

# Human activity recognition method using joint deep learning and acceleration signal

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## ABSTRACT

Many studies have been conducted on human activity recognition (HAR) in the last decade. Accordingly, deep learning algorithms have been given more attention in terms of classification of human daily activities. Deep neural networks (DNNs) compute and extract complex features on voluminous data through some hidden layers that require large memory and powerful graphics processing units (GPUs). So, this study proposes a new joint learning (JL) approach to classify human activities using inertial sensors. To this end, a large complex donor model based on a convolutional neural network (CNN) is used to transfer knowledge to a smaller model based on CNN referred to as the acceptor model. The acceptor model can be deployed on mobile devices and low-power hardware due to decreased computing costs and memory consumption. The wireless sensor data mining (WISDM) dataset is used to test the proposed model. According to the experimental results, the HAR system based on the JL algorithm outperforms than other methods.

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## 1. INTRODUCTION

Inertial sensors such as gyroscopes, accelerometers, and magnetometers are widely used in various fields, including human activities and patient monitoring [1], [2], sports activities [3], and Persian character recognition due to the development of their manufacturing technology, cheapness, portability, wearability, and support for various communication protocols, e.g., Wi-Fi and Bluetooth. These sensors have advantages in the field of human activities, including the possibility of attaching them to certain parts of the body and easily collecting valuable data from people's daily activities such as sitting, walking, jumping, and cycling. Accelerometers and gyroscopes are the most common sensors embedded in smartphones. Accelerometers are electronic sensors that measure the acceleration applied to the sensor in the x, y, and z axes, while gyroscopes are devices for measuring angular velocity or maintaining rotational motion. Once raw signals are collected, there are first processed by inertial sensors to remove noise and then are recognized and classified.

Recently, there have been many studies on the classification of data collected from inertial sensors. Machine learning algorithms such as multilayer perceptron, support vector machine, and decision tree, have

achieved successful results. However, manual feature extraction by these algorithms requires specialized knowledge and is sometimes not possible due to large volume of inputs. Meanwhile, the emergence of powerful deep learning tools, e.g., convolutional neural network (CNN) [4] and long short-term memory (LSTM) [5]–[7] and their success in various fields in the past decade have led to a high capability to extract features from large volumes of data. So, researchers can search and extract high-level features and complex patterns that were previously difficult to be extracted or could not be extracted automatically in layers without the need to use traditional methods and manual feature extraction. Accordingly, they can achieve the best pre-processing and feature selection in the defined framework by using deep learning algorithms and applying a huge amount of data.

Nowadays, deep learning models have received more attention from researchers than traditional models and have provided a significant contribution to improving advanced functions. However, they have many parameters due to their complexity and large size. Thus, such complex models can be trained on powerful graphics processing units (GPUs) and tensor processing units (TPUs). It should be noted that they require high computational costs and large storage spaces. In this way, deploying massive deep learning models on low-power hardware devices such as smartphones, robots, and embedded chips is a challenging issue that has drawn researchers' attention to investigate methods for reducing computational costs and number of parameters in deep learning models without reducing their speed and accuracy. These methods have been optimized by replacing computationally intensive operations, pruning approaches, quantizing model parameters to reduce memory requirements and increase inference speed, using hash methods, as well as developing faster and more lightweight architectures for inference [8]–[10].

There are many studies on the human activity recognition (HAR), the data of which has been collected by the use of inertial sensors with deep learning techniques. For example, in a study by Yen *et al.* [11], 6 daily HARs by a CNN were investigated. Xu *et al.* [12] applied a HAR method based on improved 1D-CNN to 11 human activities. Hsu *et al.* [3] developed a wearable sport activity classification system and the associated deep learning-based sport activity classification algorithm for accurately recognizing sports activities. Many studies have been conducted on monitoring elderly people's activities. For example, Shang *et al.* [13] investigated the monitoring of elderly people's bathing activities through data collection by wrist-mounted accelerometers. They also used the CNN model for classification. According to the calculations, the CNN layers require a memory of 343.94 MB.

Santoyo-Ramón *et al.* [14] investigated the effects of sensor sampling frequency on fall detection during daily activities based on raw acceleration signals captured by wearable sensors and classified the data using the CNN. In their study, Lawal and Bano [4] designed an integrated two-stream CNN to predict human activities and they tested the datasets from different body parts in order to predict the best positions. According to the calculations, the two-stream CNN layers consumed 9.047 MB of memory. Ignatov [15] applied a user-independent deep learning-based approach in order to classify online human activities. In this study, it is proposed to use the CNN and extract the local features along with the simple statistical features that preserve the data concerning the global form of the time series.

Various studies have combined different models, e.g., CNN with LSTM or Hidden Markov models, in order to improve the performance of these classifiers. For example, Wang *et al.* [5] introduced a hybrid LSTM\_CNN algorithm for the HAR. This algorithm handles time-dependent data with multiple features. To classify human activities, Khatun *et al.* [16] proposed a hybrid deep learning model that combines the CNN and CNN-LSTM. In a study by Sepahvand and Abdali-Mohammadi [9], the adversarial vulnerability of gait event detection through the CNN and LSTM models was investigated. Serrão *et al.* [17] applied three deep learning architectures, i.e., CNN, LSTM, and a gated recurrent unit (GRU) network, in order to classify 17 classes of the UniMiB SHAR dataset. Their applied CNN requires 1.74 MB of memory. In a study by Gupta [18], a hybrid GRU-CNN deep learning model was investigated for the accurate classification of 18 simple and complex human daily activities from the wireless sensor data mining (WISDM) dataset.

Researchers have used a combination of different algorithms and models in order to improve deep learning models. For example, Raziani and Azimbagirad [19] used a 1-D CNN model to classify human activities and investigated seven approaches based on the grey wolf optimizer (GWO), whale optimization algorithm (WOA), salp swarm algorithm (SSA), sine cosine algorithm (SCA), multiverse optimizer (MVO), particle swarm optimization (PSO), and moth flame optimization (MFO) for automatic selection of optimal meta-parameters of the CNN model. Although these methods have a good performance in classification of activities, however the high number of parameters and the computational complexity of these methods have limited their use in edge devices that have weak hardware.

In their study on the LSTM-ConvAE architecture for the HAR, Thakur *et al.* [20] suggested that CNNs, automatic encoders (AEs), and LSTMs have complementary modeling capabilities because CNNs are adept at automatic feature extraction, AEs at dimensionality reduction, and LSTMs at temporal modeling. In a study by Shang *et al.* [13], CNN and the arithmetic optimization algorithm (AOA) were used on three different

general datasets, i.e., HAR-UCI, HAR-WISDM, and HAR-KU. The calculations performed on the CNN parameters require 14.224 MB of memory. Jaber and Ravanmehr [2] proposed the use of the CNN model and an optimization technique using the ternary weight nets (TWN) model in order to reduce the complexity of the deep neural network approach, and as a result, decrease energy consumption by mobile devices to increase the accuracy of the HAR.

Sepahvand *et al.* [10] proposed an adaptive HAR real-time monitoring system in order to classify more human motions in dynamic situations using 4 machine learning algorithms, i.e., k-nearest neighbors (KNN), decision trees (DTs), artificial neural network (ANN), and support vector machines (SVMs), and a deep learning algorithm called the LSTM. The results indicated that classification by the LSTM had a higher accuracy. Muralidharan *et al.* [21] applied classic machine learning algorithms such as logistic regression, linear and kernel SVM, decision tree, and random forest in order to classify the HAR from the obtained data. They also applied a deep feedforward neural network and a 1D-CNN and compared them with the single classifier algorithms. Gil-Martín *et al.* [22] proposed a HAR system consisting of three modules, the first of which divided acceleration signals into overlapping windows and extracted the data from each window in the frequency domain. The second module recognized the activities performed in each window using a CNN model. The calculations performed on the CNN parameters required 77.06 MB of memory [23]–[25].

In this study, a very effective and promising joint learning (JL) approach is used to recognize 6 human activities including walking, jogging, going upstairs, going downstairs, sitting, and standing. In this process, the CNN-based model with a complex and heavy architecture called donor, which can extract important features from a large amount of data and make a favorable prediction, is first trained. The donor model then trains a CNN-based model with a small and light architecture called acceptor through JL. In this way, the knowledge in the larger model can be distilled into a smaller and faster model with the capability of being implemented on mobile devices so that the acceptor model can be obtained with almost the same or higher accuracy as that of the donor model.

The main goals of the study include:

- Reducing the parameters of the acceptor model in order to decrease the computing costs and memory consumption for deploying the acceptor model on the mobile device; and
- Proving that the proposed method brings about the best results on the WISDM dataset.

## 2. THE PROPOSED METHOD

### 2.1. General structure

According to Figure 1, the JL model consists of 2 modules: the donor network and the acceptor network. The donor network has a structure different from the acceptor network. The main goal is to provide a vanilla distillation framework, in the sense that a large pre-trained donor network transfers its knowledge to the acceptor network. As it can be seen in Figure 1, the signals collected by the three-axis accelerometer of the smartphone in the WISDM laboratory are first applied as inputs to the JL model. The softmax of the donor network then changes with the value of temperature ( $t$ ). The softmax output is the class probabilities produced by the donor network at the output. This temperature value depends on the input data and is obtained experimentally. The same temperature is used for the softmax of the acceptor, the output of which is called the soft prediction. The softmax activation function is used in the output layer in order to normalize the network output and convert it into a probability distribution. Also, the sum of the probabilities of all the classes is 1. All the probabilities of classes that are not output are close to 0, and the probability distribution for the true output is maximum. The cross-entropy loss function is then calculated for the soft and hard labels. Finally, the acceptor network is trained by minimizing the final loss function obtained from the soft and hard label loss functions.

### 2.2. Learning transfer method

The method of dark knowledge transfer in vanilla JL is described:  $z_s^{(i)}$  denotes the output logit vector of the last fully connected layer of the acceptor network,  $k$  is the number of target classes, and  $T$  represents a temperature coefficient. The higher its value, the more uniform distribution  $p^{(i)}$  tends to. Also,  $p^{(i)}$  is the probability of the output of the acceptor network for the  $i$ -th class, which is calculated in (1) and (2). In (2),  $z_t^{(i)}$  denotes the output logit vector of the last fully connected layer of the donor network, and  $q^{(i)}$  is the probability of the output of the donor network for the  $i$ -th class, which is calculated,

$$p^{(i)} = \frac{\exp\left(\frac{z_s^{(i)}}{T}\right)}{\sum_{i=1}^k \exp\left(\frac{z_s^{(i)}}{T}\right)} \quad (1)$$

$$q^{(i)} = \frac{\exp\left(\frac{z_t^{(i)}}{T}\right)}{\sum_{i=1}^k \exp\left(\frac{z_t^{(i)}}{T}\right)} \quad (2)$$

where  $X$  is the input data, and  $y$  is a  $k$ -dimensional vector derived using the one-hot encoding method. The cross-entropy loss functions used for the soft and hard labels are calculated as (3) and (4). The acceptor network can be trained by minimizing the following loss: where  $\alpha$  denotes the weighting factor used for the loss based on the soft and hard labels, and  $R$  is the number of input samples  $X$  as (5).

$$L_{Soft}(X, q) = -\sum_{i=1}^k q^{(i)} \log_{p^{(i)}}(X) \quad (3)$$

$$L_{Hard}(X, y) = -\sum_{i=1}^k y^{(i)} \log_{p^{(i)}}(X) \quad (4)$$

$$L_{KD} = \frac{1}{R} \sum_{x,y} ((1 - \alpha)L_{Hard}(X, y) + \alpha L_{Soft}(X, q)) \quad (5)$$

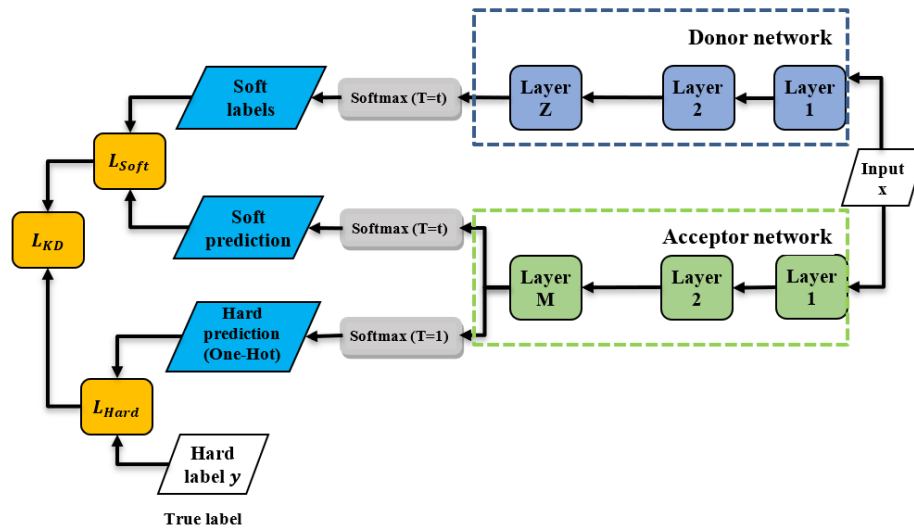


Figure 1. Joint deep learning architecture

### 3. RESULTS AND DISCUSSION

The results of the study are obtained from the performance of the donor and acceptor models based on a 1-D CNN along with the JL algorithm to increase the accuracy of the acceptor model. The Adam optimizer is used to update the Hyperparameter. The loss value is calculated using the cross-entropy function to predict the HAR. It is worth noting that the test is performed on a PC with Microsoft Windows 10, Intel(R) Core (TM) i5-11400H processor, 16 GB RAM, and Nvidia GeForce RTX3050 GPU. The evaluation criteria used for the proposed HAR algorithm in the test phase include accuracy, recall, precision, and F1-score. The main parameters true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are used to calculate the accuracy, recall, precision, and F1-score criteria.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

$$F1\_Score = 2 \cdot \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

### 3.1. Dataset

The WISDM dataset consists of 1098203 samples collected from smartphone accelerometer sensors in a laboratory environment and includes 6 different human activities, i.e., "standing", "walking", "sitting", "jogging", "going downstairs", and "going upstairs". The feature of this dataset is three-axis linear acceleration obtained with a fixed sampling rate of 20 Hz. The dataset is divided into 2 different groups: 70% for the training data and 30% for the test data.

### 3.2. Baseline

The proposed method is compared with the following studies:

- CNN [26]: In this method, CNN is used to recognize and classify human activities.
- CNN+Handcrafted features [2]: In this study, human activities are recognized using a shallow CNN model to extract local features along with statistical features.
- LSTM\_CNN [27]: In this study, the combination of LSTM and CNN models is used to improve the HAR performance.
- ConvAE\_LSTM [20]: In this study, ConvAE\_LSTM architecture is proposed, in which features are automatically extracted through CNN, AE is used for dimensionality reduction, and LSTM is used for temporal modeling.

### 3.3. Evaluation of donor model, acceptor model, and JL

In this test, the donor model with 124,126 parameters and memory consumption of ~993 KB is trained on the 6 human activities. Furthermore, the compressed acceptor model with 7.964 parameters and ~63 KB memory consumption is trained by the proposed JL method. The results of the classification evaluated by the donor model are listed Table 1, where F1-score is 91%, 90%, 97%, and 97% for going downstairs, going upstairs, sitting, and standing, respectively, and 99% for jogging and walking. Besides, the results of the classification evaluated by the acceptor model are reported in Table 2, where the maximum F1-score is 98% for walking and the minimum F1-score is 81% for going upstairs.

The confusion matrix for the 6 activities is shown in Figure 2. Jogging and walking are well classified because higher changes in the gyroscope numerical value are observed when performing these activities. Figure 2(a) shows the confusion matrix for the student model, while Figure 2(b) shows the confusion matrix for the teacher model.

Table 1. The performance of the classification by the donor CNN model

F1-Score	Recall	Precision	Activity
0.91	0.93	0.89	Downstairs
0.99	0.99	1.00	Jogging
0.97	0.94	0.99	Sitting
0.97	0.99	0.94	Standing
0.90	0.87	0.93	Upstairs
0.99	0.99	0.98	Walking
0.97			accuracy
0.95	0.95	0.95	Macro avg
0.97	0.97	0.97	Weighted avg

Table 2. The performance of the classification by the acceptor CNN model

F1-Score	Recall	Precision	Activity
0.82	0.91	0.74	Downstairs
0.97	0.95	0.99	Jogging
0.97	0.94	0.99	Sitting
0.96	0.99	0.93	Standing
0.81	0.78	0.84	Upstairs
0.98	0.98	0.98	Walking
0.94			accuracy
0.92	0.93	0.91	Macro avg
0.94	0.94	0.94	Weighted avg

Figures 3(a) and 3(b) show the accuracy of the donor and acceptor model trained by the JL method, respectively. The accuracy of the test set is more than 97% for the donor model and more than 95% for the trained acceptor model. Figures 3(c) and 3(d) show the loss values obtained from the donor and acceptor models, which are gradually decreasing.

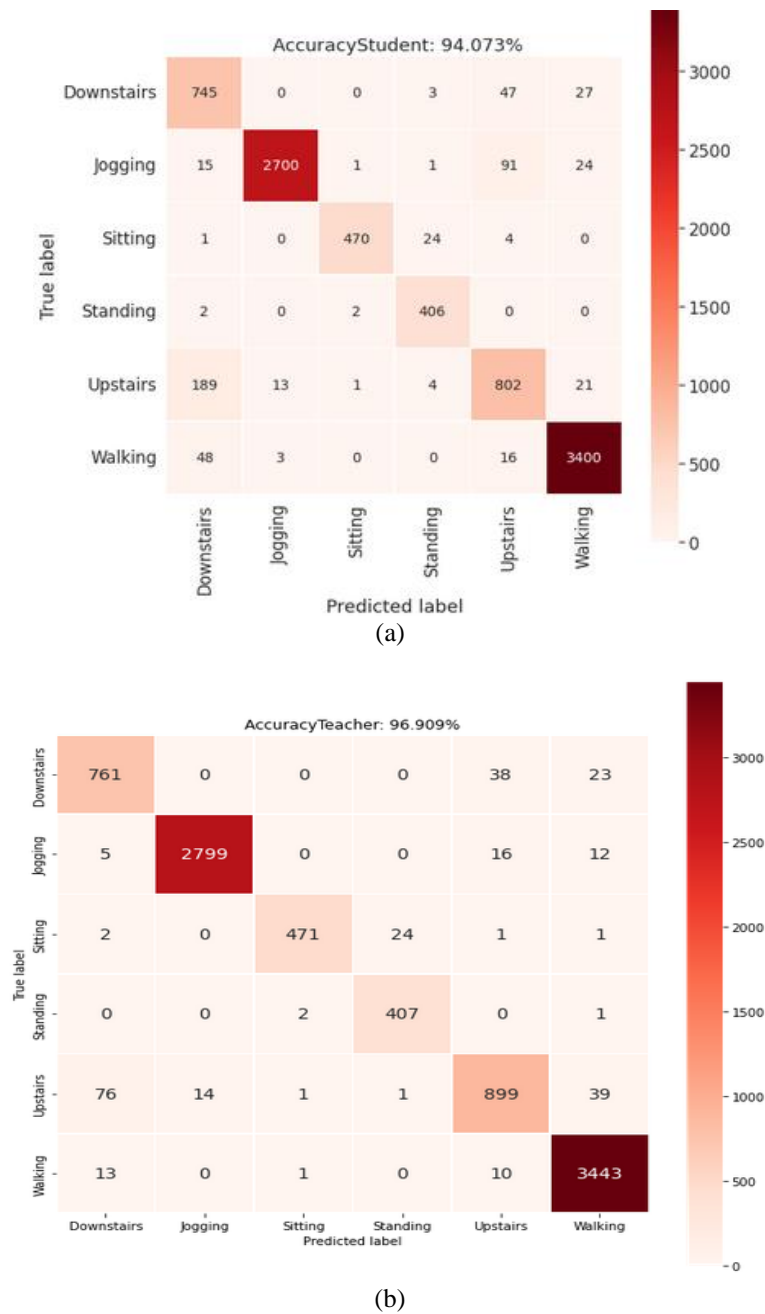


Figure 2. The confusion matrix on 6 human activities, (a) the acceptor CNN model and (b) the donor CNN model

### 3.4. Comparing the proposed method with previous studies

The accuracies of the methods used in some studies on human activities are compared with that of the proposed method using inertial sensors as shown in Table 3. The overall accuracy of the donor CNN model is 97.40%. In comparison, the CNN classification [26] increases the accuracy by 2.61. Moreover, this method increases the accuracy by 1.55 compared to the combined LSTM+CNN method [27]. The accuracy increases to 6.98 compared to CNN+Handcrafted features [2]. However, the combined ConvAE\_LSTM method [20] increases the accuracy by 1.47 compared to the proposed method. The proposed method makes a significant contribution to improving the performance and accuracy of the CNN model with a small number of parameters for deploying on low-power hardware devices through JL.

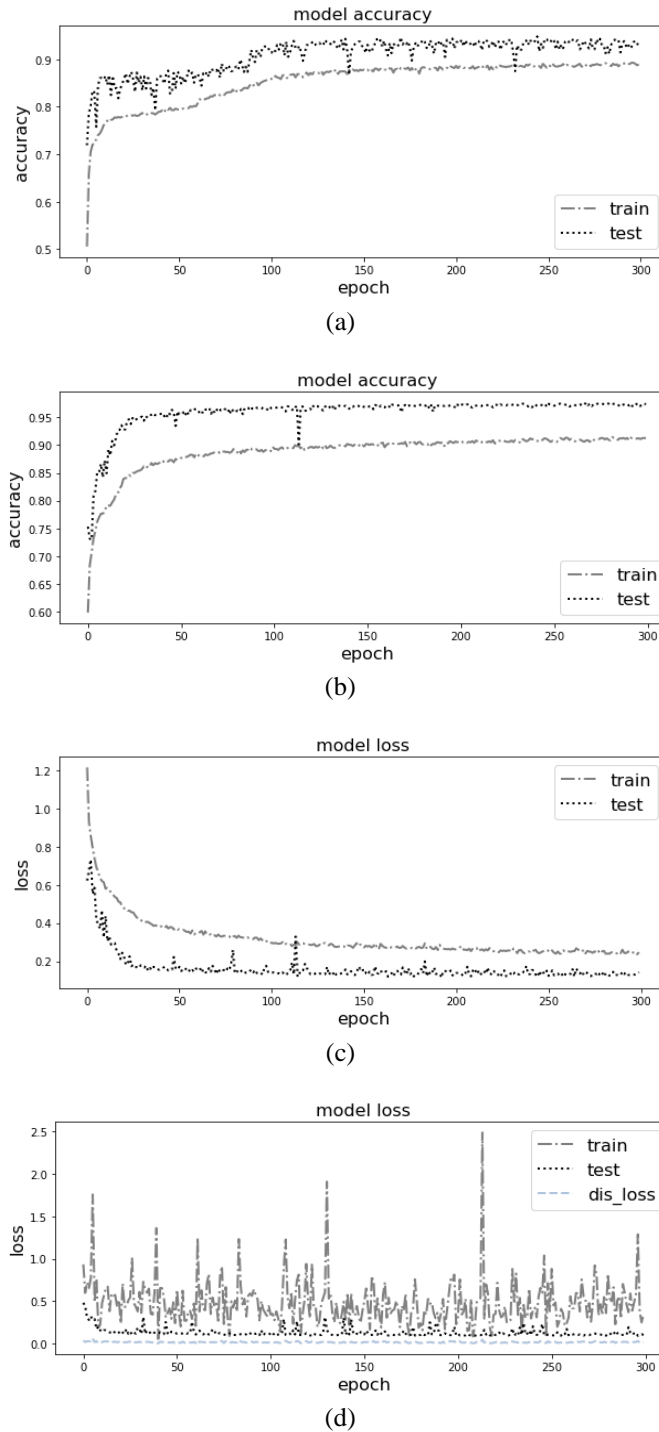


Figure 3. Learning curves during the training by the JL algorithm, (a) accuracy plot related to the donor's network, (b) accuracy plot related to the acceptor's network, (c) loss plot related to the donor's network, and (d) loss plot related to the acceptor's network

Table 3. Comparison of the proposed method with previous studies

Accuracy	Methods
94.79%	CNN [1]
95.75%	CNN+Handcrafted features [2]
95.85%	LSTM+CNN [3]
98.14%	ConvAE_LSTM [20]
96.90% ± 0.53%	CNN_Donor
94% ± 0.2%	CNN_Acceptor
95% ± 0.62%	JL_Acceptor

#### 4. CONCLUSION

This study proposes a solution to the problem of deploying deep learning models that can solve complex problems on smartphones by using a more complex donor model and a less complex acceptor model that are based on the CNN. The performance of the proposed method is tested using a dataset on human activities. By training on 6 different human activities, the donor model extracts the important and complex features of the data and achieves a good prediction with an accuracy of 97.40%. According to the experimental results, the proposed donor model achieves higher accuracy compared to the other methods. Furthermore, this model reaches an accuracy of 95.62% by transferring knowledge from the donor model to the acceptor model. The proposed method allows the use of a CNN-based model with less computational complexity and a high accuracy on mobile devices. One of our main ideas to improve the proposed method in the future is to use a meta-learning approach.

#### REFERENCES




- [1] M. Sepahvand and F. Abdali-Mohammadi, "A novel representation in genetic programming for ensemble classification of human motions based on inertial signals," *Expert Systems with Applications*, vol. 185, p. 115624, 2021, doi: 10.1016/j.eswa.2021.115624.
- [2] M. Jaber and R. Ravanmehr, "Human activity recognition via wearable devices using enhanced ternary weight convolutional neural network," *Pervasive and Mobile Computing*, vol. 83, p. 101620, 2022, doi: 10.1016/j.pmcj.2022.101620.
- [3] Y. L. Hsu, H. C. Chang, and Y. J. Chiu, "Wearable sport activity classification based on deep convolutional neural network," *IEEE Access*, vol. 7, pp. 170199–170212, 2019, doi: 10.1109/ACCESS.2019.2955545.
- [4] I. A. Lawal and S. Bano, "Deep human activity recognition with localisation of wearable sensors," *IEEE Access*, vol. 8, pp. 155060–155070, 2020, doi: 10.1109/ACCESS.2020.3017681.
- [5] L. Wang, Y. Zhou, R. Li, and L. Ding, "A fusion of a deep neural network and a hidden Markov model to recognize the multiclass abnormal behavior of elderly people," *Knowledge-Based Systems*, vol. 252, p. 109351, 2022, doi: 10.1016/j.knosys.2022.109351.
- [6] J. Tian, "Adversarial vulnerability of deep neural network-based gait event detection: a comparative study using accelerometer-based data," *Biomedical Signal Processing and Control*, vol. 73, 2022, doi: 10.1016/j.bspc.2021.103429.
- [7] W. Qi, H. Su, and A. Aliverti, "A smartphone-based adaptive recognition and real-time monitoring system for human activities," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 5, pp. 414–423, 2020, doi: 10.1109/THMS.2020.2984181.
- [8] M. Sepahvand and F. Abdali-Mohammadi, "A novel method for reducing arrhythmia classification from 12-lead ECG signals to single-lead ECG with minimal loss of accuracy through teacher-student knowledge distillation," *Information Sciences*, vol. 593, pp. 64–77, 2022, doi: 10.1016/j.ins.2022.01.030.
- [9] M. Sepahvand and F. Abdali-Mohammadi, "Overcoming limitation of dissociation between MD and MI classifications of breast cancer histopathological images through a novel decomposed feature-based knowledge distillation method," *Computers in Biology and Medicine*, vol. 145, p. 105413, 2022, doi: 10.1016/j.combiomed.2022.105413.
- [10] M. Sepahvand, F. Abdali-Mohammadi, and A. Taherkordi, "Teacher-student knowledge distillation based on decomposed deep feature representation for intelligent mobile applications," *Expert Systems with Applications*, vol. 202, p. 117474, 2022, doi: 10.1016/j.eswa.2022.117474.
- [11] C. T. Yen, J. X. Liao, and Y. K. Huang, "Human daily activity recognition performed using wearable inertial sensors combined with deep learning algorithms," *IEEE Access*, vol. 8, pp. 174105–174114, 2020, doi: 10.1109/ACCESS.2020.3025938.
- [12] Z. Xu, J. Zhao, Y. Yu, and H. Zeng, "Improved 1D-CNNs for behavior recognition using wearable sensor network," *Computer Communications*, vol. 151, pp. 165–171, 2020, doi: 10.1016/j.comcom.2020.01.012.
- [13] M. Shang, Y. Zhang, A. Y. Ali Amer, I. D'Haeseleer, and B. Vanrumste, "Bathroom activities monitoring for older adults by a wrist-mounted accelerometer using a hybrid deep learning model," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2021, pp. 7112–7115, doi: 10.1109/EMBC46164.2021.9630659.
- [14] J. A. Santoyo-Ramón, E. Casilari, and J. M. Cano-García, "A study of the influence of the sensor sampling frequency on the performance of wearable fall detectors," *Measurement: Journal of the International Measurement Confederation*, vol. 193, p. 110945, 2022, doi: 10.1016/j.measurement.2022.110945.
- [15] A. Ignatov, "Real-time human activity recognition from accelerometer data using convolutional neural networks," *Applied Soft Computing Journal*, vol. 62, pp. 915–922, 2018, doi: 10.1016/j.asoc.2017.09.027.
- [16] M. A. Khatun *et al.*, "Deep CNN-LSTM with self-attention model for human activity recognition using wearable sensor," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 10, 2022, doi: 10.1109/JTEHM.2022.3177710.
- [17] M. K. Serrão, G. de A. e Aquino, M. G. F. Costa, and C. F. F. Costa Filho, "Human activity recognition from accelerometer with convolutional and recurrent neural networks," *Polytechnica*, vol. 4, no. 1, pp. 15–25, 2021, doi: 10.1007/s41050-021-00028-8.
- [18] S. Gupta, "Deep learning based human activity recognition (HAR) using wearable sensor data," *International Journal of Information Management Data Insights*, vol. 1, no. 2, p. 100046, 2021, doi: 10.1016/j.ijime.2021.100046.
- [19] S. Raziani and M. Azimbagirad, "Deep CNN hyperparameter optimization algorithms for sensor-based human activity recognition," *Neuroscience Informatics*, vol. 2, no. 3, p. 100078, 2022, doi: 10.1016/j.neuri.2022.100078.
- [20] D. Thakur, S. Biswas, E. S. L. Ho, and S. Chattopadhyay, "ConvAE-LSTM: convolutional autoencoder long short-term memory network for smartphone-based human activity recognition," *IEEE Access*, vol. 10, pp. 4137–4156, 2022, doi: 10.1109/ACCESS.2022.3140373.
- [21] K. Muralidharan, A. Ramesh, G. Rithvik, S. Prem, A. A. Reghunaath, and M. P. Gopinath, "1D Convolution approach to human activity recognition using sensor data and comparison with machine learning algorithms," *International Journal of Cognitive Computing in Engineering*, vol. 2, pp. 130–143, 2021, doi: 10.1016/j.ijcce.2021.09.001.
- [22] M. Gil-Martín, R. San-Segundo, F. Fernández-Martínez, and J. Ferreiros-López, "Improving physical activity recognition using a new deep learning architecture and post-processing techniques," *Engineering Applications of Artificial Intelligence*, vol. 92, p. 103679, 2020, doi: 10.1016/j.engappai.2020.103679.
- [23] P. Y. Han, S. A. Perempuan Raja Sekaran, O. S. Yin, and T. T. Guang, "Principal coefficient encoding for subject-independent human activity analysis," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 4, pp. 4391–4399, 2022, doi: 10.11591/ijece.v12i4.pp4391-4399.
- [24] I. Made Agus Wirawan, R. Wardoyo, and D. Lelono, "The challenges of emotion recognition methods based on






- electroencephalogram signals: a literature review,” *International Journal of Electrical and Computer Engineering*, vol. 12, no. 2, pp. 1508–1519, 2022, doi: 10.11591/ijece.v12i2.pp1508-1519.
- [25] D. T. Phuc, T. Q. Trieu, N. Van Tinh, and D. S. Hieu, “Video captioning in Vietnamese using deep learning,” *International Journal of Electrical and Computer Engineering*, vol. 12, no. 3, pp. 3092–3103, 2022, doi: 10.11591/ijece.v12i3.pp3092-3103.
- [26] C. A. Ronao and S. B. Cho, “Human activity recognition with smartphone sensors using deep learning neural networks,” *Expert Systems with Applications*, vol. 59, pp. 235–244, 2016, doi: 10.1016/j.eswa.2016.04.032.
- [27] K. Xia, J. Huang, and H. Wang, “LSTM-CNN architecture for human activity recognition,” *IEEE Access*, vol. 8, pp. 56855–56866, 2020, doi: 10.1109/ACCESS.2020.2982225.

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