of 99.97% and with an error detection score of 0.05%. Ramanujam et al. (2021) [19] reviewed Human activity recognition using embedded sensors of wearable devices and smartphones. They stated that HAR systems are used in monitoring older people. They used a deep learning approach to extract features and make a noise-free signal. Thus, they provided a review paper comprising various accesses to deep learning techniques in HAR systems.

III. Proposed Model and Materials

In this section, we describe about the proposed model, description of the dataset and applied stacked auto-encoder structure and functionality.

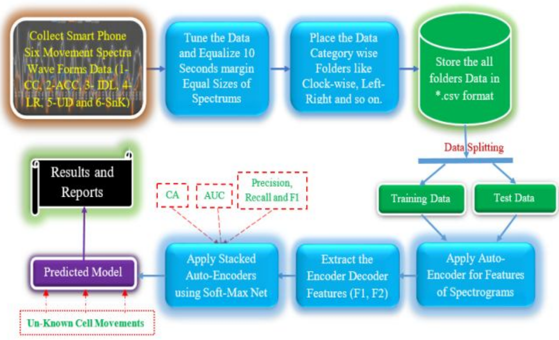


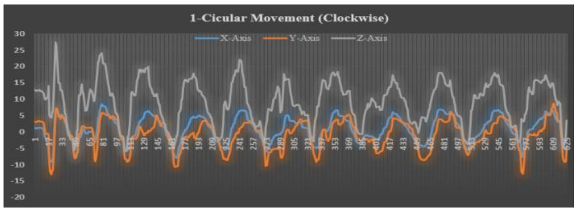
Figure 2: Proposal Model for Detecting Smartphone Movement Detection System

A. Proposed Model

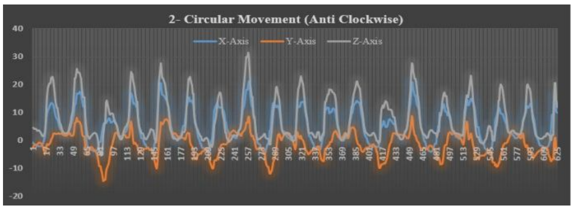
Figure 2 shows the proposed model for the intelligent identification of smartphone movement through embedded autoencoder techniques. The data is acquired using embedded system technology with cloud systems (Edge Impulse). We connect the smartphone virtually to the computer via the cloud and record the smartphone movement data in three dimensions (X, Y, and Z-axis) over ten seconds. The movements of smartphone data are stored in a relative number of individual folders in *.csv format. The data is split into 80% for training and 20% for testing, and the stacked autoencoders are applied for feature extraction. The softmax net is used for the classification and computes the performance parameter values such as CA, precision and recall, F1, and AUC. The prepared predictive model will be used for predicting smartphone moments. For analysis purposes, all performance results and relative prediction values are displayed.

B. Dataset Description

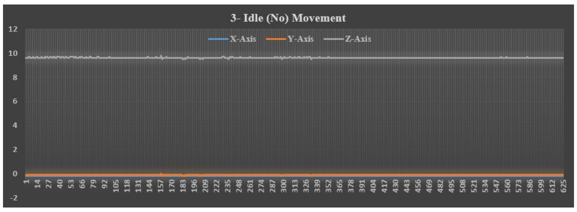
The dataset is built using embedded (Edge-Impulse) systems in the cloud. The smartphone is connected virtually to the computer. Each movement was recorded for 10 seconds in three dimensions. For this experiment, we chose smartphone movements that were clockwise and anti-clockwise cycles, idle, left and right, up and down, and wave- or snake-shaped movements. Every movement's data is stored in *.csv format in their respective individual folders. Each CSV file size is 625x3. Figure 3 shows samples of the smartphone movement waveform (X, Y, and Z axis) data images.



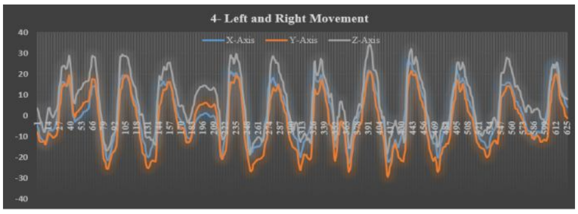
(A)Clockwise Circular Movement Clock-wise forms



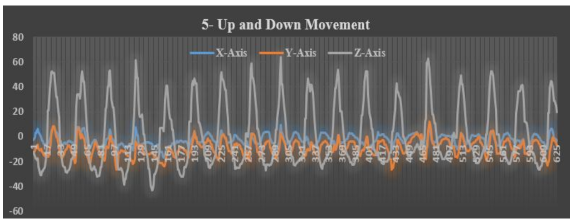
(B)Anti-Clockwise Circular Movement Anticlock-wise forms



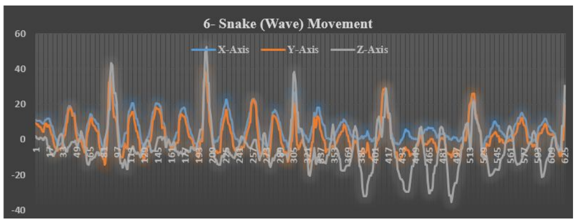
(C)Idle or No Movement Idle forms



(D)Left and Right Movement Right forms



(E)Up and Down Movement Idle forms



(F)Snake or Wave Movement wave or Snake forms

Figure 3: waveform images of each movement of the smartphone

Table1 shows the description of the dataset, which describes each movement of the smartphone, and the class number of samples of each movement code. Class 1 contains 86 samples, class 2 has 62, calss IDL samples are 107 and so on (shown in table 1).

C. Stacked Auto-Encoders

Stacked autoencoders (SAEs) are deep neural networks that are trained to encode and decode input data in an unsupervised manner. They can be used for dimensionality reduction, feature extraction, and data compression.The input data needs to be preprocessed to remove noise and normalize the values. This step is essential to ensuring that the SAE can learn meaningful representations. The first autoencoder is initialized with

TABLE 1: DATASET DESCRIPTION OF SMARTPHONE MOVEMENT CATEGORIES

Class Number	Description	Code	No of Samples
1	Cycle Clockwise	CCS	86
2	Cycle Anti-Clockwise	CUR	62
3	Idle Movement	IDL	107
4	Left to Right Movement	LRS	102
5	Up and Down Movement	UDS	99
6	Wave Form Movement	WAV	112

random weights. It is trained using backpropagation to reconstruct the input data. The second autoencoder takes the output of the first layer as its input. The weights that the first autoencoder learned are used to set up the second autoencoder. It is taught to reconstruct the first autoencoder's output. This process is repeated for each subsequent layer until the desired number of layers is reached. Once all the layers have been trained, the entire SAE is fine-tuned using supervised learning. The weights of the entire model are adjusted to minimize the error between the predicted output and the actual output. Once the model is trained, it can be used to encode new input data. The input data is fed into the first layer, and the output of each layer is used as input to the next layer. The final output is an encoded representation of the input data.

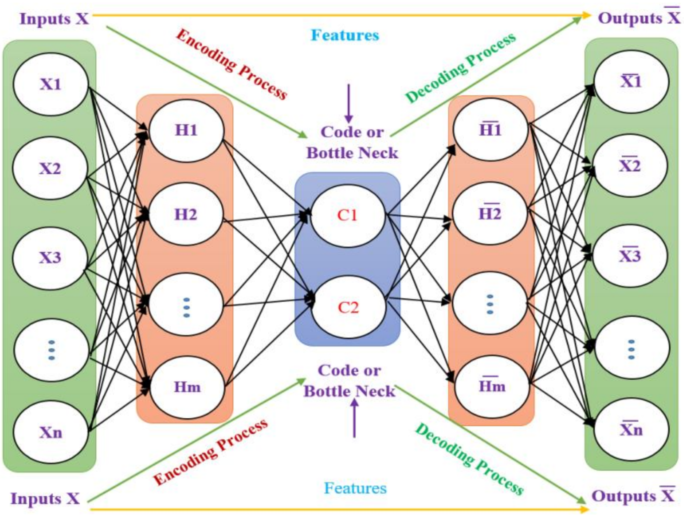


Figure 4: Stacked Auto-Encoder model

The encoded data can be decoded by reversing the process. The encoded data is fed into the last layer of the SAE, and the output of each layer is used as input to the previous layer. The final output is the reconstructed input data. . Evaluate the model: The performance of the model can be evaluated by calculating the reconstruction error. The reconstruction error is the difference between the original input data and the reconstructed data. The figure shows the detailed description of stacked autoencoders process. As per experimental construction, we used total 569 samples of 6 category of movements. We extaract the features in two steps that the first encoder produces 100 features connected to the second encoder. Lastly, the softmax layer classifies the six momemts of smartphone.

D. Performance Parmeters

Accuracy: An instrument's ability to accurately measure a value is what defines its accuracy. The measurement's proximity to a standard or the value of truth determines its accuracy. Low readings can reduce calculation errors and small readings can be used to determine accuracy [20]. It measures the proportion of all observations that have been correctly classified.

$$\text{Accuracy} = \frac{(\text{TP+TN})}{(\text{TP+FP+FN+TN})} \qquad (1)$$

Precision: Based on the information that its digital values convey, the precision activity demonstrates how to compare multiple measurements to one another [21]. However, accuracy is not taken into account in its calculation.

$$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})} \qquad (2)$$

Recall: Based on all the inspections in a class, the ratio of correctly predicted positives is called recall.

$$\text{Recall} = \frac{\text{TP}}{(\text{TP+FN})} \qquad (3)$$

F1 score: a weighted average of precision and recall combined.

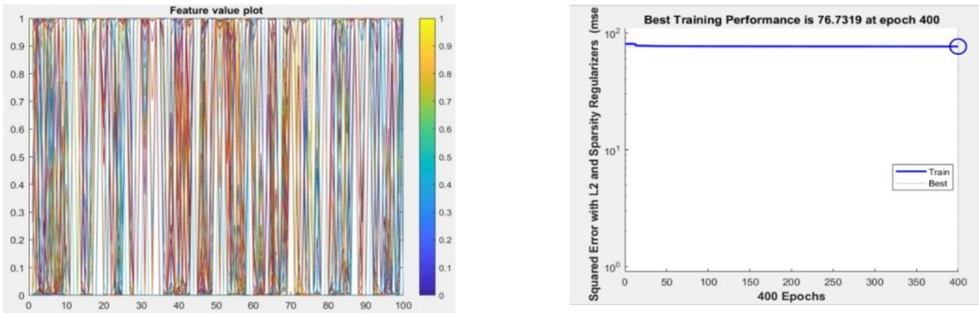
$$\text{F1 Score} = \frac{2*(\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})} \qquad (4)$$

ROC: A comprehensive analysis of the classification model is provided by the functioning measures, the Receiver Operating Characteristics (ROC) curve and the Area Under the Curve (AUC). [22] AUC is a numerical representation of the ROC curve of a binary classifier that takes a value between 0 and 1 and encapsulates the operation by adding the confusion matrices at all thresholds. Using a confusion matrix, AUC can be used to determine how accurately the model divides positive and negative values. An actual class is represented by a row in a confusion matrix, while a predicted class is represented by a column.

IV. Results and Discussion

In this section, we describe the analysis and implementation of stacked auto-encoders on a mobile movement dataset. We got 99.8% training accuracy, 100% testing accuracy, and an AUC value of 1.

A. Performance Analysis of Autoencoders

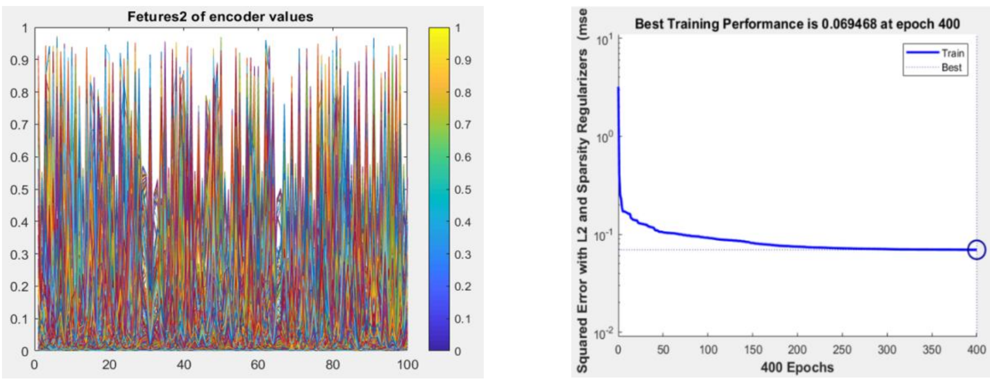


(A) 100 features values Autoencoder 1

(B) Best Training Performance of Autoencoder 1

Figure 5: Auto-Encoder1 features and Performance analysis

The data set is in a cell of size 1x569. Each cell contains 3x625 double-type values. The network structure of the autoencoder-1 is as follows: trainData is 1x569, hidden layer neurons are 100, maximum epochs are 400, and L2WeightRegularization is 0.004. In this experiment, the data was first given to the autoencoder-1. The autoencoder-1 produced 100 features for each data cell. Features1 is the result of autoencoder1 and trainData. The size of feature set 1 (feat1) was 100x569, and the best performance was 76.7319 at epoch 400. All feature values were mapped to 0–1 values. Figure 5(A) shows the 100 feature values, and Figure 5(B) depicts the performance analysis of Autoencoder-1. The X-axis represents the epochs, and the Y-axis represents the mean squared error. The blue line represents the training performance, and the dotted line specifies the best performance line.



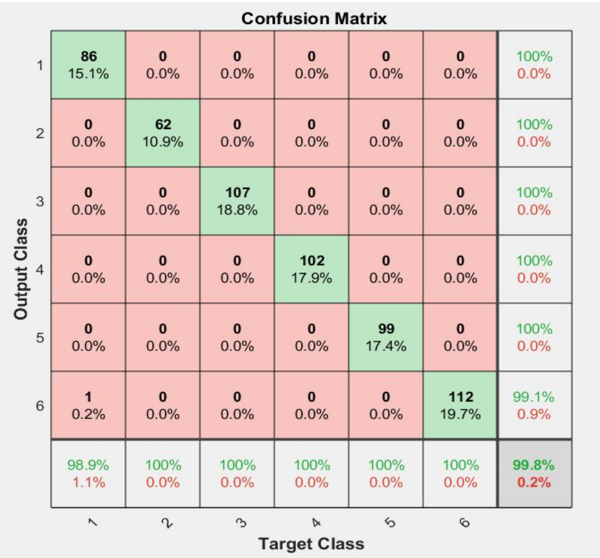
(A) 100 features values Autoencoder 2

(B) Best Training Performance of Autoencoder 2

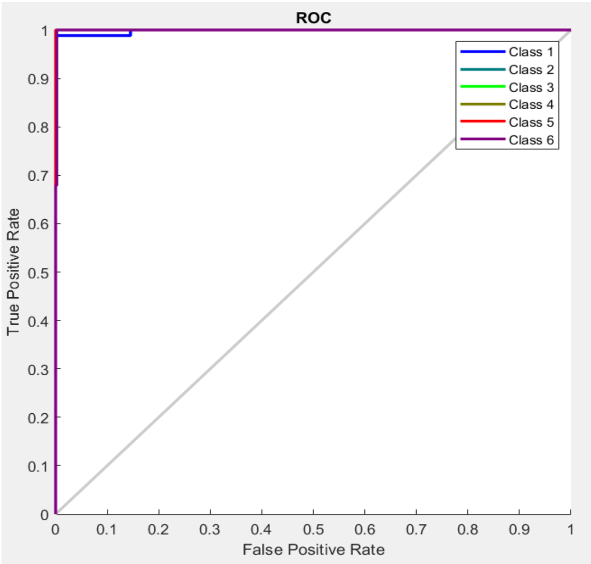
Figure 6: Auto-Encoder2 features and Performance analysis

The autoencoder-2 network was built with 100 neurons in each hidden layer. Feat1 of the autoencoder-1 is the input of the autoencoder-2. The autoencoder-2 was trained on feature 1, with maximum epochs of 400 and L2WeightRegularization of 0.002. Features2 Features1 is the result of autoencoder-2. The second autoencoder produced 100 tuned features for each cell data; the size of feature set 2 (feat2) was 100x569, and the best performance was 0.069468 at epoch 400. All feature values were mapped to 0–1 values. Figure 6(A) shows the 100 feature values of encoder 2, and Figure 6(B) depicts the performance analysis of autoencoder network 2. The X-axis represents the epochs, and the Y-axis represents the Mean Squared Error. The blue line represents the training performance, and the dotted line specifies the best performance line.

B. Performance Analysis of SoftMax and Stacked Auto-Encoders



(A)Confusion Matrix Movements of Smartphone Movement 1 to 6 classes



(B)ROC curves Movements of Smartphone Movement 1 to 6 classes

Note*: 1-Cycle Clockwise, 2-Cycle Anti-Clockwise, 3-Idle, 4-Left to Right, 5-Up and Down 6-Wave Form Movements

Figure 7: Confusion Matrix and ROC curve analysis

After extracting features using both autoencoders, we can use them as inputs to train a softmax classifier. The trainSoftmaxLayer function is used to train a softmax layer for a six-class classification problem. Softmax is trained with the functions trainSoftmaxLayer of features2 (produced by autoencoder 2) and train-labels with a maximum of 400 epochs. Once we have trained the autoencoders and softmax layer, we can combine them into a single network using the stack function. Combine the autoencoders and softmax layer into a single network, referred to as StackedNet, which is defined as a stack of autoencoder1, autoencoder2, and softmax. The figure shows the classification of six movements in smartphone analysis with a confusion matrix and ROC curves. According to the observations, the stacked autoencoder performs well, with a training accuracy value of 0.998 (99.8%) and a testing accuracy of 100% (testing dataset of the smartphone with six movements). The precision value is 0.997, and the recall value is 0.999. In this, only one event of class 1 was misclassified. The remaining classes were classified accurately.

V. Conclusion

In recent days, the frequency of smartphone use has been very high, and it has become a part of everyone's life. Embedded machine learning is a current emerging topic that solves many problems and provides better solutions for complex problems using cloud-based systems. The Intelligent Embedded ML Approach for Smartphone Movement Identification using Stacked Auto-Encoders is a promising method for accurately identifying different types of movements using sensor data from a smartphone. The use of stacked auto-encoders allows for the creation of a deep learning model that can learn complex features from the data, leading to higher accuracy in movement identification. The results of the proposed approach stacked auto-encoder model accuracy and computational efficiency, making it a viable solution for real-time movement identification on smartphones. The stacked auto-encoder model was able to achieve an accuracy of over 99.8%. Overall, the use of stacked auto-encoders in combination with embedded advanced machine learning techniques provides a powerful approach for accurately identifying movement types using smartphone sensor data.

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