Deep Learning for Personal Activity Recognition Under More Complex and Different Placement Positions of Smart Phone

(RDPARF)

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***Abstract*—Personal Activity Recognition (PAR) is an indispensable research area as it is widely used in applications such as security, healthcare, gaming, surveillance and remote patient monitoring. With sensors introduced in smart phones, data collection for PAR made easy. However, PAR is non-trivial and difficult task due to bulk of data to be processed, complexity and sensor placement positions. Deep learning is found to be scalable and efficient in processing such data. However, the main problem with existing solutions is that, they could recognize up to 6 or 8 actions only. Besides, they suffer from accurate recognition of other actions and also deal with complexity and different placement positions of smart phone. To address this problem, in this paper, we proposed a framework named Robust Deep Personal Action Recognition Framework (RDPARF) which is based on enhanced Convolutional Neural Network (CNN) model which is trained to recognize 12 actions. RDPARF is realized with our proposed algorithm known as Enhanced CNN for Robust Personal Activity Recognition (ECNN-RPAR). This algorithm has provision for early stopping checkpoint to optimize resource consumption and faster convergence. Experiments are made with MHealth benchmark dataset collected from UCI repository. Our empirical results revealed that ECNN-RPAR could recognize 12 actions under more complex and different placement positions of smart phone besides outperforming the state of the art exhibiting highest accuracy with 96.25%.**

Keywords—Human activity recognition; deep learning; CNN; MHealth dataset; artificial intelligence

I. Introduction

Human action recognition (HAR) has become an important research area. Particularly, smart phones came with sensors that are useful to know the activities of humans. At the same time wearable devices are available for monitoring human health or actions. Smart phones became handy to collect data pertaining to human actions. However, based on the position of sensor or smart phone on human body, the data contains details of specific human action that can be discovered automatically using machine learning (ML) and deep learning (DL) techniques [1]. As the position or placement of wearable device or sensor plays crucial role, it is important to consider different positions and corresponding action recognition possibilities. It is observed that learning based approaches in the form of ML and DL techniques have potential to learn from large volumes of historical data and gain knowledge pertaining to activity recognition [4].

Extensive review of literature has revealed that the existing methods could recognize different number of human activities. Table 1 shows the details of different methods and how many actions they can recognize. In the same fashion, there are different devices that are used for the research on HAR as presented in Table 2. Literature has shown many existing approaches and their ability to recognize different human activities. In [5] a multi-model approach is designed to deal with automatic recognition of human activities. They used different methods for classification besides providing their merits, challenges, and future possibilities. Nandy et al. [7] uses smart phones and wearable devices to obtain data suitable for human activity recognition. In [8] an ultrasonic sensor grid is used in smart hone environment to collect data about human behaviour. In [11], there is an effort to monitor humans automatically besides knowing their actions in an adaptive fashion. In [12], there is exploration of different methods used for automatic recognition of human activities. In [14] adversarial learning is explored in order to improve training quality that leads to higher level of accuracy in human action recognition. From the literature, it is found that the main problem with existing solutions is that, they could recognize up to 6 or 8 actions only. Besides, they suffer from accurate recognition of other actions and deal with complexity and different placement positions of smart phone. Our contributions in this paper are as follows.

1) We proposed a framework named Robust Deep Personal Action Recognition Framework (RDPARF) which is based on enhanced Convolutional Neural Network (CNN) model which is trained to recognize 12 actions.

2) An algorithm known as Enhanced CNN for Robust Personal Activity Recognition (ECNN-RPAR) is proposed to realize RDPARF.

3) An application is built to evaluate RDPARF and its underling algorithm for performance in detecting more human actions.

The remainder of the paper is structured as follows. Section 2 reviews prior works on automatic human action recognition based on ML and DL techniques. Section 3 presents the proposed framework, procedures, and proposed algorithm. Section 4 presents result of experiments. Section 5 draws conclusions and bestows scope for future possibilities.

II. Related Work

This section reviews related works pertaining to human activity recognition using sensors associated with devices like smart phones. Chen et al. [1] explored various ML models that make use of data collected from smart phone sensors to recognize human activities. They used a cycle detection algorithm to know the trends on the user behaviour. They discussed about different positions from which sensors are operated and the impact of the positions in human activity recognition. Nweke et al. [2] explored on the importance of data fusion and usage of multiple ML techniques for human activity recognition. Their work includes number of models and approaches that are existing for this kind of research. Gani et al. [3] explored different sensor placement positions targeting specific human actions. They proposed a ML based methodology for detection of various human actions. Thakur and Biswas [4] investigated on ML and DL models that are suitable for human activity recognition based on the data collected by smart phones. In [5] a multi-model approach is designed to deal with automatic recognition of human activities. They used different methods for classification besides providing their merits, challenges and future possibilities.

Suto et al. [6] studied different ML models that are suitable for human activity recognition. Their study has significance in terms of their approaches that work for offline and also online based human activity recognition. They found that sensor data changes based on its position and the position of sensor has to do with which kind of action it supports for recognition. Nandy et al. [7] uses smart phones and wearable devices to obtain data suitable for human activity recognition. From the data, they explored feature importance in order to leverage learning based phenomena in activity recognition. In [8] an ultrasonic sensor grid is used in smart hone environment to collect data about human behaviour. Their approach was found to be non-intrusive in recognizing human activities. Cornacchia et al. [9] reviews different existing studies on human activity recognition that are based on the data collected from wearable sensors. They investigated it with simple sensors and also hybrid sensors. Zdravevski et al. [10] considered Ambient Assisted Living (AAL) environment with feature engineering towards improving accuracy in activity recognition.

In [11], there is an effort to monitor humans automatically besides knowing their actions in an adaptive fashion. Based on the smart phone collected data, their research reveals the utility of automatic human action recognition in healthcare domain. In [12], there is exploration of different methods used for automatic recognition of human activities.

They also explored different approaches for federated learning to improve intelligence required for recognition. In [13] a novel approach is proposed considering swarm optimization algorithm and hybrid diversity enhancement. Besides it follows a selective ensemble approach towards improving detection accuracy further. In [14] adversarial learning is explored in order to improve training quality that leads to higher level of accuracy in human action recognition. A bidirectional LSTM method is explored in [15] for detection of human actions.

A boosting approach is exploited in [16] for to know well-being of humans based on their actions. Sensors of smart phone are used in [17] to obtain data pertaining to human behaviour for analysis and authentication purposes. Feature selection enhancement is the main research focus in [18] for leveraging detection performance.

Machine learning and opportunistic sensing based approach are explored in [19] and [20] respectively for monitoring humans about their actions. Other important researches found in the literature include feature extraction and deep learning [21], classification of sports and daily activities using ML models [22], deep learning for knowing human physical actions [23], monitoring of player activities in presence of mobility [24] and passive mobile sensing for continuous authentication [25].

As presented in Table 1, different prior works are summarized in terms of the activities, position of sensors and the techniques used for activity recognition.

As presented in Table 2, it is observed that different kinds of devices and sensors are used for finding human activities and behaviour associated with physical and mental health of humans. From the literature, it is found that the main problem with existing solutions is that, they could recognize up to 6 or 8 actions only. Besides, they suffer from accurate recognition of other actions and also deal with complexity and different placement positions of smart phone. This paper proposes a framework with underlying algorithm for addressing those issues.

TABLE I. Shows Summary of Techniques Found in Literature Along with Activities and Sensor Positions

Reference	Person's Actions	Smartphone Position	ML / DL Technique	#Activities
[26]	Sitting, standing, stairs-down, stairs-up, jogging, walking	Not Available	J48, LR, MLP	6
[27]	Walking, cycling, running, stairs-up, stairs-down, inactive, driving	Shirt pocket, pant pocket, handbag and hand.	DT, NB, C4.5, KNN and SVM	7
[28]	Sitting, standing and walking	Hand, belt, pocket and handbag	HMM and SVM	3
[29]	Walking, slow walk, fast walk, running, aerobic dancing, stairs-up and stairs-down.	Pant pocket and hand	MLP, SVM, RF, LMT and LR	6
[30]	Walking, jogging, kitchen activity and assembly line activity	Not mentioned	CNN	3

[31]	Walking, running, stairs-up, stairs-down and static.	Front pocket of coat and trousers' back pocket	NB, DT and SMO	5
[32]	Standing, sitting, walking, jogging, stairs-up and stairs-down.	Not mentioned	Ensemble of MLP, LR and J48	6
[33]	Walking, sitting and standing	Not mentioned	CNN	3
[34]	Walking, jumping, running, falling, quick walk, step walk, stairs-up and stairs-down.	Cloth pocket, trouser pocket and waist	CNN	8
[35]	Sitting, standing, walking, stairs-up, stairs-down and lying down.	Not mentioned	SVM	6
[36]	Sitting, standing, walking, stairs-up, stairs-down and lying down.	Not mentioned	KNN	6
[37]	Walking, sitting, standing, stairs-up, stairs-down and lying	Pocket	CNN	6
[38]	Walking, sitting, standing, running, cycling, stairs-up and stairs-down.	Pant pocket	SVM	7
[39]	Walking, sitting, standing and stairs-up.	Bag, belt, shirt pocket and right pant pocket.	LR	4
[40]	Staying still, walking and running.	Bag, pocket and hand	CNN	3
[41]	Sitting, standing, walking, jumping and lying	Not Mentioned	ML techniques with unsupervised learning	5
[42]	Sitting, walking, standing, stairs-up, stairs-down and lying	Not Mentioned	SVM with multiple classes	6
[43]	Walking, standing, running, casual movement, cycling and public transport	Not mentioned	Deep learning	6
[44]	Walking, standing, sitting, running and cycling.	In hand and trouser pocket	Adaboost	5
[45]	Walking, sitting, stairs-up, stairs-down, lying and climbing.	Not Mentioned	DT, SVM, KNN and Ensemble Learning	6
[46]	Sitting, walking, lying, stair-up, stairs-down, lying	Waist	RNN	6
[47]	Walking, sitting, standing, stairs-up, stairs-down.	Waist and belt	KNN and SVM	5
[48]	Walking, fast walk, running, static, stairs-up and stairs-down.	Backpack, shirt pocket and pant pocket	ELM and Ensemble Learning	7
[49]	Walking, standing, sitting, running, stairs-up and stairs-down.	Waist and belt	MLP	6

TABLE II. SHOWS DIFFERENT KINDS OF SENSORS USED IN THE PRIOR STUDIES TOWARDS FINDING HUMAN ACTIVITIES LINKED TO DIFFERENT APPLICATIONS

Reference	Device Type	Details
[50]	Sensors in wearable devices	Focused on the importance of wearable biosensors in healthcare industry.
[51]	Sensors in smartphone	Study designed to know physical activity and weight loss possibilities.
[52]	Sensors in smartphone	Study meant for to find long-term diseases and sensor usage in healthcare.
[53]	Sensors in smartphone	Study uses sensors to know mental disorders of humans
[54]	Sensors in smartphone	Investigation into bipolar disorders using IoS and Android smart phones
[55]	Sensors in smartphone	Explores human behavior liked to healthcare analytics
[56]	Sensors in smartphone and wearable devices	Studies on the mental health of humans
[57]	Sensors in smartphone	Explores mental health of humans using ML techniques
[58]	Sensors in smartphone	Explores human activity recognition, categorization and feature engineering.
[59]	Wireless Sensors	Studies the possibilities in remote healthcare and latest methods in the process.

III. PROPOSED WORK

We proposed a deep learning based framework for automatic recognition of personal activities based on the smart phone sensor data. Several researchers have contributed earlier towards personal activity recognition as explored in [26], [27] and [28] to mention few. However, the number of activities recognized is limited to 3 to 8. However, in real world, smart phone sensors could be positioned and it is possible to recognise more activities. Towards this end, in our research, we could experiment with more complex activities due to different placement positions. Our system recognizes 12 actions such as "standing still, sitting and relaxing, laying down, walking, climbing stairs, waists bends forward, frontal elevation of arms, knees bending, cycling, jogging, running and jump front & back".

A. *Our Framework*

Our framework is illustrated in Fig. 1. The given M-Health dataset that contains smart phone sensors generated data under complex and different placement positions is used by the framework to explore possibilities of recognising 12 actions.

The dataset is subjected to pre-processing feature extraction. Then an enhanced CNN classifier is trained on the chosen features. The training of deep learning model has resulted in a knowledge model known as personal activity recognition system which is saved to persistent storage for reuse. This model is a multi-class classifier as we intend to recognize 12 personal activities. The pre-processing splits data into training and test set in order to have experiments without over fitting. We also defined an Early Stopping strategy based on validation loss value. If there is no change in validation loss after given patience value, this point is considered to be early stopping condition. This strategy has proved to be good as it could avoid over fitting issues. The saved trained model is reused with test data to perform personal activity recognition.

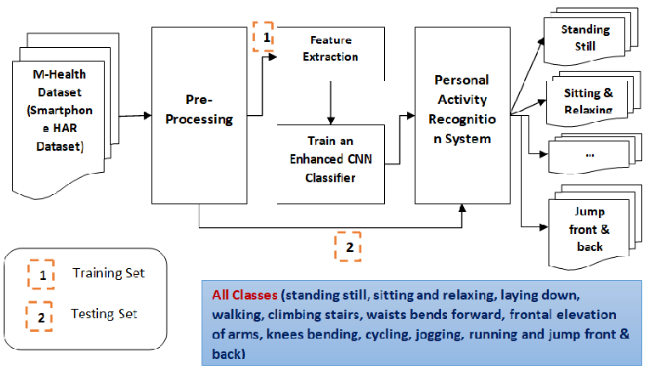

Fig. 1. Proposed framework known as robust deep personal action recognition.

Framework (RDPARF) for personal activity recognition considering more complex and different placement positions of smart phone

We enhanced CNN model to meet our requirement in this research. Layers are configured in such a way that they tend to produce best results with multi-class classification. CNN model is enhanced as one size does not fit all. In other words, the CNN used to solve one problem cannot be directly used for another problem.

B. Enhanced CNN Model

We configured an enhanced CNN model in such a way that it is best suited for multi-class classification of personal activities. The dataset used for empirical study has sensor positions that are diversified to realize more human actions. The model performs convolutional operations to acquire features from the given data. It has carefully chosen hyperparameters set to improve prediction performance.

xIn Table 3 the sensor data input vector is denoted as $x_i^0 = [x_1, \ldots \ldots, x_N]$ where N refers to the per window values. The outcome of the first convolutional layer is observed and it can be expressed as in Eq. 1. Table 1 shows all the notions used in the proposed model.

$$c_i^{1,j} = \sigma\left(b_j^1 + \sum_{m=1}^{M} w_m^{1,j} x_{i+m-1}^{0,j}\right), \quad (1)$$

Where layer index is denoted by l, activation function is denoted by σ, the bias term for given feature map is denoted as b_j, filter size is denoted by M and weight for given feature map is denoted by w_m^j. In the same fashion, the outcome of l^{th} convolutional layer is expressed as in Eq. 2.

$$c_i^{l,j} = \sigma\left(b_j^l + \sum_{m=1}^{M} w_m^{l,j} x_{i+m-1}^{l-1,j}\right). \quad (2)$$

Here $c_i^{l,j}$ is used to obtain summary of nearby outputs through pooling layer which is meant for optimizing feature maps. We used max pooling as it is characterized by using resulting max value as expressed in Eq. 3.

$$p_i^{l,j} = max_{r \in R}\left(c_{i \times T+r}^{l,j}\right), \quad (3)$$

where pooling size is denoted by R and stride by T. In the enhanced CNN architecture many convolutional and pooling layers are stacked to ensure a hierarchical feature extractor. The extracted features can have ability to discriminateamong the personal activities. They have capability to discriminate simple to complex activities. In order to recognize personal activities fully connected layer and softmax layer are combined. This combination forms a top-most layer. The features obtained from convolutional layers and pooling layers are transformed into feature vectors denoted as $p^l = [p_1, \ldots.. p_2]$ where number of units is denoted as l in the ultimate pooling layer. The outcome of these layers is given as input to fully connected layer as expressed in Eq. 4.

$$h_i^j = \sum_j w_{ji}^{l-1}\left(\sigma\left(p_i^{l-1}\right) + b_i^{l-1}\right) \quad (4)$$

TABLE III. SHOWS DIFFERENT KINDS OF SENSORS USED IN THE PRIOR STUDIES TOWARDS FINDING HUMAN ACTIVITIES LINKED TO DIFFERENT APPLICATIONS

Reference	Device Type	Details
[50]	Sensors in wearable devices	Focused on the importance of wearable biosensors in healthcare industry.
[51]	Sensors in smartphone	Study designed to know physical activity and weight loss possibilities.
[52]	Sensors in smartphone	Study meant for to find long-term diseases and sensor usage in healthcare.
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[57]	Sensors in smartphone	Explores mental health of humans using ML techniques
[58]	Sensors in smartphone	Explores human activity recognition, categorization and feature engineering.
[59]	Wireless Sensors	Studies the possibilities in remote healthcare and latest methods in the process.

Where activation function denoted as σ and it is same as that of previous layers. The bias terms is denoted as $b_i^{l-1}$and the w_{ji}^{l-1} denotes weights associated with i^{th} and j^{th} nodes in the l-1 layer. The softmax layer, which is expressed as Eq. 5, is the final layer in the deep network for performance classification.

$$(c|p)=\text{argmax}_{c\in C}\frac{\exp(p^{L-1}w^{L}+b^{L})}{\sum_{k=1}^{N_C}\exp(p^{L-1}w_k)}, \quad (5)$$

Where the activity class is denoted as c, p is the index of last layer while the number of activity classes is denoted as N_C. Equations from 1 through 4 perform forward propagation that result in getting error values of the network. SGD is used in training to minimize error cost and also update weights. Sensor data is used in the training process in the form of mini batches. In the fully connected layer back propagation is performed which is expressed as in Eq. 6.

$$\frac{\partial E}{\partial w_{ij}^{l}} = y_i{}^{l}\frac{\partial E}{\partial x_j^{l+1}}, \quad (6)$$

where the cost function is denoted by E, weight from $u_i{}^{l}$ and $u_i{}^{l+1}$ in the l+1 layer is denoted by w_{ij}^{l}. Computation of $y_i{}^{l}$is done as expressed in Eq. 7.

$$y_i{}^{l} =(x_i{}^{l}) + b_i{}^{l} \quad (7)$$

Weights are adjusted using backpropagation in convolutional layers. This process is expressed as in Eq. 8.

$$\frac{\partial E}{\partial w_{ab}} = \sum_{i=0}^{N-M-1}\frac{\partial E}{\partial x_{ij}^{l}}y_{(i+a)}^{l-1}, \quad (8)$$

where map function is denoted as $y_{(i+a)}^{l-1}$which is equal to $\sigma\left(x_{(i+a)}^{l-1}\right) + b^{l-1}$. The results of $\frac{\partial E}{\partial y_{ij}^{l}}\sigma'(x_{ij}^{l})$ are equal to that of $\frac{\partial E}{\partial x_{ij}^{l}}$. The process of back and forward propagations are continued until stopping condition is met.

C. Regularization

When it comes to weights in the network, it is possible that large weights can lead to weight vector to have local minimum due to small amendments to gradient descent in the optimization process. Thus it makes it difficult in exploring weight space. Therefore, it is required to have regularization mechanism to deal with large weights. It is achieved by adding penalizing term to every set of weights as given in Eq. 9.

$$\text{E}=E_0 + \lambda\sum_w w^2, \quad (9)$$

where $\lambda\sum_w w^2$ is the penalizing term and E_0 is the cost function prior to regularization. As the cost function is updated, the learning rule is updated and it is expressed as in Eq. 10.

$$w_i = (1-\eta\lambda)w_i - \eta(\frac{\partial E_0}{\partial w_i}) \quad (10)$$

where the weight decay factor is denoted by $1-\eta\lambda$. Gradient descent can be momentum based to have velocity to parameters that are under optimization. It is done such that only velocity is changed but not the position associated with the weight space. For each weight variable in $\upsilon = [\upsilon_1, \dots, \upsilon_K]$, there is corresponding velocity variable. The update of gradient descent rule is then expressed as in Eq. 11 and Eq. 12.

$$\upsilon \rightarrow \upsilon' = \mu\upsilon - \eta\nabla E, \quad (11)$$

$$w \rightarrow w' = w + \upsilon' \quad (12)$$

where the momentum coefficient is denoted as μ.

We used dropout appropriately to get rid of overfitting problem. It is achieved by doing so instead of amending cost function. The overfitting problem is solved by temporary deletion of nodes without changing input and output neurons. It makes the training process more efficient. This process also makes neurons not to be influenced by other neurons while learning features. For each given training sample, dropout is followed by consideration of an include probability which is done independent of nodes. In the proposed enhanced CNN model dropout is used in fully connected layer of the network.

D. Hyperparameter Tuning

In the proposed enhanced CNN architecture, there are large number of possibilities of hyper parameter combinations. We followed a greedy tuning process in order to assess the effect of hyper-parameter tuning on the network. The tuning is experimented in terms of pooling size, filter size, number of feature maps and even number of layers in the network. In our empirical study we explored with network layers 1 to 4, feature maps from 10 through 200 with interval of 10, pooling size considered from 1x2 through 1x15 and filter size is considered from 1x3 through 1x15. In all our experiments one softmax layer is used. Finally, best performing hyper-parameters are used.

E. Proposed Framework

We proposed an algorithm known as Enhanced CNN for Robust Personal Activity Recognition (ECNN-RPAR). It is designed and implemented to realize our PAR framework named Robust Deep Personal Action Recognition Framework (RDPARF).

Algorithm 1: Enhanced CNN for Robust Personal Activity Recognition

Algorithm: Enhanced CNN for Robust Personal Activity Recognition (ECNN-RPAR)

Inputs

MHealth dataset D (reflects more complex and different placement positions of smart phone)

Batch size n

Number of epochs m

Output

Multi-class classification results of PAR R (12 classes)

Performance evaluation results P

1. Begin
2. ***D'***←DataPreparation(***D***)
3. (***T1***, ***T2***)←SplitData(***D'***)
4. Initialize CNN model
5. Add max pooling layer
6. Add convolutional layer
7. Add batch normalization layer
8. Add convolutional layer

```
Add batch normalization layer
Add linear layer
Add batch normalization layer
Add linear layer
Add softmax layer
Tuning hyper-parameters
Compile the model M
For each epoch e in m
   For each batch b in n
    IF early stopping criterion is FALSE Then
Update M using T1
      Else
         Break
   End For
End For
(R,P)←ModelTesting(M, T2)
Display R
Display P
End
```

D: Dataset	***D'***: Pro-processed dataset
m: Number of epochs	***n***: Batch size
R: Classification results	***T1***: Training set
T2: Test set	***M***: Proposed model
e: each epoch	***b***: each batch
P: Performance statistics	

As presented in Algorithm 1, it takes MHealth dataset ***D***, number of epochs ***m***, number of batches ***n***as input and generates personal activity recognition results ***R***along with performance statistics. It has data preparation phase 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 enhanced CNN model. Afterwards, it configures all the layers as per the proposed model. Hyper-parameter tuning is carried out. Then there is an iterative process based on given number of epochs and batch size to train the model using ***T1***. The model training process gets terminated if it satisfies early stopping criterion. This is considered because it is important to stop training before it overfits. 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***and performance statistics ***P***.

IV. EXPERIMENTAL RESULTS

Experiments are made with the proposed enhanced CNN which is used in the framework and underlying algorithm named ECNN-RPAR. The enhanced CNN is designed and implemented to cover all PAR classes under more complex and different placement positions of smart phone. Number of epochs used in the empirical study is 200 but it is subjected to early stopping criterion. Dropout is set to 0.5, batch size is 400, window size for data splitting is 50 and step value is set to 25. Total number of classes (including normal/no action class) is 13, size of max pool is 2 and stride of max pool is set to 2. Dataset for our empirical study is collected from [60] which reflects more complex and different placement positions of smart phone. The experimental results are provided in terms of confusion matrix as presented in Fig. 2.

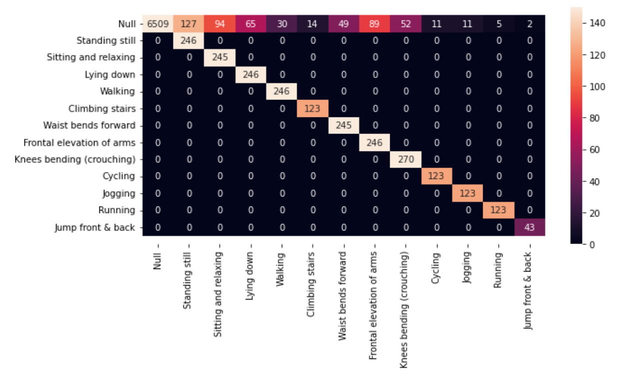

Fig. 2. Confusion matrix reflecting prediction performance of the proposed model for 12 classes.

As the statistics are provided through confusion matrix for all 12 classes, performance of the proposed algorithm ECNN-RPAR is ascertained. With 200 epochs used in experiments, the training loss and validation loss [65] are observed in presence of early stopping criteria.

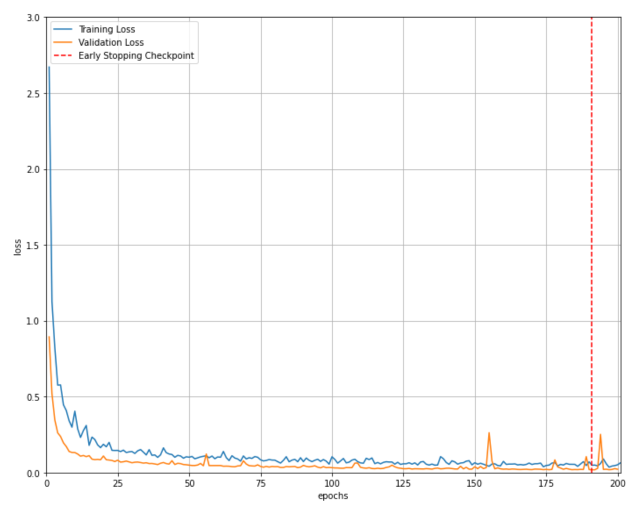

Fig. 3. Loss dynamics and early stopping criterion check point.

As presented in Fig. 3, visualization of the performance of ECNN-RPAR [63,64] is provided against number of epochs. Number of epochs used in experiments is 200 but it is subjected to early stopping criterion.

As the number of epochs is increased, it is observed that the training and validation loss is reduced gradually. Reduced loss indicates improved performance.

As presented in Table 4, the personal action recognition [61] performance of the proposed algorithm ECNN-RPAR is provided.

TABLE IV. PERFORMANCE OF THE PROPOSED MODEL

PAR Model	Performance (%)			
	Precision	Recall	F-1 Score	Accuracy
Proposed (ECNN-RPAR)	89.12	85.32	87.17	96.25

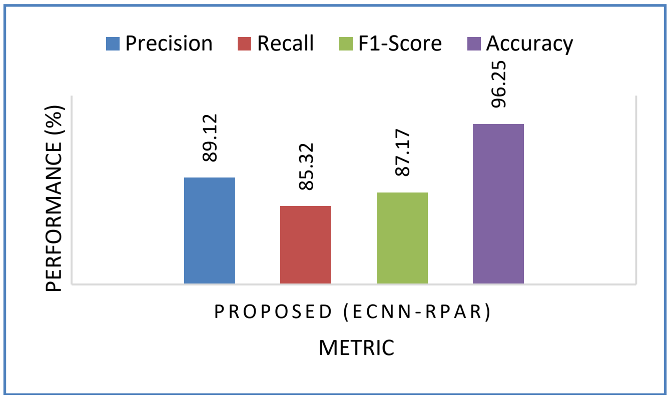

Fig. 4. Personal action recognition performance of proposed ECNN-RPAR algorithm.

As presented in Fig. 4, the action recognition performance of the proposed ECNN-RPAR algorithm is provided. It could achieve detection of 12 classes with 89.12% precision, 85.32% recall, 87.17% F1-score and 96.25% accuracy.

TABLE V. PERFORMANCE OF PROPOSED ECNN-RPAR ALGORITHM COMPARED WITH EXISTING MODELS

PAR Models	Performance (%)			
	Precision	Recall	F-1 Score	Accuracy
ANN	75.48	69.34	72.27	79.36
Baseline CNN	78.45	75.78	77.09	81.58
LSTM	80.25	73.23	76.57	85.73
Proposed (ECNN-RPAR)	89.12	85.32	87.17	96.25

As presented in Table 5, the personal action recognition performance of the proposed ECNN-RPAR algorithm is compared against the state of the art.

Performance of proposed ECNN-RPAR [62] algorithm is compared against ANN model, baseline CNN and LSTM.ANN showed least performance among all models. Its precision is 75.48%, recall 69.34%, F1-score 72.27% and accuracy 79.36%. Baseline CNN model showed performance better than that of ANN. CNN achieved 78.45% precision, 75.78% recall, 77.09% F1-score and 81.58% accuracy. LSTM showed better performance over CNN with 80.25% precision, 73.23% recall, 76.57% F1-score and 85.73% accuracy. The proposed ECNN-RPAR algorithm showed highest performance with 89.12% precision, 85.32% recall, 87.17% F1-score and 96.25% accuracy. It is observed from the results that the existing methods showed comparatively poor performance in accurately predicting 12 personal actions.

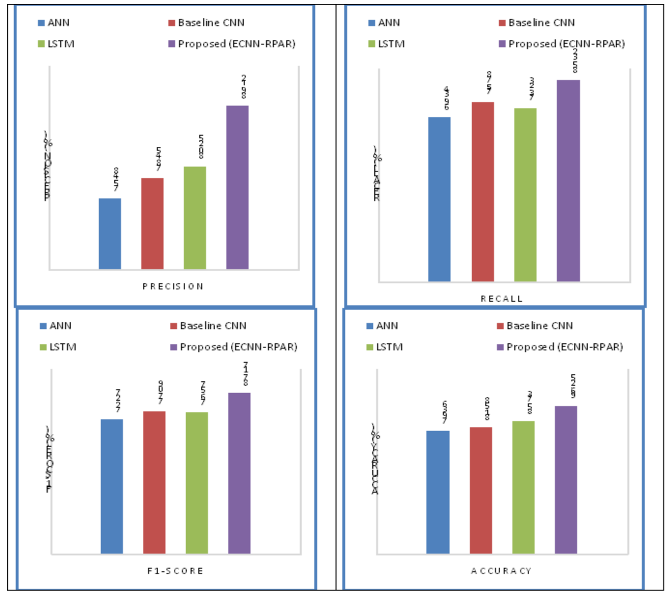

Fig. 5. Performance Of Proposed ECNN-RPAR Algorithm Compared With Existing Models.

V. CONCLUSION AND FUTURE WORK

We proposed a framework named Robust Deep Personal Action Recognition Framework (RDPARF) which is based on enhanced Convolutional Neural Network (CNN) model which is trained to recognize 12 actions. The given M-Health dataset that contains smartphone sensors generated data under complex and different placement positions is used by the framework to explore possibilities of recognising more actions. The dataset is subjected to pre-processing feature extraction. Then an enhanced CNN classifier is trained on the chosen features. The training of deep learning model has resulted in a knowledge model known as personal activity recognition system which is saved to persistent storage for reuse. RDPARF is realized with our proposed algorithm known as Enhanced CNN for Robust Personal Activity Recognition (ECNN-RPAR). This algorithm has provision for early stopping checkpoint to optimize resource consumption and faster convergence. Experiments are made with MHealth benchmark dataset collected from UCI repository. Our empirical results revealed that ECNN-RPAR could recognize 12 actions under more complex and different placement positions of smart phone besides outperforming the state of the art exhibiting highest accuracy with 96.25%. However, we have directions for future scope of our work. First, it is interesting to explore pre-trained deep models with transfer learning towards performance improvement. Second, usage of hybrid deep learning models with our framework could leverage performance. Third, usage of Generative Adversarial Network (GAN) along with deep models for generator and discriminator is another direction for future work.

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