



Enhancing Smartphone Motion Sensing with Embedded Deep Learning

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Received 9 June 2024, Revised 3 October 2024, Accepted 25 October 2024

Abstract: Embedded systems and smartphones are vital in real-time applications, inspiring our interaction with technology. Smartphones possess various sensors like accelerometers, gyroscopes, and magnetometers. Deep Learning (DL) models enhance the capabilities of sensors, enabling them to perform real-time analysis and decision-making with accuracy and speed. This study demonstrates an intelligent system that detects smartphone movements using deep learning (DL) techniques such as convolutional neural networks (CNN) and stacked autoencoders (SAEs). The dataset has six smartphone movements, with 921 samples split into 695 for training and 226 for testing. The best training performance was achieved by Auto-Encoder 1 and Auto-Encoder 2. The SAEs had high classification accuracy (CA) and AUC values of 0.996 and 1.0, respectively. Similarly, CNN performed well with CA and AUC values of 0.991 and 0.998. These results show that CNN and SAEs are effective in identifying smartphone movements. The findings help improve smartphone apps and understand how well they can identify movement. The study indicates that CNN and SAE are influential in accurately identifying smartphone movements. Future research can improve motion detection by integrating more sensor data and advanced models. Using advanced deep learning architectures like RNNs or transformers can enhance the understanding and accuracy of predicting smartphone movements.

Keywords: Auto-Encoder, CNN, Embedded Machine Learning, Smart Phone, Sensor Data

1. INTRODUCTION

Smartphones are ubiquitous and have many features [1]. They have accelerometers, gyroscopes, and magnetometers that track movement and orientation. By using DL models, we can create intelligent apps to analyze this sensor data (SD) in real-time and make decisions. The "Intelligent Smart Phone Movement Identification Embedded System" is a system that uses smartphone sensors to recognize and classify smartphone movements accurately. It uses advanced DL models to analyze the SD and detect user movements. The system uses the smartphone's magnetometer, gyroscope, and accelerometer to record precise motion data in real-time. It relies on real-time embedded systems to process the SD quickly and efficiently. The system has sensor interfaces, data acquisition modules, processing units, and decision-making algorithms. These components work together to read the SD and interpret the movements. The sensors continuously record the phone's orientation, acceleration, and angular velocity, providing much data to understand how the user moves. Once the

movements are identified, the embedded system can act or give feedback to the user or other apps on the smartphone [2] [3]. DL models are used in this system to process and understand SD. These algorithms learn and detect various movements using a vast quantity of labeled data. The system can identify smartphone gestures such as clock and anti-clock cycles, up-down, left-right, wave or snake cycles, and idle mode. It accurately distinguishes these movements and provides real-time feedback on smartphone movements. This system has many benefits, including tracking physical activities without wearable devices [4]. It eliminates the need for bulky accessories and improves user convenience. The medical and fitness industries use these systems that monitor physical activity patterns and assist people in becoming more fit. It combines DL with smartphones to accurately identify and analyze movement. The research addresses smartphone movement identification challenges and proposes an intelligent solution using embedded DL models. The paper will review existing literature, discuss advancements and limitations, and present the proposed



model and materials used for experimentation. **The paper's remaining sections are described as**

- The **literature review** thoroughly examines previous research and publications on smartphone movement identification and embedded DL models. Researchers' methods, algorithms, and techniques will be discussed in this. The review identifies literature gaps, challenges, and opportunities to form our model.
- **Proposed Model and Materials:** We present our intelligent smartphone movement identification model using embedded DL. Our model's training method is architecture and network design. The dataset, pre-processing methods, and hardware and software requirements for our experiments will also be discussed.
- The experimental results of our model are shown in the **results and discussion** sections. We evaluated our approaches using performance metrics like F1 score, accuracy, precision, and recall. By comparing our findings to methods reviewed in the literature, we can identify the strengths and weaknesses of our model. We will provide a detailed explanation of the reasons behind the results.
- **Conclusion:** We summarize our intelligent smartphone movement identification research using embedded DL models. We emphasize the importance of our approach and its potential impact on field applications. Our findings, limitations, and future research will be discussed.

2. LITERATURE REVIEW

Smartphone technology has improved and now allows for new uses in recognizing human activities and healthcare applications. Researchers Huang et al. [5] have suggested using a cell phone dongle for blood lipid testing. The dongle has shown promising results, with high correlation coefficients (0.903) and low variation (4.575%). It indicates that the dongle is accurate and reliable, considering it a useful tool for cholesterol monitoring in the future. Johnson et al. [6] have developed an algorithm that can automatically detect whether a smartphone is used by the driver or passenger in a moving vehicle. This technology can help prevent distracted driving, especially for iPhones and other smartphones that currently cannot differentiate between driver and passenger usage. Masud et al. [7] have introduced a smartphone-based approach to assess depression levels by monitoring daily activities. This method is cost-effective and non-intrusive and has achieved high accuracy (87.2%) in identifying severe depression cases. It offers a promising way to assess and monitor depression, providing timely intervention and support for individuals with mental health disorders. Qi et al. [8] proposed a smartphone-based human (HAR) activity recognition and automatic labelling framework. This framework uses signals from Microsoft Kinect cameras and smartphones to

label everyday tasks accurately. Compared to other models, their methodology and algorithm perform better in accuracy assessment. Researchers studied and discussed a method called DL-based sensor-based activity recognition. They also proposed a FL-PMI technique to Enhancing Efficiency and Accuracy of intelligent healthcare systems. Wang et al. [9] performed a survey of DL for sensor-based movement identification. They researched recent advancements, challenges, and potential solutions in DL-based motion identification. The survey discussed sensor modality, deep models, and applications in detail. It also provided insights into the factors contributing to improved performance in DL models. Arikumar et al. [10] introduced an approach known as FL-PMI, which combines deep (DRL) reinforcement learning, federated (FL) learning, and Bi-LSTM. Their method achieved high accuracy and addressed computational costs, memory usage, and data transmission challenges in intelligent healthcare systems. It improved efficiency, reduced resource requirements, and decreased data transmission by 36.73%. The FL-PMI outperformed other systems in accuracy, precision, F1-score, and recall, demonstrating its effectiveness in sensor-based Motion Identification. Liu et al. [11] presented a security mechanism using channel state information to detect rogue Wi-Fi devices. Their mechanism achieved a high accuracy of 96% in detecting rogue connections and had a low false alarm rate. It was also eight times faster than existing solutions regarding detection speed. This research enhances security and mitigates vulnerabilities in Wi-Fi networks, WLAN, and IoT environments. The study [12] addressed vulnerabilities in biometric-based authentication methods by introducing Lip Pass, a lip-reading-based authentication system. Their DL approach, combined with Doppler profiles and smartphone acoustic sensing, achieved high accuracy rates in user identification and spoofed detection. Lip-reading-based authentication can enhance privacy protection on mobile devices and is resilient to ambient environmental factors. Recent research has focused on how to use DL techniques, like CNNs, to make systems more accurate and efficient. Table I summarizes research on smartphone sensor data (SSD) for HAR using different ML and DL models. Studies focus on dataset size, sensor types, model architecture, and performance metrics.

Ponciano et al. [20] have created a way utilizing smartphones and sensors to measure and analyze the timed-up and going test parameters. This method makes it easier to collect and process data, which can be used to group test results and identify patterns related to balance changes, neurological disorders, and other conditions. The proposed architecture shows promise for comprehensive analysis and assessment in physiotherapy. The study [21] proposed a deep neural network architecture for HAR that encodes SD as images and uses computer vision (CV) techniques. This method performs better than other methods in terms of F1-value and accuracy rate by using fusion residual networks and different layers of deep residual networks. Testing on various datasets supports the idea that this method can

TABLE I. Key Studies of the Existing Research Works On Smart-Phone Sensor Data

Ref. No.	Author & Year	Aim and Description	Results and Models Analysis
[13]	Jiang et al.	The study utilizes a smartphone-based HAR system, utilizing CNN, to investigate the correlation between health issues and six physical activities.	The CNN achieved a recognition accuracy of 97.5% for a UCI HAR dataset.
[14]	Zhou et al.	study developed a smartphone-based HAR using CNN, synthesizing a 6 GB sensor dataset from various smartphone accelerometers, magnetometers, gyroscopes, and barometers.	CNN achieved 97.5% accuracy, while J48 achieved 95.5% accuracy.
[15]	Ravi et al.	The proposed DL approach utilizes SD analytics on wearable or mobile devices for efficient on-node processing, utilizing CNN models on diverse datasets.	Active-Miles achieved a 95.7% accuracy rate, WISDM v1.1-98.6%, WISDM v2.0-92.7%, Skoda-95.3%, and DaphnetFoG-95.8% for each dataset.
[16]	Zebin et al.	The study assessed the DL system's execution time and memory HAR system on affordable smartphone gadgets, focusing on developing a CNN for HAR tasks.	The proposed CNN model demonstrated a remarkable accuracy (96.4%) in a five-class dynamic and static activity identification setup.
[17]	Qi et al.	The authors developed a novel FR-DCNN model for HAR, utilizing smartphones, ISP algorithms, and an SS module to improve the effectiveness and extend the entropy of IMU sensors' raw data.	The FR-DCNN model demonstrated a remarkable prediction time of 0.0029 seconds with a 95.27% accuracy for HAR.
[18]	Xia et al.	The authors developed a DNN that integrates CLs and LSTM for automatic feature extraction and classification of activity data, resulting in significant enhancements.	The model demonstrated high accuracy on three public datasets, with 95.78% accuracy on UCI-HAR, 95.85% accuracy on WISDM, and 92.63% accuracy on opportunity.
[19]	Ye et al.	The authors explored the performance limits of combining two-stream and recurrent neural networks, highlighting spatial structure and appropriate fusion methods, and proposing ConvLSTM networks with two-stream ConvNet.	The proposed method achieves an accuracy rate of 69.4% on HMDB51 and 93.9% on UCF101 datasets, demonstrating its effectiveness in activity recognition tasks.

help make data-driven decisions for HAR. The comparative analysis of fusion layers using a specific dataset shows that the Conv3 fusion layer performed the best with high accuracy. Dasgupta et al. [22] studied how economic and healthcare factors in US counties were related and how social distancing measures affected people's movement. They used data from mobile devices to analyze this. The study found that places with stay-at-home orders significantly decreased movement than places without orders. This showed that some people had more privilege to stay home than others. The study shows that social distancing is essential in addressing inequalities during health crises like COVID-19. Auto-encoders are models that can learn from data without supervision. They can be used for tasks like reducing dimensions, detecting anomalies, and extracting features. They are good at finding patterns in data. They can be used to detect human activities using SSD. A study by Alo et al. [23] showed that their deep-stacked auto-encoder algorithm, along with features that don't change with orientation, can accurately identify complex human activities with a high level of accuracy. This is better than traditional ML methods and deep belief networks. This approach can be helpful for health monitoring, fall

detection, and emotion detection. Another study by Garcia et al. [24] proposed a multi-class approach for HAR based on an auto-encoder ensembling model. The findings suggested that this strategy is more successful than other approaches. The group of autonomous auto-encoders had a higher accuracy in comparison to other models like EkVN. The autonomous auto-encoders also outperformed EkVN regarding user accuracy, showing better performance in most users. However, different models like JiangYin and Haetal slightly outperformed the autonomous auto-encoders and EkVN regarding average accuracy. Wu et al. [25] emphasized the importance of road surface maintenance and proposed an automatic pothole detection system using smartphone vibration sensors.

Researchers Hasanuzzaman et al. [26] have studied DL-based HAR systems in wearable devices and smartphones. They found that these systems have unique features, advantages, and limitations. One study [26] focused on the transpiration influences on the flow of a vertical, shallow body's boundaries in natural convection. They used numerical analysis to understand the impact of parameters on fluid dynamics and heat transfer. Another study [27]

reviewed DNN methodologies for automatic feature extraction in HAR. They discussed the implementation, design, advantages, and disadvantages of these methodologies, as well as their performance evaluation. The study also highlighted challenges and discussed various DL functionalities used in sensor-based recognition systems for wearables and smartphones, providing insights into their uniqueness, advantages, and limitations. In a study by Rana et al. [28], a system was developed to monitor and assess the roughness of road surfaces using vehicle dynamics and smartphones. This system aims to improve road maintenance and driving conditions. Kołakowska et al. [29] reviewed several identifications of emotion techniques using SSD data. Their analysis provides insights into advancements, challenges, and potential applications in the field of emotion detection in mobile computing. Nooruddin et al. [30] reviewed fall detection systems to help keep older adults and those prone to falls safe. They discussed various sensors, algorithms, and techniques, along with the challenges and future directions in the field. Strackiewicz et al. [31] systematically reviewed smartphone-based HAR for healthcare purposes. They analyzed the existing literature and highlighted these methods' strengths, limitations, and potential applications in monitoring and analyzing HAR.

3. MODELS AND MATERIALS

The proposed ML models for identifying alcohol consumers using a vowelized voice dataset can be implemented using a pre-processed vowelized voice dataset. In the pre-processing, we remove noise and normalize the audio levels. The pre-processed data is split into training and testing sets. The training set is used to train the model, while the testing set is used to evaluate the model's performance. For this, we use 10-fold cross-validation. We chose some suitable machine-learning algorithms for this task. The chosen algorithms are k-NN, C4.5, SVM, and Random Forest algorithms, as well as NNs. The selected ML algorithm is trained on the training set using the extracted voice features. The model's performance is evaluated using accuracy, precision, recall, and F1-score metrics. A collection of voice recordings of people pronouncing different vowels. The dataset should include both alcohol consumers and non-alcohol consumers.

A. Proposal Model

The proposed model in **Figure 1** is for a Smart Phone Moment Identification System. The research aims to collect movement data from smartphones using embedded sensors. The data is collected using embedded systems connected to a computer and stored for easy access. The data undergoes preprocessing steps to improve its quality. The preprocessed data is then divided into training and testing sets. Stacked Auto-Encoders and CNN models are used to learn patterns from the data. The models are fine-tuned to improve their performance. Finally, the models are compared and tested to accurately predict and classify smartphone movement patterns, which can be used in activity recognition and related applications.

B. Data Collection and Dataset Description

Figure 2 shows the SSD analysis's Data Collection, Expansion, and Data storage processes. Smartphones' embedded systems (ES) acquire data from built-in sensors like magnetometers, accelerometers, gyroscopes, and GPS receivers. These sensors continuously measure the smartphone's position, orientation, velocity, and acceleration. The ES transmits the acquired SD of the smartphone to the computer system. We can achieve this by using either wired or wireless communication protocols like USB, Bluetooth, or Wi-Fi. Computer systems like laptops, Desktops, or servers receive the SD transmitted by the smartphone's embedded system. It establishes a connection with the smartphone and prepares to process the received data. The computer system processes the received data from a sensor to derive meaningful information about the smartphone's movement. The computer system uses algorithms and software applications to interpret the SD and extract relevant motion-related parameters. The system analyses the smartphone's movement patterns using the processed SD. It can generate visualizations, graphs, or reports that provide insights into the smartphone's motion behavior over time. This analysis can be helpful for research, diagnostics, or monitoring purposes.

The computer system integrates the analyzed motion data with various applications or software systems. It can provide input to virtual or augmented reality applications, where the smartphone's movement influences the displayed content or virtual interactions. The computer system can synchronize the processed motion data with other devices or platforms. Based on the analyzed data, it can send feedback or commands back to the smartphone. For instance, it can trigger notifications, adjust settings, or control other connected devices based on the smartphone's movement. The computer system can store the processed motion data for further analysis or historical reference. It can perform advanced data analytics, pattern recognition, or ML techniques based on the data provided to gain insights or improve future motion-related algorithms. **Figure 3** displays the six types of motions of the smartphone sensor signals in detail: clockwise motion (**Figure 3 (A)**), Anti-clockwise motion (**Figure 3 (B)**), Idle, and so on (**Figure 3 (C, D, E, F)**). **Table II** describes signal form descriptions for different movement patterns, including clockwise circular, anticlockwise circular, idle, left and proper, right forms, up and down, inactive forms, and snake or wave movement. The total samples for each available class code range from 82 to 160, indicating the overall size of the dataset for each specific movement pattern. Training samples provide necessary data to teach the model about the characteristics and patterns associated with each movement class, with varying numbers for each class. Testing samples analyze the task's performance and generalization ability of the trained models or algorithms, providing a benchmark for assessing how well the model can classify or predict movement patterns. The number of testing samples varies, ranging from 20 to 48 for different movement classes.

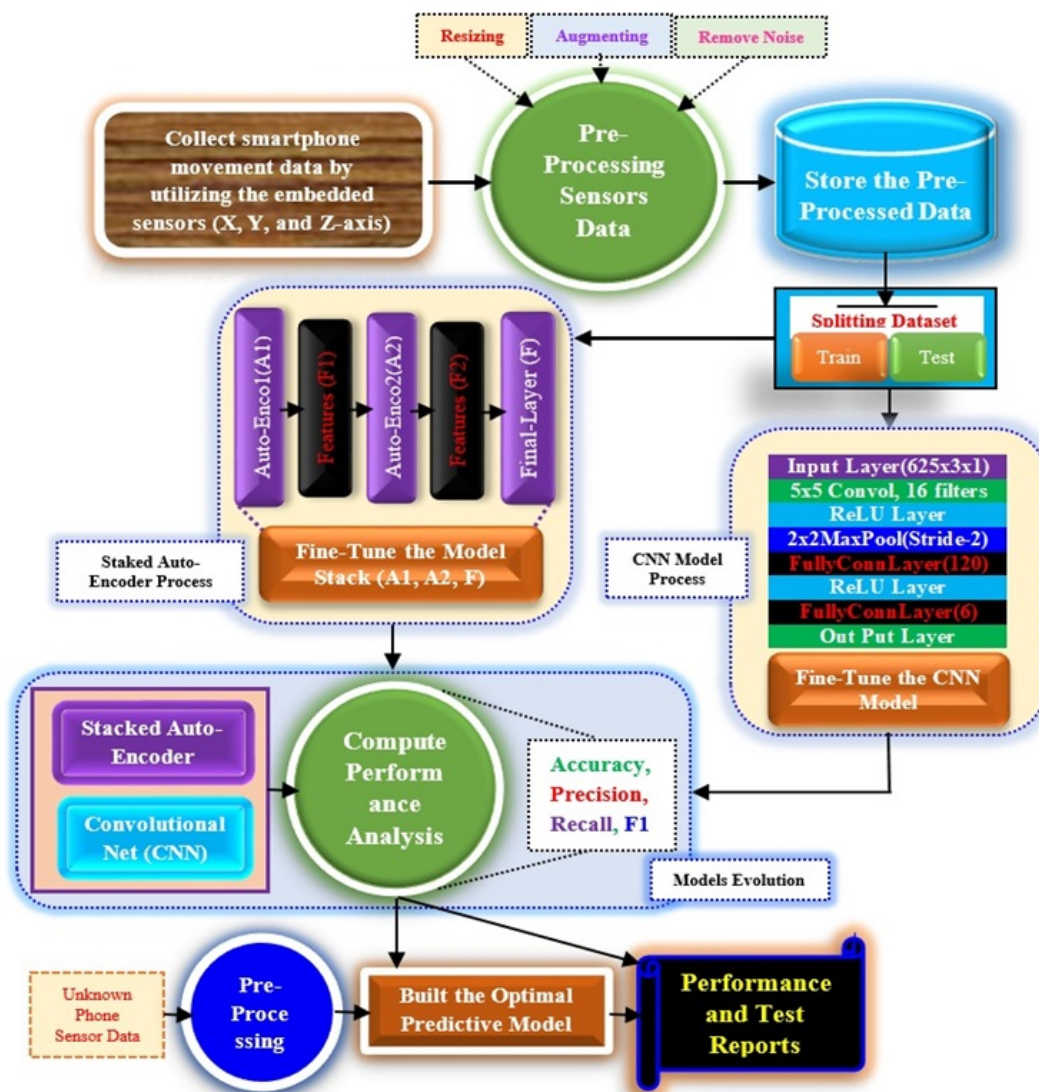


Figure 1. Proposal Model of Smart Phone Moment Identification System

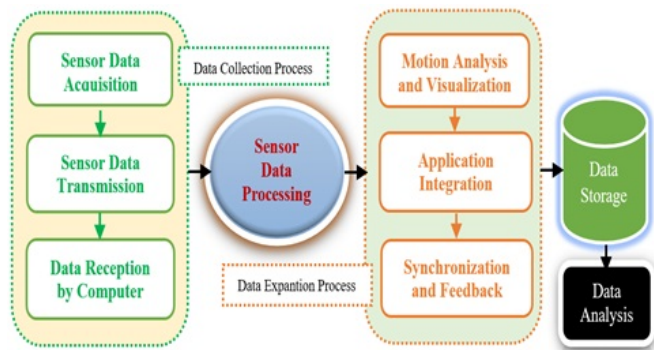


Figure 2. **Figure 1.** Smartphone Sensor Data analysis: Data Collection, Expansion, and Data storage processes

C. CNN Architecture

Figure 4 shows the user-defined CNN model. This simple CNN architecture takes a 625x3 as input and applies layers with complete connections, pooling, and convolution to learn and classify the source data into among the six categories.

DataInputLayer: This layer specifies the input data shape as [625 3 1], demonstrating that the input consists of 625x3 sensor 3-axis data. **Convolution2DLayer:** This layer adds Sixteen 5x5 filters to the supplied image. The filters learn the incoming data’s spatial properties[32]. **ReLUlayer:** The O/P of the layer that came before it is applied element-by-element by this layer using the Rectified (ReLU) Linear unit function of activation. ReLU brings nonlinearity into the framework of networks.

TABLE II. Smart Phone Sensor Signal Dataset Description

Class (Code)	Smartphone Sensor Signal Form Description	Total Samples	Training Samples	Testing Samples
CCM (1)	Clockwise Circular Sensor Signal Movement	127	96	32
ACM (2)	Anti-Clockwise Circular Sensor Signal Movement	92	72	20
IDM (3)	Idle or No Sensor Signal Movement	167	127	40
LRM (4)	Left and Right Sensor Signal Movement	177	132	45
UDM (5)	Up and Down Sensor Signal Movement	171	129	43
WAM (6)	Snake or Wave Sensor Signal Movement	187	139	48
Total	Six Types of Movements	921	695	226

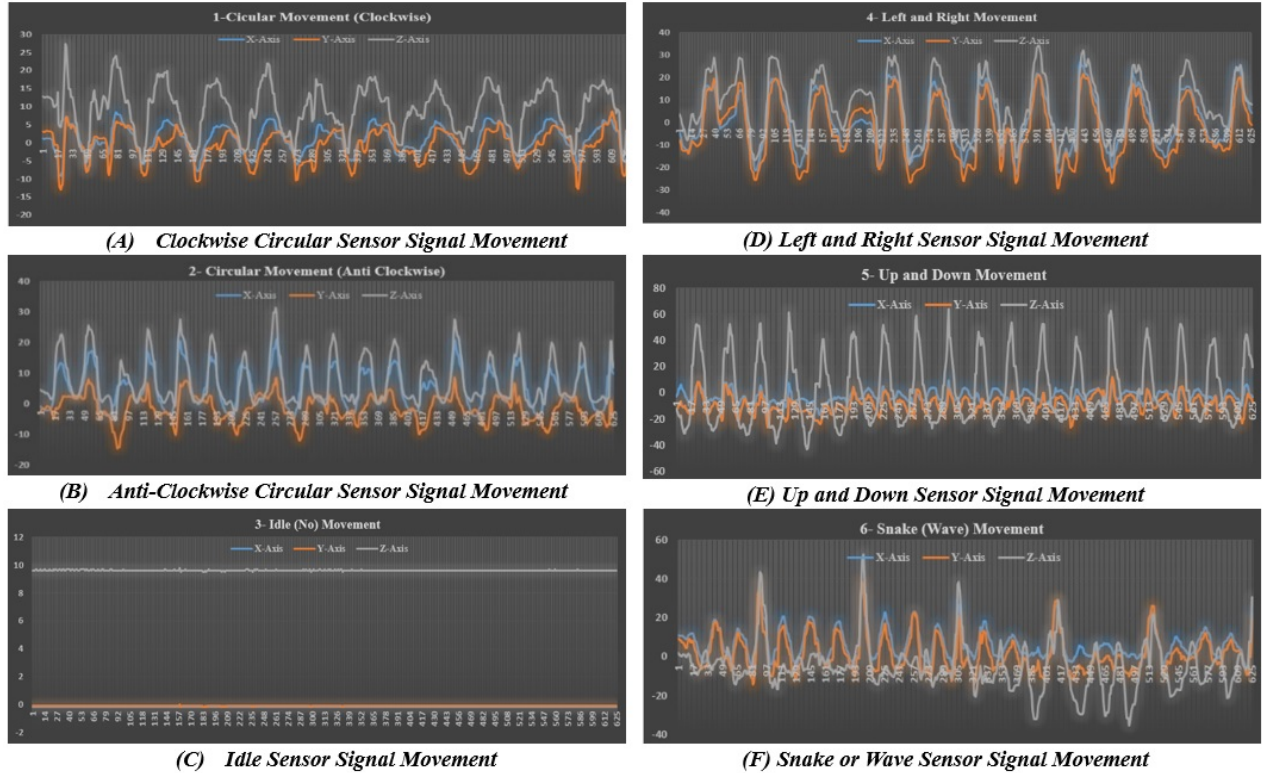


Figure 3. Smartphone Signals for all Movement Classes

MaxPooling2DLayer: This layer uses max pooling that has a 2x2 stride to reduce the spatial dimensions of the maps of features by a ratio of two. It helps capture the most salient features while reducing computational complexity[33].

FullyConnectedLayers: This layer consists of 120 neurons and is fully connected to the previous layer. It learns higher-level features by combining the extracted spatial features. This layer consists of 6 neurons, representing the number of classes in the classification task. It maps the learned features to the respective courses.

SoftmaxLayer: The softmax activation (SAF) function is used in this layer to normalize the previous layer's O/Ps into probability values. It provides the final predicted probabilities for each class.

ClassificationOutputLayer: This layer computes the loss and performs the classification based on the predicted probabilities and the ground truth labels. The I/P of the (8-layer) CNN model is the SSD in four dimensions. The total training samples are 695, with each sample size [625 3] having one channel. The first layer of the Data Input specifies the input data shape as [625 3 1], demonstrating that the input consists of 625x3 sensor 3-axis data. In the Convolution2D Layer, let X be the layer of I/P, combining Batch Size, Width, Height, and Channels. Let 'W' be the weight tensor of the shape of combinations of FilterWidth, Filter-Height, InputChannels, and O/P Channels. Let b represent the bias vector that shapes the O/P channels. The

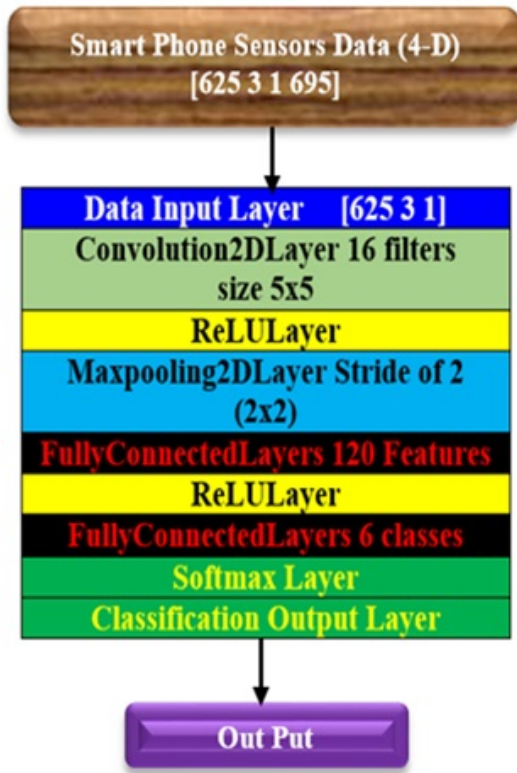


Figure 4. 8-Layer CNN simple Model for Smart-Phone Sensor Data Analysis

feature map Y is described as

$$Y[i, j, k] = ReLU \left(\sum_{m,n,p} (X[m, n, p] \times W[i, j, p, k]) \right) \quad (1)$$

Where 'm' in range (filter-width), for 'n' in range (filter-Height), for 'p' in range (input-channels, (input-channels)+b[k]). ReLU Layer: Let X is I/P Layer. The O/P Y is computed as Eq. (2).

$$Y = \max(0, X) \quad (2)$$

Maxpooling2DLayer: Let X is layer of I/P, with shape (batch size, width, height, channels). The pool's size should reflect the dimensions of the pooling window (width, height). Let stride be the stride parameter used in the pooling procedure. O/P feature map Y is calculated as Eq. (3).

$$Y[i, j, k] = \max(X[m, n, k]) \quad (3)$$

Where 'm' is in Range(istride,istride + pool_size[0]) range for n in range (jstride, jstride + pool_size[1]) **Connected Layer:** With shape (BatchSize, InputSize), let X serve as the input to the layer. Shape's weight matrix (InputSize, OutputSize) can be represented by W . Shape's bias vector (OutputSize), let b be. The result, Y , is calculated as

$$Y[i, j, k] = ReLU(X * W + b) \quad (4)$$

ReLU Layer: Let X serve as the layer's input. The result, Y , is calculated as

$$Y = \max(0, X) \quad (5)$$

Fully Connected Layer: With shape (BatchSize, InputSize), let X serve as the input to the layer. The O/P Y is calculated as W is the shape's weight matrix (InputSize, OutputSize), and b is its bias vector (OutputSize).

$$Y = X \times W + b \quad (6)$$

Softmax Layer: With shape (BatchSize, InputSize), let X serve as the input to the layer. The result, Y , is calculated as

$$Y[i, j] = \frac{e^{X[i,j]}}{\sum e^{X[i,k]}} \quad (7)$$

Where k in range (1, InputSize))

D. Staked Auto-Encoder

Figure 5 illustrates the component diagram of the various layers of the 2-Layer Stacked Auto-encoder, where each layer consists of an encoder and a decoder, and softmax layers. The Input (I/P L) Layer represents the I/P data that flows into the auto-encoder. The Layer 1 Encoder that this block performs a linear transformation and applies a non-linear activation function to compress the I/P data into a lower-dimensional representation. The first auto-encoder compresses the input, capturing its essential features and reducing its dimensionality. The second auto-encoder further squeezes the O/Ps from Auto-Encoder 1, extracting higher-level representations of I/P Data. The Layer 2 Decoder receives the compressed representation from Layer 2's encoder and reconstructs the data by applying reverse transformation and activation. The softmax layer takes the O/P from Layer 2's decoder and performs from and uses the softmax (SMF) function, which makes them probabilities for each class. The O/P layer of the model provides the final classification result, identifying the most probable class for a given input based on the probabilities obtained from the softmax layer [34].

Layer1: Let X is the Dataset with elements set $X_1, X_2 \dots X_m$ then the Auto-Encoder 1's encoder denotes Eq. (1) and computation as follows as

$$E^{(1)} = f(X * W^{(1)} + b^{(1)}) \quad (8)$$

where $W(1)$ is the weight matrix, $b(1)$ is the bias vector, and f represents the activation function for the encoder of the first layer. The Auto-Encoder 1's encoder denotes $D(1)$ and computation as follows as

$$D^{(1)} = f(E^{(1)} \times W'^{(1)} + b^{(1)}) \quad (9)$$

Here, $E(1)$ is the encoded representation, $W'(1)$ is the transpose of the weight matrix, $b(1)$ is the bias vector, and f represents the activation function for the decoder of the first layer.

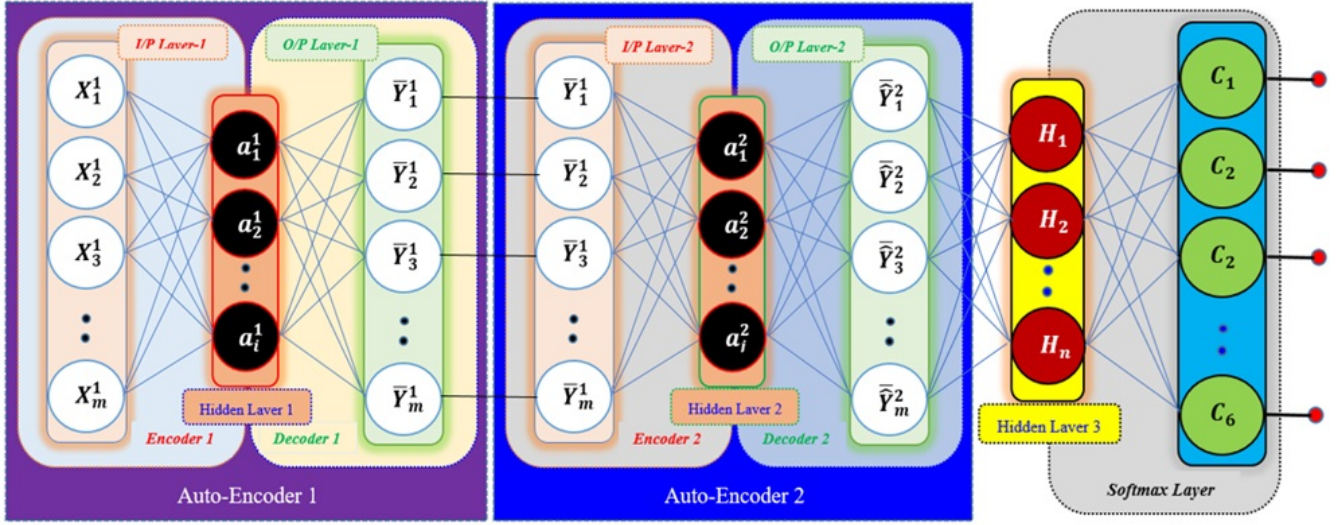


Figure 5. 2-Layer Stacked Auto-Encoder Model for Smart-Phone Sensor Data Analysis

Layer 2: The Auto-Encoder-2's encoder denotes E(2) and computation as follows as

$$E^{(2)} = f(E^{(1)} * W^{(2)} + b^{(2)}) \quad (10)$$

where W(2) is the weight matrix, the bias vector is b(2), and the activation function for the first layer's encoder is denoted by f. The Auto-Encoder-2's encoder denotes D(2) and computation as follows as

$$D^{(2)} = f(E^{(2)} * W'^{(2)} + b^{(2)}) \quad (11)$$

Here, E(2) is the encoded representation, W'(2) is the transpose of the weight matrix, b(2) is the bias vector, and f represents the activation function for the decoder of the first layer.

Softmax Layer: Assuming the input to the softmax layer is denoted as Z, that is O/P of Auto-Encoder-2, and it has dimensionality (BatchSize, NumClasses), where NumClasses is the total number of classes in the classification job and BatchSize is the number of samples. The input Z is sent into the SoftMax algorithm, which computes the probabilities for each class. The probabilities are calculated by exponentiating the input values and normalizing them across all classes. The SoftMax function can be defined as

$$P(\text{Class } i) = \frac{e^{Z[:,i]}}{\sum (e^{Z[:,j]}, \text{axis} = 1)} \quad (12)$$

Here, P(class i) represents the probability of class i, Z[:, i] denotes the values of the i-th class in the input Z, and sum(exp(Z), axis=1) calculates the sum of exponentiated values across all classes. In classification tasks, a common loss function used with SoftMax is the cross-entropy loss. The cross-entropy loss may be computed using the actual labels Y and the projected probability P.

$$L = - \sum (Y * \log(P)), \text{axis} = 1 \quad (13)$$

Predicted \ Actual	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total
Class 1	TP1	FP1->2	FP1->3	FP1->4	FP1->5	FP1->6	T1
Class 2	FP2->1	TP2	FP2->3	FP2->4	FP2->5	FP2->6	T2
Class 3	FP3->1	FP3->2	TP3	FP3->4	FP3->5	FP3->6	T3
Class 4	FP4->1	FP4->2	FP4->3	TP4	FP4->5	FP4->6	T4
Class 5	FP5->1	FP5->2	FP5->3	FP5->4	TP5	FP5->6	T5
Class 6	FP6->1	FP6->2	FP6->3	FP6->4	FP6->5	TP6	T6
Total	T1	T2	T3	T4	T5	T6	T

Figure 6. General Confusion Matrix for 6-classes

Here, Y represents the one-hot encoded true labels, log(P) denotes the element-wise logarithm of the predicted probabilities, and the sum is taken across the classes (axis=1). For multi-class issues with classification, the softmax layer is usually used in the O/P component of a neural network. The overall objective of the stacked auto-encoder combines the pre-training and fine-tuning objectives.

$$L_{total} = (\lambda^1 * L_{pretrain}^1 + \lambda^2 * L_{pretrain}^2 + \lambda_{task} * L_{task}) \quad (14)$$

Here, λ_1 , λ_2 , and λ_{task} are weighting factors that control the importance of each component in the overall objective. $L_{pretrain}^1$ and $L_{pretrain}^2$ represent the reconstruction losses for the pre-training of the respective layers, and L_{task} represents the loss function specific to the task being performed.

E. Confusion Matrix and Performance Parameters

In **Figure 6**, a confusion matrix represents a problem with six classes. The matrix uses arrows to show when a class is misclassified as another class. For example, if an arrow from FP1 to 2 indicates that instances of Class 1 were misclassified as Class 2.

The AUC is an efficiency statistic used in ML to assess the performance of a model used for classification. It is

computed by finding the ROC curve. A ROC curve is a comparison of true (TPR) and false (FPR) favorable rates for various categorization thresholds [35] [36]. CA (Classification Accuracy) is the number of successfully categorized samples divided by the overall number of data points in a dataset. It is a fundamental performance statistic for assessing the entire accuracy of a classification system [37]. The computations are as follows:

$$CA = \frac{\text{No.OfCorrectlyClassifiedInstances}}{\text{TotalNumberOfInstances}} \quad (15)$$

F1 score is recall and precision's harmonic means, two other important performance metrics for classification models. The F1 score considers both precision and recall and gives a fair assessment of the system's efficiency [38]. It is calculated as

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

Precision is the TP ratio to the sum of TP and FP instances. It measures how many positive instances model predictors are true positive instances.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (17)$$

Recall is defined as a percentage of TP to the total of TP and FN occurrences. It measures how many of the actual positive instances the model has correctly identified.

$$\text{Precision} = \frac{TP}{TP + FN} \quad (18)$$

4. RESULT ANALYSIS

This section shows that the embedded DL models identify smartphone movements well. These models use DL algorithms on the smartphone, allowing them to identify real-time movements. This makes them useful for things like fitness tracking and augmented reality. The analysis of the results shows that embedded DL models have a lot of potential and advantages for identifying smartphone movements. This research helps advance the field of intelligent smartphone applications and can inspire future research.

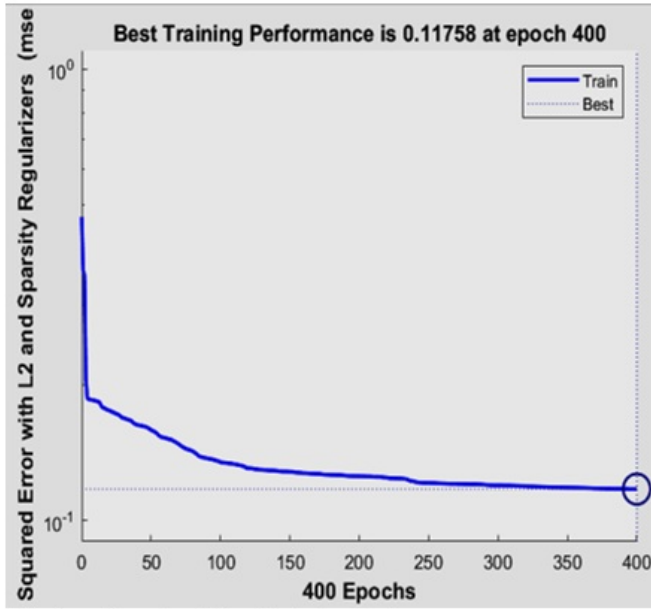
A. Two-Layer Stacking Auto-Encoder Results Analysis

Load the data from the WaveTrain.mat and WaveTest.mat files using the load() function. Assign the loaded data to the appropriate variables: trainData, trainLabels, testData, and test Labels. Preprocess the training and testing data by dividing each element of the cell array by the maximum absolute value of the array using the cell fun() function. Set the parameters for the autoencoder1. Define hiddenSize1 as 100, MaxEpochs as 400, L2WeightRegularization as 0.004, SparsityRegularization as 4, SparsityProportion as 0.15, and ScaleData as false. Train the first autoencoder using the trainAutoencoder() function with train data and the defined parameters. Store TrainedAutoencoder in autoenc1. Encode the training data using autoenc1 and store the result in feat1. Set the

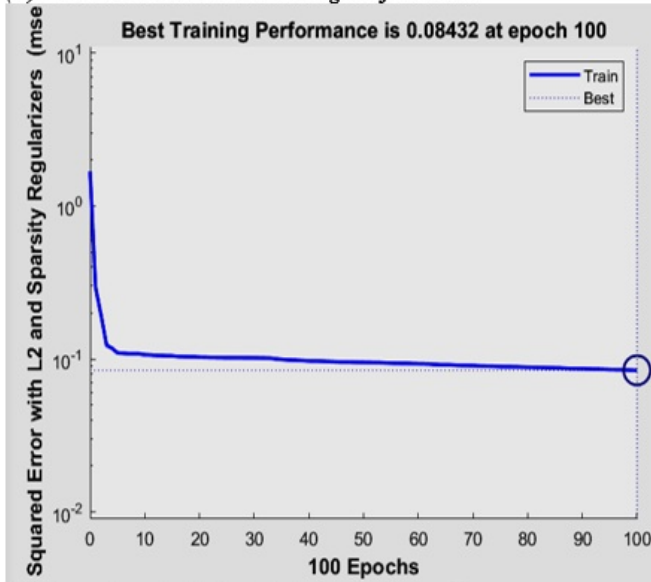
parameters for the autoencoder2. Define hiddenSize2 as 50, MaxEpochs as 100, L2WeightRegularization as 0.002, SparsityRegularization as 4, SparsityProportion as 0.1, and ScaleData as false. Train the second autoencoder using the trainAutoencoder() function with feat1 and the defined parameters. Store TrainedAutoencoder in autoenc2. Encode the features feat1 using the encode method of autoenc2 and save the resulting features as feat2. Train the softmax layer with the TrainSoftmaxLayer function using the encoded features feat2 and the training labels trainable with the specified hyperparameters MaxEpochs. Save the resulting softmax layer as softnet. Stack the three trained neural networks (autoenc1, autoenc2, and softnet) together using the stack function and save the resulting stacked neural network as stackednet. Convert the training data TrainData into a matrix xTrain with the size inputSize (the number of features) by numeral (TrainData) (the number of training samples) by flattening each training data element. Fine-tune the stacked neural network stackednet with the training matrix xTrain and corresponding training labels trainLabels using the train function.

Figure 7 shows the Best Training Performance (MSE) analysis of Auto-Encoder 1 and Auto-Encoder 2 in the Stacking Auto-Encoder model. In this, Figure 7(A) shows the best performance analysis with a 0.11758 MSE value at epoch 400 of Auto-Encoder 1. Figure 7(B) shows the best performance analysis with the 0.08432 MSE value of Auto-Encoder 2 at epoch 100.

Figure 8 shows the confusion matrix of the Stacking Auto-Encoder for the testing dataset. As per the Confusion matrix analysis, most of the five classes performed well with 100% accuracy. In class 3, one miss calculated value is classified as class 1. The testing dataset has an accuracy (99.6%), whereas the training dataset has an overall accuracy (99.8%). The model's performance was assessed using various parameters. The performance measures' full analysis is shown in Table III. The accuracy of correctly classifying instances for most classes was perfect, with a score of 1.00. However, class 3 had a slightly lower accuracy of 98.5%. The model also had high AUC values, indicating its ability to distinguish between different classes accurately. For every class, the F1 scores—which gauge how well memory and accuracy are balanced—were very high. Most classes had excellent precision values, indicating zero false positives, and recall values, indicating no false negatives. Overall, the stacked autoencoder model performed excellently across all classes, with high AUC values, accurate predictions, and balanced precision and recall. The average performance measures further confirmed the model's effectiveness, with high values for AUC, precision, recall, accuracy, and F1-score. These results demonstrate that the model can accurately identify and classify different movement types.



(A) Auto-Encoder 1 Best Training Performance



(B) Auto-Encoder 2 Best Training Performance

Figure 7. Best Training Performance (MSE) Analysis

B. Eight-Layer Convolution Neural Network (CNN) Results Analysis

Figure 9 shows the progress of Smart Phone movement SD Set Training using a CNN architecture with eight levels. Sensor signal data is sent, divided into six classes, and processed using convolution2dLayer and ReLULayer for non-linearity. The input size is maintained by setting the 'Padding' option. The maxPooling2dLayer reduces the spatial dimensions of the previous layer's O/P by a factor of 2 using a 2x2 window and a stride of 2. The FullyConnectedLayer has 120 output neurons and receives

Output Class	1	2	3	4	5	6	Accuracy
1	32 14.0%	0 0.0%	1 0.4%	0 0.0%	0 0.0%	0 0.0%	97.0% 3.0%
2	0 0.0%	20 8.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	39 17.1%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	45 19.7%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	43 18.9%	0 0.0%	100% 0.0%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	48 21.1%	100% 0.0%
Overall	100% 0.0%	100% 0.0%	97.5% 2.5%	100% 0.0%	100% 0.0%	100% 0.0%	99.6% 0.4%

Figure 8. Confusion Matrix of the Stacking Auto-Encoder for 6-classes

TABLE III. PERFORMANCE PARAMETERS FOR EACH CLASS OF STACKING AUTO-ENCODER

Class	AUC	CA	F1	Prec.	Rec.
CCM (1)	1.00	1.00	0.985	1.000	0.970
ACM (2)	1.00	1.00	1.000	1.000	1.000
IDM (3)	0.99	0.98	0.987	0.975	1.000
LRM (4)	1.00	1.00	1.000	1.000	1.000
UDM (5)	1.00	1.00	1.000	1.000	1.000
WAM (6)	1.00	1.00	1.000	1.000	1.000
Overall	1.00	0.996	0.9953	0.9958	0.995

flattened input from the previous layer. Another ReLU activation layer is applied after the FullyConnectedLayers. The FullyConnectedLayers (FCL) is a layer with six O/P neurons representing measurements or members of different classes in a classification task. The (SAF) softmax activation function is used by the SoftMax Layer (SML) to create a probability distribution among the classes. Calculating the cross-entropy loss between the actual and predicted label probabilities is the task of the last layer, ClassificationLayer. The training progress for the Smart Phone Movement SD Set is shown in Figure 9. The red line displays the loss numbers, while the blue line depicts the training procedure. The mini-batch loss function takes 4 seconds to handle the training dataset. A GPU that is hardware, is used in the training process. The smoothed training accuracy points are represented by the dark blue line, and the training accuracy for each iteration is shown by the light blue line. The training loss value for each iteration is shown by the light red line. Figure 10 shows the Best Training



Figure 9. CNN Smart Phone movement Sensor Data Set Training Progress

```
>> CNN2
Training on single GPU.
Initializing input data normalization.
```

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:00	25.00%	4.9888	0.0010
3	50	00:00:00	81.25%	0.5293	0.0010
6	100	00:00:01	90.62%	0.1593	0.0010
9	150	00:00:01	100.00%	0.0586	0.0010
10	170	00:00:02	100.00%	0.0162	0.0010

Figure 10. Best Training Process Step by Step with Time Elapsed and Base Learning Rate

Process with Minibatch Accuracy and Loss Values. The input describes the training process of a CNN employing small batch sizes. Epochs, which are made up of many iterations each, are used to separate the training process. In the first epoch, at the first iteration, the mini-batch accuracy is 25.00%, and the mini-batch loss is 4.9888. The training time elapsed is 00:00:00. After training for three epochs, at the 50th iteration of the third epoch, the mini-batch accuracy has improved to 81.25%, and the mini-batch loss has reduced to 0.5293. The training time elapsed is still 00:00:00. At the 100th iteration of the sixth epoch, the mini-batch accuracy has increased to 90.62%, and the mini-batch loss has significantly reduced to 0.1593. The training time has elapsed now 00:00:01. Finally, at the last epoch, the training is completed at the 170th iteration (Epoch 10, Iteration 170). The mini-batch accuracy remains 100.00%, reducing the loss to 0.0162. The total training time elapsed is 4 seconds. Figure 11 shows the Best Training Process with Minibatch Accuracy and Loss Values. Figure 11 (A) shows the analysis of CNN's best mini-batch accuracy. It achieved one at 170 iterations (10 epochs). Figure 11 (B) indicates the study of CNN's best mini-batch loss value.

Figure 12 shows the CNN confusion matrix for the Testing Dataset and analysis. Table IV shows the per-

TABLE IV. PERFORMANCE PARAMETERS FOR EACH CLASS OF THE CNN MODEL

Class	AUC	CA	F1	Prec.	Rec.
CCM (1)	0.991	0.969	0.984	0.969	1.000
ACM (2)	1.00	1.00	1.000	1.000	1.000
IDM (3)	1.00	1.00	1.000	1.000	1.000
LRM (4)	1.00	1.00	1.000	1.000	1.000
UDM (5)	0.997	0.977	0.988	0.977	1.000
WAM (6)	1.00	1.00	0.978	1.000	0.960
Overall	0.998	0.991	0.992	0.991	0.993

formance parameters of the Stacking Auto-Encoder. The class CCM demonstrates an AUC value of 0.991, indicating excellent performance in distinguishing positive and negative instances. The classification accuracy is 0.969, suggesting that 96.9% of cases were correctly classified. The F1 score, which combines precision and recall, is 0.984, indicating a successful balance between recall and precision. The precision is 0.969, representing the symmetry of all instances that were correctly predicted to be positive. The recall is 1.000, demonstrating that all positive instances were correctly identified. The Class ACM demonstrates outstanding performance in all measures. The AUC value of 1.000 indicates perfect discrimination between positive and negative instances. The classification accuracy of 1.000 means that all the cases were correctly classified. The F1 score, precision, and recall are all 1.000, suggesting flawless performance in predicting positive instances. Class 2, classes 3, and 4 perform well. Class UDM achieves high scores across all performance measures. The AUC value of 0.997 indicates excellent discrimination ability. The classification accuracy is 0.977, suggesting that 97.7% of instances were correctly classified. The F1 value is 0.988, showing a good balance. The precision is 0.977, and the recall is 1.000 with good balance. Class WAM demonstrates high performance in most measures. When the AUC is 1.000, the discriminating ability is flawless. The accuracy of classification is 1.000, indicating that every case was accurately categorized. Recall is 0.960, accuracy is 1.000, and F1 score is 0.978, suggesting that the dataset is well-balanced for the model. The overall performance of the classification model is excellent, with an AUC value of 0.998, indicating high discrimination ability. The classification accuracy is 0.991, suggesting that 99.1% of instances were correctly classified. The F1 score of 0.992 reflects a good balance of precision of 0.991 and recall of 0.993.

5. DISCUSSIONS

This research discusses the advantages of using embedded DL models to identify smartphone movements. These models can use DL algorithms directly on the smartphone without relying on cloud-based processing. The research compares these embedded models to similar studies and discusses the trade-offs in complexity and computational requirements. The smartphone can identify movements in real time using embedded DL models. This is useful for applica-



TABLE V. SOME OF THE RESEARCH WORKS COMPARED WITH PRESENT RESEARCH AND ANALYSIS

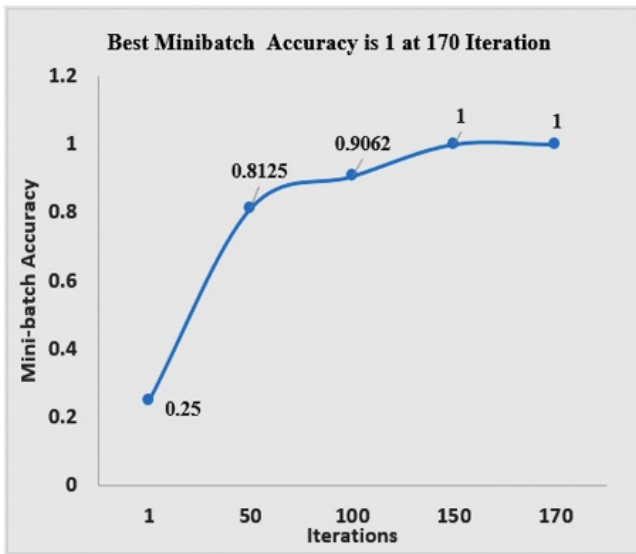
Ref. No.	Author & Year	Description	Results and Models Analysis
[39]	Strackiewicz et al.	Using the UniMiB-SHAR public dataset, the authors proposed a DL method for HAR that makes use of the Resnet architecture.	The leave-one-subject evaluation yielded significant results, with accuracy rising from 78.24% to 80.09% and the F1-score from 78.40% to 79.36%.
[40]	Ignatov et al.	The proposed method utilizes CNNs to achieve real-time HAR from smartphones' accelerometers.	CNN + stat. features + data centring achieved 97.63% accuracy.
[41]	Mutegeki et al.	Introduced a holistic DL-based HAR architecture, CNN-LSTM, enhancing predictive accuracy and reducing model complexity.	Achieved 99% accuracy on the iSPL dataset and 92% on the UCI HAR public dataset.
[42]	Huang et al.	A novel method for automatically extracting activity recognition features from mobile sensor signals that capture scale invariance and local dependence.	The CNN-based model achieved 88.19% accuracy, outperforming the best algorithm (PCA-ECDF).
[43]	Rahman et al.	The approach employs CNNs for real-time HAR from smartphone accelerometer data.	The CNN model achieved a high accuracy of 85.1%.
[44]	de et al.	Introduced the use of CNNs and RNNs (LSTM and GRU) for activity identification from SSD, achieving improved accuracy on the UniMiB SHAR dataset.	Using a GRU network, the 5-fold cross-validation achieved 95.49% accuracy for 17 activity categories.
[45]	Aquino et al.	The study aimed to improve the interpretability of 1-D CNN models in HAR applications.	1-D CNN achieved 0.978 accuracy using SD and signal intensity techniques, and BUI network averaged 0.937 accuracy.
[46]	Gamble et al.	Introduced a DL approach using a 1D-CNN model for HAR and HARI by extracting features from smartphone accelerometer and gyroscope signals.	The 1D-CNN model achieved 96.77% accuracy for activity categorization and 82.37% for identity classification.
[47]	Aquino et al.	Introduced a novel XAI method utilizing t-SNE learned features in one-dimensional CNNs, showcasing performance on public datasets SHO and HAPT.	CNN models achieved 0.98 accuracy on the SHO dataset and 0.93 accuracy on the HAPT dataset.
Present study		Experiment on synthesis (real-world) dataset	8-layer CNN-Model achieved AUC: 0.998 and Accuracy: 99.1%.
Present study		Experiment on synthesis (real-world) dataset	2-layer Auto-Encoder achieved AUC: 1.0 and Accuracy: 99.6%.

tions like fitness tracking, health monitoring, and augmented reality, where immediate feedback is essential. The research shows that both 2-layer Stacked Auto-Encoders and 8-layer CNNs perform well in accurately classifying smartphone movements. Both models in this analysis have achieved perfect accuracy in classifying smartphone movements. The 2-layer Stacked Auto-Encoders performed better than the CNN model, with higher values for all classes and overall AUC and CA. It indicates that the Stacked Auto-Encoders are more effective and reliable in accurately classifying smartphone movements. Other researchers have also proposed models for DL with different datasets, but they have achieved moderate accuracy compared to the proposed model in this analysis. Peppas et al. [48] suggested a real-time CNN model that effectively recognizes human physical activity using accelerometer data on a mobile device. It achieved a high classification accuracy of 94.18% on the WISDM dataset and 79.12% on the Actitracker dataset. Thakur et al. [49] proposed a unified architecture called "ConvAE-LSTM" that combines CNNs, auto-encoders, and

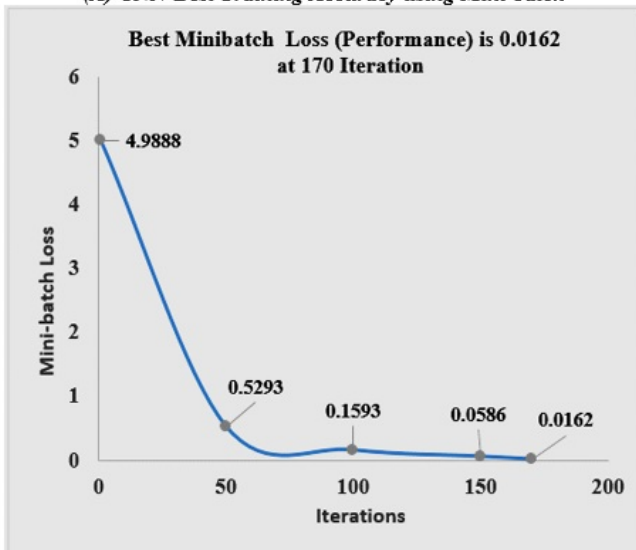
LSTM networks for smartphone-based activity recognition. Their model achieved a remarkable accuracy of 95.69% on the OPPORTUNITY dataset, surpassing the accuracy of Random Forest and Support Vector Machine models. Khan et al. [50] conducted experiments and collected a comprehensive dataset of nine daily activities. They trained various ML models on SD from smartphones and wearable devices. The random forest algorithm achieved a test accuracy of 95%, while a custom-built Bi-LSTM model outperformed it with an improved accuracy of 98.1%. Table V compares the proposed model with other research models in the analysis.

6. CONCLUSIONS AND FUTURE WORK

This study shows that using DL like CNN and SAEs can accurately identify different types of smartphone movements. The SAEs performed well during training, with Auto-Encoder 1 and Auto-Encoder 2 achieving the best results at epochs 400 and 100, respectively. The SAEs also performed well regarding AUC, CA, F1-score, precision, and recall, meaning they can accurately identify



(A) CNN-Best Training Accuracy using Mini-batch



(B) CNN Best- Training performance using Mini-Batch(Loss)

Figure 11. Best Training Process with Minibatch Accuracy and Loss Values

and classify smartphone movements. The CNN model also performed well, showing high values for AUC, CA, F1-score, precision, and recall. The study indicates that CNNs can capture complex patterns and features from the input data. Implementing these DL models for smartphone movement identification can have real-time applications in fitness tracking, health monitoring, and augmented reality. The researchers found that using models directly on smartphones can identify movement in real time without relying on cloud-based processing. These models, such as CNNs and SAEs, are accurate and perform well, which can improve smartphone applications. Future researchers may explore more advanced DL methods like RNNs or TMs to

		Confusion Matrix						
		1	2	3	4	5	6	
Output Class	1	31 13.6%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	2	0 0.0%	20 8.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	3	0 0.0%	0 0.0%	40 17.5%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	4	0 0.0%	0 0.0%	0 0.0%	45 19.7%	0 0.0%	0 0.0%	100% 0.0%
	5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	42 18.4%	0 0.0%	100% 0.0%
	6	1 0.4%	0 0.0%	0 0.0%	0 0.0%	1 0.4%	48 21.1%	96.0% 4.0%
		96.9% 3.1%	100% 0.0%	100% 0.0%	100% 0.0%	97.7% 2.3%	100% 0.0%	99.1% 0.9%
		Target Class						

Figure 12. CNN Confusion Matrix for the Testing Dataset

improve accuracy. The goal is to make the system practical and valuable for different applications. Future work may involve developing techniques that allow the models to adapt to other users, activities, and smartphone sensors. The researchers will continue to enhance the models and optimize their performance.

ACKNOWLEDGMENTS: The authors express their gratitude to the **Aditya Institute of Technology and Management**, Tekkali, Srikakulam, AP, India for their unwavering support throughout the research, and extend special thanks to Director **Prof. VV Nageswara Rao**, Principal **Dr. A. S. Srinivasa Rao**, and **Dr. Vital DST FIST Lab** central coordinator.

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