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DPARF: A DEEP LEARNING BASED INTELLIGENT FRAMEWORK FOR AUTOMATIC RECOGNITION OF PERSONAL ACTIVITY USING SMARTPHONE DATASET

BHAGYA REKHA SANGISETTI [1] SURESH PABBOJU [2]

[1] Research Scholar,Osmania University,Assistant Professor, Anurag University , Hydearabd,Telangana
bhagyarekha2001@gmail.com

[2] Professor ,Department of IT, Chaitanya Bharathi Institute of Technology, Hyderabad, Telangana
plpsuresh@gmail.com

ABSTRACT

In the contemporary era, technological innovations such as Internet of Things (IoT) and Artificial Intelligence (AI) can offer unprecedented solutions to real world problems. IoT technology has paved way for sensor enabled data collection while AI enables learning and prediction to solve variety of problems. Personal Activity Recognition (PAR) is an important problem in many applications such as surveillance, security, computer gaming, sports, remote monitoring of humans or patients, healthcare, and military to mention few. Deep Learning (DL) techniques are widely used for solving PAR problem by processing data captured by sensors. IoT use cases or smart phones are capable of capturing accelerometer data that can be used to establish movements and thus recognize human activities. Existing methods based on deep learning witnessed success in PAR activities. Long Short-Term Memory (LSTM) is one such technique which could detect human activities with high accuracy. However, it is desired to improve it further towards leveraging prediction performance. Towards this end, in this paper, we proposed a framework known as Deep Personal Action Recognition Framework (DPARF) for automatic recognition of human activities. The framework is realized with our enhanced LSTM model known as CNN-5LSTM which is designed to improve accuracy in activity recognition. We proposed an algorithm known Enhanced LSTM with CNN for Automatic Personal Activity Recognition (ELSTM-CNN-APAR). This algorithm takes care of feature selection and processing of data consisting of temporal sequences. A standard PAR smartphone dataset from UCI repository is used in the empirical study. The experimental results revealed that our proposed model outperforms many existing models with 93.04% accuracy. It can be used to have an automated PAR Decision Support System (PAR-DSS) which may be integrated with a real time PAR system in question.

Keywords: *Personal Activity Recognition, Artificial Intelligence, Deep Learning, Enhanced LSTM, Smartphone Dataset*

1. INTRODUCTION

Personal activity recognition is one of the important research areas with widely used applications like healthcare, crime investigation, monitoring and surveillance to mention few. HAR can be done with different approaches such as vision based and sensor data based. Senor data based approaches are data-driven and they are non-invasive in nature. In this paper also we preferred sensor based approaches where smartphone based sensors are simple and effective for data collection. Fortunately, there are datasets available for different actions associated with HAR [1]. The datasets are particularly explored in [1], [11] and [15]. Garcia-Gonzalez *et al*. [1] discussed bout real time HAR dataset and proposed Support Vector Machine (SVM) based method for automatic HAR. They considered only few actions such as driving, walking, active and inactive. Sikder and Nahid [11] focused on HAR dataset with more activities involved. Micucci *et al*. [15] investigated on existing HAR datasets that are sensor based and made a new dataset named UniMiB SHAR.

There are researches using ML and deep learning models. ML models are explored in [23], [31] and [32]. In [23] Support Vector Machine (SVM) model is used for HAR. It is one of the most widely used methods in ML based solutions. In [31] and [32]

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Personal Activity Recognition (PAR) methods are proposed to exploit ML and feature selection approaches. There are several deep learning based approaches, as explored in [4], [6], [10] and [12], that could leverage detection performance. CNN is used in many existing methods towards feature extraction. There is usage of LSTM also for dealing with temporal data. Ensemble of different methods is the main focus in [2], [9] and [20]. They investigated on different baseline models to have ensemble learning and decision is made through majority voting approach or stacking approach. From the literature, we found many useful insights for our research. First CNN and LSTM models are widely used for feature extraction and temporal data classification respectively for HAR system. However, it is found that there is need for improving HAR in order to have better performance. Our work in this paper are as follows.

2. We proposed a framework known as Deep Personal Action Recognition Framework (DPARF) for automatic recognition of human activities. The framework is realized with our enhanced LSTM model along CNN known as CNN-5LSTM which is designed to improve accuracy in activity recognition.

3. We proposed an algorithm known Enhanced LSTM with CNN for Automatic Personal Activity Recognition (ELSTM-CNN-APAR).

4. We evaluated our model CNN-5LSTM using a standard PAR smartphone dataset from UCI repository is used in the empirical study. The experimental results revealed that our proposed model outperforms many existing models. The remainder of the paper is structured as follows. Section 2 reviews related work on HAR detection models using ML and deep learning. Section 3 covers our methodology, proposed model and underlying algorithm for PAR. Section 4 presents results of our empirical study. Section 5 concludes our work and provides directions for future scope of the research.

2. LITERATURE REVIEW

This section reviews literature on HAR methods using ML and deep learning. Garcia-Gonzalez *et al.* [1] discussed bout real time HAR dataset and proposed Support Vector Machine (SVM) based method for automatic HAR. They considered only few actions such as driving, walking, active and inactive. They intend to improve it using deep learning models in future. Xu *et al.* [2] proposed a methodology for HAR using cascade ensemble approach. It has made an ensemble of features obtained from fast Fourier transform and hand crafted features. Siirtola and Roning [3] focused on human AI collaboration and proposed an incremental approach towards personalizing action recognition. They explored both supervised and non-supervised methods towards HAR. In future then indent to improve their method with body-independent approach. Ankita *et al.* [4] a hybrid approach is proposed combining the usage of convolutional layers and LSTM model with 2 layers for HAR. This model is designed to handle temporal dimensions of data well. They intend to improve it further with different combinations of deep learning methods. Thakur and Biswas [5] explored HAR with features extracted using handcrafted approach and also through deep learning. In the process they used convention CNN method for HAR. In future then intend to work with different dynamic actions and deep learning models for better performance.

Ghate and Hemalatha [6] opined that deep learning models could improve performance of HAR. In the process, they proposed multiple hybrid models based on deep learning. They used LSTM with different combinations for performance improvement. They intend to explore multiple datasets in future with their proposed model. Bouchabou *et al.* [7] focused on sensor based approaches for HAR. Their investigation has revealed that deep learning models are more accurate than traditional ML models. Wu *et al.* [8] proposed a methodology using linear and non-linear methods towards pedestrian dead reckoning. Their method does not use any prior knowledge in order to achieve desired results. Tan *et al.* [9] proposed an ensemble based method to learn from training data and perform HAR. It makes use of GRU and CNN with deep ensemble phenomenon. Wan *et al.* [10] used CNN for feature extraction and other deep learning models like LSTM for HAR. Then they replaced LSTM with SVM and other models for performance evaluation. They intend to optimize neural network based models in future for further improvement in HAR.

Sikder and Nahid [11] focused on HAR dataset with more activities involved. Qi *et al.* [12] proposed a fast and robust DCNN for HAR. It comprises of methods like signal processing, data compression, signal selection, deep CNN model for feature extraction and then classification. They intend to improve their method with transfer learning in future towards faster convergence. Mekruksavanich and Jitpattanakul [13] explored LSTM for HAR and then improved it further to realize a 4-layer CNN-LSTM where there is division of labour between LSTM and CNN for classification and feature extraction respectively. Then intend to improve it further with different hyper parameter tuning approaches. Voicu

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et al. [14] proposed a ML based method for HAR. They also explored MLP technique and found its efficiency due to its neural network based phenomenon. In future they intend to add activities like falling, riding bike and driving. Micucci *et al*. [15] investigated on existing HAR datasets that are sensor based and made a new dataset named UniMiB SHAR. Wang *et al*. [16] made a survey of existing methods based on ML techniques for HAR while Shoaib *et al*. [17] studied motion sensors (wearable) for HAR research. The work of Lima *et al*. [18] is similar to that of [16] but they explored different HAR methods in detail.

Almaslukh *et al*. [19] proposed a method based on deep autoencoding for HAR. It is stacked autoencoder approach that exploits underlying encoder and decoder functions. Chen *et al*. [20] proposed an ensemble approach with majority voting approach to determine final detection results. Other important work found in literature include data mining scheme [21], RF [22], SVM [23], multiple feature extraction methods [24], stroke patient research [25], SVM-KNN hybrid approach [26], survey of HAR models [27], interval determination approach [28], self-learning scheme [29] and feature level sensor fusion method [30]. Sangisetti and Pabboju in [31], [32] and [33] focused on different methods for Personal Activity Recognition (PAR) using ML techniques. From the literature, we found many useful insights for our research. First CNN and LSTM models are widely used for feature extraction and temporal data classification respectively for HAR system. However, it is found that there is need for improving HAR in order to have better performance.

3. MATERIALS AND METHODS

This section presents our methodology, proposed model and underlying algorithm for PAR.

3.1 Dataset

Dataset for this research is collected from UCI repository [561]. It has data obtained through sensors. It consists of different activities of 30 volunteers of different age groups. The activities captured through sensing include lying, sitting, standing, walking, walking downstairs and walking upstairs. The data is obtained using accelerometer and gyroscope. It has 10299 instances consisting of 561 highlights. Each instance contains both acceleration collected from accelerometer, triaxial angular speed collected from gyroscope, activity label and the subject involved in analysis.

3.2 Proposed Framework

we proposed a framework known as Deep Personal Action Recognition Framework (DPARF) for automatic recognition of human activities. The framework is realized with our enhanced LSTM model known as 5-ConvLSTM which is designed to improve accuracy in activity recognition. We proposed an algorithm known Enhanced LSTM with CNN for Automatic Personal Activity Recognition (ELSTM-CNN-APAR). This algorithm takes care of feature selection and processing of data consisting of temporal sequences. Architectural overview of our framework DPARF is presented in Figure 1. It exploits CNN and LSTM layers for PAR. The framework takes smartphone sensor data collected through accelerometer and gyroscope. The raw data is subjected to pre-processing and the outcome is normalized through ReLU activation layer. Afterwards, the resultant data is fed to LSTM. We enhanced LSTM to have 5 LSTM layers instead of conventional LSTM. It is designed to ascertain temporal dynamics of data generated by sensors. The outcome of the five layered LSTM is subjected to six-way softmax layer which performs multi-class classification to realize PAR.

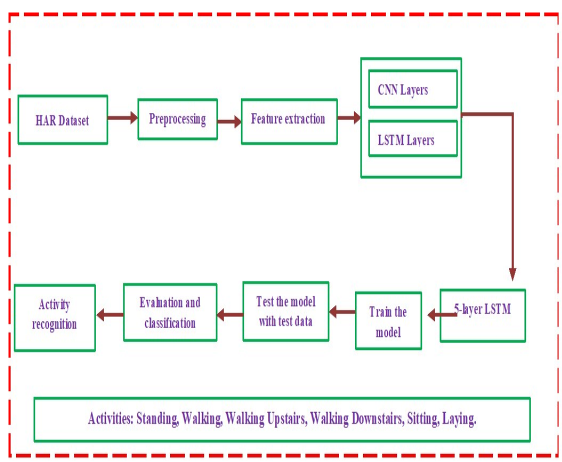

Figure 1: Proposed Deep Personal Action Recognition Framework (DPARF)

The framework has pre-processing, feature extraction and construction of CNN-LSTM model. In the model, LSTM part is enhanced in order to have five layers for better discrimination of temporal data. The enhanced LSTM model is named as 5-ConvLSTM. Therefore, the proposed framework has

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underlying hybrid model named CNN-5-ConvLSTM. Once the model is trained with training data, the resultant model is saved for further usage. Then the saved model is used to work on the test data which is un labelled in nature. Afterwards, the model is evaluated to ascertain its performance statistics.

3.3 Enhanced LSTM

LSTM is a variant of RNN model with memory cell that is suitable for understanding temporal or time sequence data. That is the reason LSTM is used in our design of the framework. LSTM cell and its state plays crucial role in processing data. The network has chain of LSTM cells with linear interactions.

The LSTM model has provision to add or remove state of its cells. It could increase input threshold, forget it and output it in order to manage self-loop efficiently leading to dynamism in learning process. In order words, it overcomes the problem of vanishing gradient. We preferred LSTM based approach as it is relevant to our problem besides it is widely used in robotics, speech recognition and image analysis to mention few.

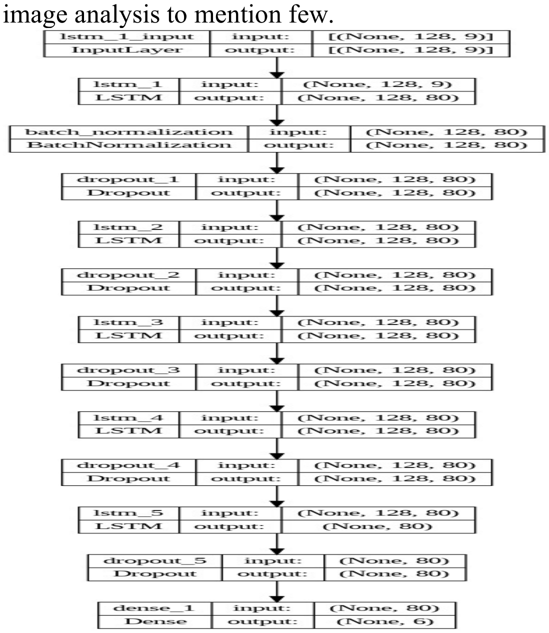

Figure 2: Proposed 5-ConvLSTM model architecture

We enhanced the LSTM model with 5 layers as presented in Figure 2. With increased layers, it is found to be more capable in learning based PAR. End to end approach is followed in order to achieve PAR. Data sequence is the input to the model. It is of time series data where sliding window is essential to ascertain data.

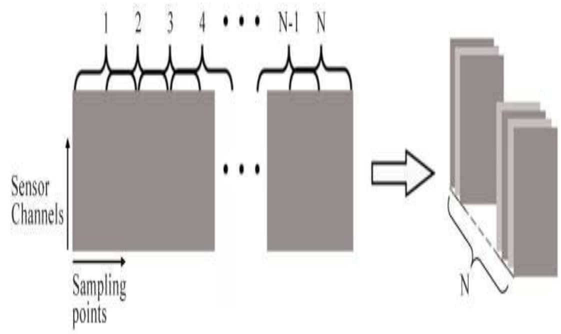

Figure 3: Segmentation of sensor data

As presented in Figure 3, sensor data is segmented in order to have meaningful and compact data for further processing. It is achieved by considering with sliding window based observation and segmentation.

3.4 Our Network

Our final proposed deep neural network named as CNN-5-LSTM is illustrated in Figure 4. It has different layers to detect personal activities of humans. The input data is subjected to linear interpolation, normalization of data and scaling and segmentation. With the enhanced LSTM with five layers, each layer consists of 32 neurons. It is used to improve the extraction of features with temporal dimensions. LSTM layers are followed by convolutional layer with 64 filters. Afterwards a max-pooling layer with pooling size 2 and stride 2 is used. It is followed by another convolutional layer with 28 filters. Global average pooling layer (GAP) follows the second convolutional layer. Then there is batch normalization layer (BN) layer. At the end of the network, there is dense layer with softmax inn order to achieve multi-class classification.

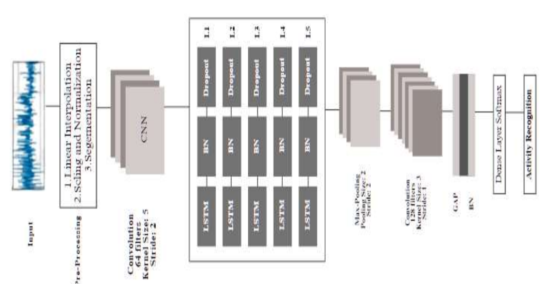

Figure 4: Overview of our architecture named CNN-5-LSTM

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Since LSTM is a variant RNN, LSTM is preferred as RNN suffers from gradient vanishing problem. With five layers of LSTM, the architecture is improved to make it robust in dealing with temporal data. Each layer has 32 neurons. The usage of gates in each cell helps in controlling the data flow. Each cell has its activation function expressed as in Eq. 1.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

The activation process at given time t and t-1 is denoted by ht and ht-1. A non-linear activation is denoted by σ. The underlying weight matrices are denoted as wi,h and wh,h while hidden bias vector is denoted as b. Each LSTM layer gives result that has three dimensions such as samples, temporal aspects and dimension. Convolutional layer exploits kernels to perform convolution on inputs. It acts like a filter and gets activated with the help of non-linear activation process expressed as in Eq. 2.

$$y_i = b_i + \sum_{x_i \in x} W_{ij} * x_i \quad (2)$$

In the convolutional layers ReLU is the activation function used. In order to improve performance by identification of identical neurons the expression in Eq. 3 is used.

$$(n_h - f + 1) \ / S \ X \ (nw - f + 1) \ / \ S \ X nc \quad (3)$$

In the proposed architecture two convolutional layers are used. The first one has 64 kernels with 1 x 5 kernel size and stride 2 towards feature extraction. In the second convolution, 128 kernels are used with 1 x 3 size and stride 1. The max pooling layer lies between two convolutional layers is meant for downsampling to reduce parameters and reduces interference noise. GAP layer is used instead of traditional fully connected layer at the end. GAP is better equipped to deal with spatial information. The BN layer is used to adjust weight parameters towards faster convergence. It performs normalization and reconstructs given input against each batch in the training process to improve accuracy and speed. The final softmax layer is meant for multi-class classification.

3.5 Proposed Algorithm

In order to exploit our novel model named CNN-5-ConvLSTM, we proposed an algorithm that is used for automatic PAR.

Algorithm: Enhanced LSTM with CNN for Automatic Personal Activity Recognition (ELSTM-CNN-APAR)
Input: Smart phone sensor dataset ***D***, number of epochs ***m***, batch size ***n***
Output: PAR and classification results ***R***

1. Begin
2. ***D'***←PreProcess(***D***)
3. (***T1***, ***T2***)←SplitData(***D'***)
4. Initialize deep model
5. Add 5 LSTM layers with 32 neurons
6. Add convolutional layer with 64 filters
7. Add map pooling layer with pool size 2
8. Add convolutional layer with 128 filters
9. Add global average pooling layer
10. Add batch normalization layer
11. Add softmax layer
12. Compile the model ***M***
13. For each epoch ***e*** in ***m***
14.   For each batch ***b*** in ***n***
15.   Update ***M*** using ***T1***
16.   End For
17. End For
18. ***R***←TestModel(***M***, ***T2***)
19. Display ***R***
20. End

Algorithm 1: Enhanced LSTM with CNN for Automatic Personal Activity Recognition

As presented in Algorithm 1, it takes smart phone sensor dataset ***D***, number of epochs ***m***, number of batches ***n*** as input and generates personal activity recognition results ***R***. It has pre-processing to improve given dataset with the help of linear interpolation, scaling and segmentation. Then it splits data into 80% training set and 20% test set. Then it initializes our novel deep network model. Afterwards, it configures all the layers as per the proposed CNN-5LSTM model illustrated in Figure 4. Then there is an iterative process based on given number of epochs and batch size to train the model using ***T1***. Once the model is trained, it gains knowledge from the training process. This will result in a knowledge model that is saved to persistent storage for further reuse. This saved model is loaded in the testing phase and every instance of test set ***T2*** is subjected to prediction of personal activities. Finally, the algorithm returns personal activity recognition results ***R***.

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3.6 Evaluation Metrics

Based on confusion matrix, the evaluation of the proposed algorithm is compared with the state of the art.

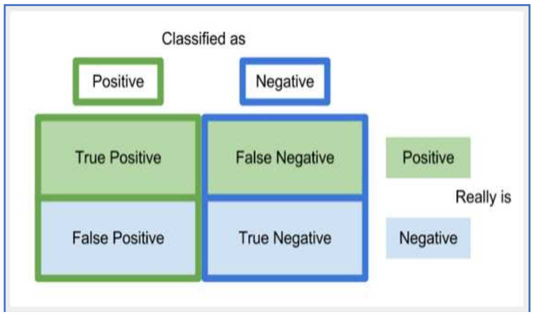

Figure 5: Confusion matrix

Based on the confusion matrix presented in Figure 5, the confusion matrix shows the measures like true positive (TP), false positive (FP), false negative (FN) and true negative (TN). These are determined by comparing result of ML algorithm when compared with the ground truth.

Table 1: Performance metric used for evaluation

Metric	Formula	Value range	Best Value
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	[0; 1]	1

As presented in Table 1, accuracy is the performance metric provided along with its mathematical expression, value range and possible best value.

4. RESULTS AND DISCUSSIONS

This section presents experimental results of our work. It provides appropriate visualizations pertaining to PAR. Besides it presents performance of the proposed framework compared against existing PAR models.

4.1 Data Analysis

This section presents analysis of data through exploration of it from different useful perspectives.

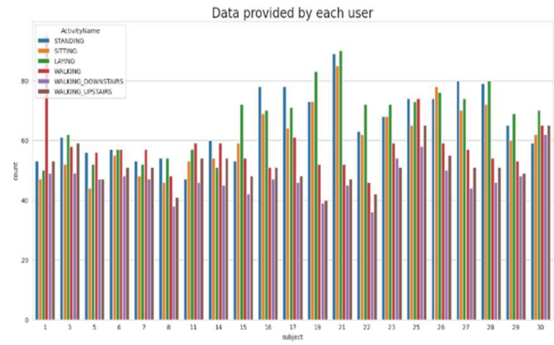

Figure 6: Visualizing each feature data in dataset provided by 30 users

As presented in Figure 6, the personal activity dynamics are provided. It shows the trends in activities and quantification of activities.

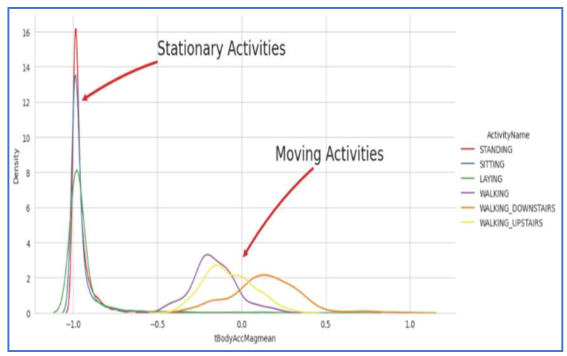

Figure 7: Visualizing the static and dynamic activities

As presented in Figure 7, stationary and moving activities are visualized. Two activities such as laying, sitting and standing come under static activities while the rest are known as moving activities. The mean value of body acceleration is used to discriminate static and moving activities.

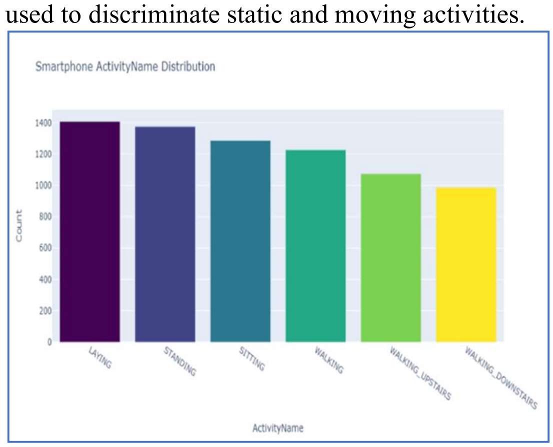

Figure 8: Visualizing the activity name distribution in the dataset

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As presented in Figure 8, different personal activities are analysed to know data distribution dynamics in the given dataset. There is balance in the activities provided in the dataset.

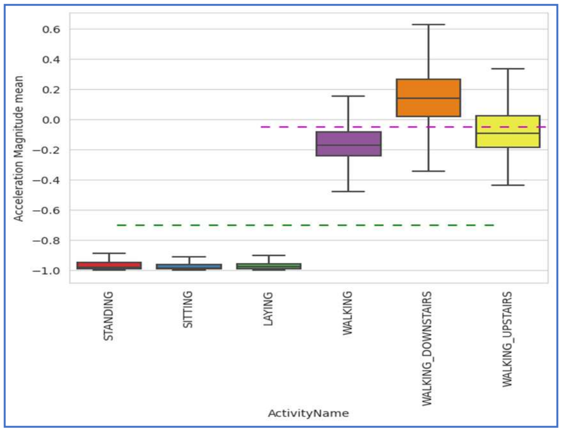

Figure 9: Visualizing Static And Dynamic Activities In Box Plot

As presented in Figure 9, the mean of acceleration magnitude is visualized against each activity. If the mean is less than 0.8, the activity is one of the static one. If the mean is more than 0.6, it is either walking upstairs or downstairs or walking. If the mean is greater than zero, then it is walking downstairs.

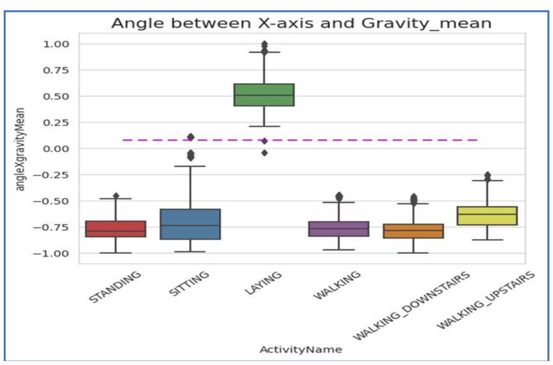

Figure 10: Visualizing Activity Name And Its Angle X Gravity Mean

As presented in Figure 10, angle X gravity mean is visualized against each activity. If the mean is greater than 0, it is related to laying otherwise, there is one of the other activities.

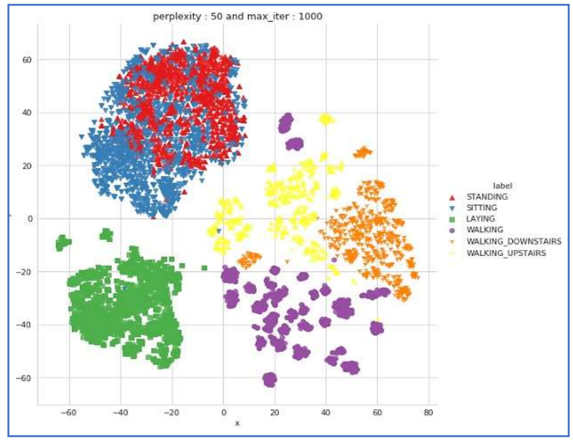

Figure 11: Visualizing the clustering of all features with T-SNE

As presented in Figure 11, different clusters of features are visualized. It reflects the discrimination and severability among activities. Thus the feature representation in clusters help in understanding activity dynamics. It is observed that except sitting and standing all other activities are separable.

4.2 Results of Personal Activity Recognition

This section presents experimental results in terms of personal activity recognition statistics that lead to performance analysis.

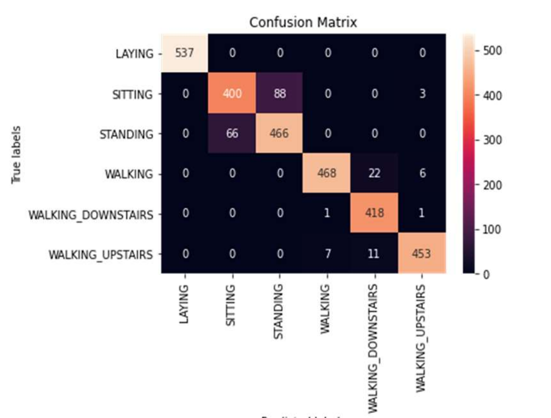

Figure 12: Confusion Matrix Reflecting The Correct And Wrong Predictions For All Classes

As presented in Figure 12, for each class the prediction details are provided.

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Table 2: Accuracy Performance Comparison Of PAR Models

PAR Model	Accuracy
ANN	89.08%
CNN-GRU	90.44%
LSTM	91.01%
LSTM With 2_Layer	91.7%
CNN-5LSTM	93.04%

As presented in Table 2, accuracy of different PAR models is provided along with the proposed model which exploits 5 layer CNN where as ANN ,CNN-GRU LSTM , LSTM With 2_Layer ,LSTM all these algorithms are compared out of which CNN-5-LSTM is outperformance with accuracy of 93.04%.

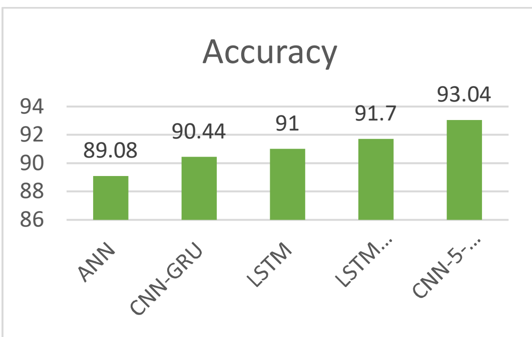

Figure 13: Accuracy Comparison Among PAR Models

As presented in Figure 13, the performance of the proposed CNN-5LSTM model is compared against many existing models in terms of accuracy in PAR. Higher in accuracy indicates better performance. The existing models consist of both linear and non-linear models. It also has shallow neural network and deep neural network based models. The proposed model outperforms all existing models with highest accuracy 93.04%.

5. CONCLUSIONS

In this paper, we proposed a framework known as Deep Personal Action Recognition Framework (DPARF) for automatic recognition of human activities. The framework is realized with our enhanced LSTM model known as CNN-5LSTM which is designed to improve accuracy in activity recognition with CNN integration. We proposed an algorithm known Enhanced LSTM with CNN for Automatic Personal Activity Recognition (ELSTM-CNN-APAR). This algorithm takes care of feature selection and processing of data consisting of temporal sequences. Our final deep neural network named as CNN-5LSTM is illustrated in Figure 4. It has different layers to detect personal activities of humans. The input data is subjected to linear interpolation, normalization of data and scaling and segmentation. With the enhanced LSTM with five layers, each layer consists of 32 neurons. It is used to improve the extraction of features with temporal dimensions. LSTM layers are followed by convolutional layer with 64 filters. Afterwards a max-pooling layer with pooling size 2 and stride 2 is used. It is followed by another convolutional layer with 28 filters. Global average pooling layer (GAP) follows the second convolutional layer. Then there is batch normalization layer (BN) layer. At the end of the network, there is dense layer with softmax inn order to achieve multi-class classification. A standard PAR smartphone dataset from UCI repository is used in the empirical study. The experimental results revealed that our proposed model outperforms many existing models with 93.04% accuracy. It can be used to have an automated PAR Decision Support System (PAR-DSS) which may be integrated with a real time PAR system in question. In future we intend to improve our framework further and investigate with more sophisticated dataset to generalize our framework for PAR.

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