RESEARCH ARTICLE

Stacked deep analytic model for human activity recognition on a UCI HAR database [version 1; peer review: 2 approved with reservations]

Ying Han Pang¹, Liew Yee Ping¹, Goh Fan Ling², Ooi Shih Yin¹, Khoh Wee How¹

¹Faculty of Information Science and Technology, Multimedia University, Ayer Keroh, Melaka, 75450, Malaysia

²Millapp Sdn Bhd, Bangsar South, Kuala Lumpur, 59200, Malaysia

V1 First published: 15 Oct 2021, 10:1046
<https://doi.org/10.12688/f1000research.73174.1>
 Second version: 18 Feb 2022, 10:1046
<https://doi.org/10.12688/f1000research.73174.2>
 Latest published: 01 Apr 2022, 10:1046
<https://doi.org/10.12688/f1000research.73174.3>

Abstract

Background

Owing to low cost and ubiquity, human activity recognition using smartphones is emerging as a trendy mobile application in diverse appliances such as assisted living, healthcare monitoring, etc. Analysing this one-dimensional time-series signal is rather challenging due to its spatial and temporal variances. Numerous deep neural networks (DNNs) are conducted to unveil deep features of complex real-world data. However, the drawback of DNNs is the un-interpretation of the network's internal logic to achieve the output. Furthermore, a huge training sample size (i.e. millions of samples) is required to ensure great performance.

Methods

In this work, a simpler yet effective stacked deep network, known as Stacked Discriminant Feature Learning (SDFL), is proposed to analyse inertial motion data for activity recognition. Contrary to DNNs, this deep model extracts rich features without the prerequisite of a gigantic training sample set and tenuous hyper-parameter tuning. SDFL is a stacking deep network with multiple learning modules, appearing in a serialized layout for multi-level feature learning from shallow to deeper features. In each learning module, Rayleigh coefficient optimized learning is accomplished to extort discriminant features. A subject-independent protocol is implemented where the system model (trained by data from a group of users) is used to recognize data from another group of users.

Results

Empirical results demonstrate that SDFL surpasses state-of-the-art methods, including DNNs like Convolutional Neural Network, Deep Belief Network, etc., with ~97% accuracy from the UCI HAR database

Open Peer Review

Approval Status

	1	2
version 3 (revision) 01 Apr 2022		
version 2 (revision) 18 Feb 2022	view	view

version 1 15 Oct 2021	view	view

1. **Cheng-Yaw Low** , Yonsei University,
Seoul, South Korea

Institute for Basic Science, Daejeon, South
Korea

2. **Andrews Samraj** , Mahendra Engineering
College, Namakkal, India

Any reports and responses or comments on the article can be found at the end of the article.

with thousands of training samples. Additionally, the model training time of SDFL is merely a few minutes, compared with DNNs, which require hours for model training.

Conclusions

The supremacy of SDFL is corroborated in analysing motion data for human activity recognition requiring no GPU but only a CPU with a fast-learning rate.

Keywords

smartphone, one-dimensional motion signal, activity recognition, stacking deep network, discriminant learning

Corresponding author: Ying Han Pang (yhpang@mmu.edu.my)

Author roles: **Pang YH:** Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Methodology, Writing – Original Draft Preparation; **Ping LY:** Formal Analysis, Validation; **Ling GF:** Formal Analysis, Software, Validation; **Yin OS:** Formal Analysis, Methodology, Writing – Review & Editing; **How KW:** Investigation, Methodology, Validation

Competing interests: No competing interests were disclosed.

Grant information: This study was funded by the Fundamental Research Grant Scheme (FRGS) from the Ministry of Education Malaysia – FRGS/1/2020/ICT02/MMU/02/7. The funder had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Copyright: © 2021 Pang YH *et al.* This is an open access article distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

How to cite this article: Pang YH, Ping LY, Ling GF *et al.* **Stacked deep analytic model for human activity recognition on a UCI HAR database [version 1; peer review: 2 approved with reservations]** F1000Research 2021, **10**:1046 <https://doi.org/10.12688/f1000research.73174.1>

First published: 15 Oct 2021, **10**:1046 <https://doi.org/10.12688/f1000research.73174.1>

Introduction

Human activity recognition (HAR) can be categorized into vision-based and sensor-based. In vision-based HAR, an image sequence, in the form of video, recording the human activity is captured by a camera.¹ This sequence will be analysed to recognize the nature of an action. This system is applied for surveillance, human-computer interaction and healthcare monitoring. For sensor-based HAR, human activities are captured by inertial sensors, such as accelerometers, gyroscopes or magnetometers. Among these approaches, sensors are more favourable due to their lightweight nature, portability and low energy usage.² With the advancement of mobile technology, smartphones are equipped with high-end components. Accelerometer and gyroscope sensors embedded in the smartphone make it feasible as an acquisition device for HAR. Smartphone-based HAR has been an area of contemporary research in recent years.^{3–9} In this work, we categorize the smartphone-based HAR as part of the sensor-based HAR. Activity inertial signals are collected through smartphone sensors.

Related work

Hand-crafted approaches using manually computed statistical features have been proposed.^{10–12} These authors applied various machine learning techniques such as decision tree, logistic regression, multilayer perceptron, naïve Bayes, Support Vector Machine etc. to classify the detected activities. The performance of the handcrafted approaches might be affected when dealing with complex scenarios due to their feature representation incapability. The algorithms could easily plummet into the local minimum despite the global optimal.

Hence, various deep neural networks (DNNs) were explored in HAR owing to the capability of extracting informative features. DNN is a machine learner that can automatically unearth the data characteristics hierarchically from lower to higher levels.¹³ The work of Ronao and Cho (2016),¹⁴ Lee *et al.* (2017)¹⁵ and Ignatov (2018)¹⁶ explored the deep convolutional neural networks by exploiting the activity characteristics in the one-dimensional time-series signals captured by the smartphone inertial sensors. The empirical results substantiated that the extracted deep features were crucial for data representation with promising recognition performance.

Zeng *et al.* (2014) proposed a modified convolutional neural network to extract scale-invariant characteristics and local dependency of the acceleration time-series signal.¹⁷ The weight sharing mechanism in the convolutional layer was modified. Unlike in the vanilla model where the local filter weights were shared by all positions within the input space, the authors incorporated a more relax weight sharing strategy (partial weight sharing) to enhance the performance.

Recurrent Neural Network (RNN) was proposed to process sequential data by analysing previously inputted data and processing it linearly. Due to the vanishing gradient problem, RNN was enhanced and Long Short-Term Memory – LSTM was introduced. Chen *et al.* (2016) explored the feasibility of LSTM in predicting human activities.¹⁸ Empirical results demonstrated an encouraging performance of LSTM in HAR. Further, an enhanced version of LSTM, known as bidirectional LSTM, was proposed.¹⁹ Unlike LSTM, bidirectional LSTM tackles both past and future information during the feature analysis. With this, a richer description of features could be extracted for classification.

A cascade ensemble learning (CELearning) model was proposed for smartphone-based HAR.²⁰ There are multiple layers in this aggregation network and the model goes deeper layer by layer. Each layer contains Extremely Gradient Boosting Trees, Random Forest, Extremely Randomized Trees and Softmax Regression. The CELearning model gains higher performance, and the training process is rather simple and efficient. Besides, Hierarchical Multi-View Aggregation Network (HMFAN) is also one of the aggregation models.²¹ This model integrates features from various feature spaces in a hierarchical context. In this network, three aggregation modules from the aspect of feature, position and modality levels are designed.

Motivation and contributions

In DNNs, there are learning modular components in multiple processing layers for multiple-level feature abstraction. These layers are trained based on a versatile learning principle, which does not require any manual design by experts.²² These DNNs accomplish excellent performances in pattern recognition. However, these networks are not well trained if they have limited training samples, leading to performance degradation. Furthermore, there is a lack of theoretical ground on how to fine-tune the gigantic hyper-parameter series.²¹ The outstanding accomplishment of DNNs can only be achieved if and only if sufficient training data is accessible for fine-tuning the large parameter set. A high specification of GPU is needed to train the network from gargantuan datasets.

Thus, a stacking-based deep learning model for smartphone-based HAR is proposed. Inspired by the hierarchical learning in the DNNs, the proposed stacked learning network is aggregated with multiple learning modules, one after another, in a hierarchical framework. Specifically, a discriminant learning function is implemented in each module for discriminant

mapping to generate discriminative features, level by level. The lower (generic) to higher level (deeper) features are input to a classifier for activity identification. This proposed approach is termed Stacked Discriminant Feature Learning, coined as SDFL.

The contributions of this work are summarized in three-fold:

1. A deep analytic model is proposed for smartphone based HAR to extract deep features without the need of a gigantic training set and tenuous hyper-parameter tuning.
2. An adaptable modular model is developed with a discriminant learning function in each module to extract discriminant features from lower to higher levels demanding no graphics processing unit (GPU) but only a central processing unit (CPU) with a fast-learning rate.
3. An experimental analysis using various performance evaluation metrics (i.e. recall, precision, the area under the curve, computational time, etc.) with subject-independent protocol implementation in which there is no overlap in subjects between training and testing sets.

Methods

Smartphone inertial sensors were used to capture 3-axial linear (total) acceleration and 3-axial angular velocity signals. These signals were pre-processed into time- and frequency-domain features, as listed in [Table 1](#). Next, the pre-processed data was inputted into the Stacked Discriminant Feature Learning (SDFL) for feature learning. The extracted feature template was fed into the nearest-neighbour (NN) classifier for classification. The overview of the system is illustrated in [Figure 1](#).

Table 1. Pre-processed features as input data into the Stacked Discriminant Feature Learning (SDFL) system.

Function	Feature
Mean	Average value
Std dev	Standard deviation
Median	Median absolute value
Max	Largest value in array
Min	Smallest value in array
Sma	Signal magnitude area
Energy	Average sum of squares
Iqr	Interquartile range
Entropy	Signal entropy
ArCoeff	Auto-regression coefficients
Correlation	Correlation coefficient
MaxFreqInd	Largest frequency component
MeanFreq	Frequency signal weighted average
Skewness	Frequency signal skewness
Kurtosis	Frequency signal kurtosis
EnergyBand	Energy of a frequency interval
Angle	Angle between two vectors

Figure 1. Overview of the proposed Stacked Discriminant Feature Learning (SDFL) system.

Figure 2. Stacked Discriminant Feature Learning (SDFL) framework.

SDFL is a pile of multiple discriminant learning layers interleaved with a nonlinear activation unit, as illustrated in Figure 2. By cascading multiple discriminant learning modules, each layer of SDFL learns based on the input data and the learned nonlinear features of the preceding module. The depth of the stacking layer is determined using the database subset. If the performance is not improving but showing degradation, the depth of the stacking layer is determined. In this case, the depth of three showed the optimal performance, so we adopted this architecture with three layers. To be detailed, the first discriminant learning module learns based on the input data and the second learning module learns based on an input vector (concatenating the input data and the learned features of the first learning module). This is similar to the third learning process where the third learning module learns based on an input vector (comprising the input data and the learned features of the second learning module).

Let $\{(x_i, y_i)\}_{i=1}^N$ be a set of N transformed data, y_i is the class label of x_i , C is the number of training classes, each of C classes has a mean μ_j and total mean vector $\mu = \frac{1}{N} \sum_{i=1}^N m_j \mu_j$ with m_j denotes the number of training samples for j th class. In the first learning layer, the input vector is the transformed data x_i . The computation of the intrapersonal scatter matrix Σ_{intra} and interpersonal scatter matrix Σ_{inter} are defined as:

$$\Sigma_{intra} = \sum_{j=1}^C \sum_{x_i \in C_j} (x_i - \mu_j)(x_i - \mu_j)^T \quad (1)$$

$$\Sigma_{inter} = \sum_{j=1}^C \mu_j (\mu_j - \mu)(\mu_j - \mu)^T \quad (2)$$

where T denotes a transpose operation. Next, a linear transformation Φ is computed by maximizing the *Rayleigh coefficient*. With this optimization, the data from the same person could be projected close to each other, while data from different people is projected as far apart as possible. This optimization function is termed as Fisher's criterion,²³

$$\mathcal{J}(\Phi) = \frac{|\Phi^T \Sigma_{inter} \Phi|}{|\Phi^T \Sigma_{intra} \Phi|} \quad (3)$$

The mapping Φ is constructed through solving the generalized eigenvalue problem,

$$\Sigma_{inter} \Phi = \lambda \Sigma_{intra} \Phi \quad (4)$$

The learned features are produced through the projection of the input data x_i onto the mapping subspace,

$$\hat{x}_i = \Phi^T x_i \quad (5)$$

$\hat{\mathbf{x}}$ is transformed to $C - 1$ dimensions. We denote l for the index of modular layer in SDFL. The learned feature vector of the first modular unit is notated as $\hat{\mathbf{x}}_i^{(l=1)} = \hat{\mathbf{x}}_i^{(1)}$. A nonlinear input-output mapping is applied to $\hat{\mathbf{x}}_i^{(1)}$ via a nonlinear activation function. In this study, we adopt a sigmoid function, $\tilde{\mathbf{x}}_i = S(\hat{\mathbf{x}}_i) = \frac{1}{1+e^{-\hat{\mathbf{x}}_i}}$ for the nonlinear projection. To be specific, $\tilde{\mathbf{x}}_i^{(1)} = \frac{1}{1+e^{-\hat{\mathbf{x}}_i^{(1)}}}$ is the nonlinear learned features of the first modular unit.

For deeper modules, the input vector of the respective module is a stacking vector containing the input data and the learned features, i.e. $\mathbf{z}_i^{(l)} = [\mathbf{x}_i, \tilde{\mathbf{x}}_i^{(l-1)}]$ where $l = 2$ and 3 . The intrapersonal scatter matrix $\Sigma_{intra}^{(l)}$ and interpersonal scatter matrix $\Sigma_{inter}^{(l)}$ are formulated,

$$\Sigma_{intra}^{(l)} = \sum_{j=1}^C \sum_{\mathbf{z}_i^{(l)} \in C_j} (\mathbf{z}_i^{(l)} - \boldsymbol{\mu}_j^{(l)}) (\mathbf{z}_i^{(l)} - \boldsymbol{\mu}_j^{(l)})^T \quad (6)$$

$$\Sigma_{inter}^{(l)} = \sum_{j=1}^C \boldsymbol{\mu}_j^{(l)} (\boldsymbol{\mu}_j^{(l)} - \boldsymbol{\mu}^{(l)}) (\boldsymbol{\mu}_j^{(l)} - \boldsymbol{\mu}^{(l)})^T \quad (7)$$

In this case, $\boldsymbol{\mu}_j^{(l)}$ is the j th class mean computed from the input vectors of j th class, $\mathbf{z}_i^{(l)} \in C_j$ and the total mean vector $\boldsymbol{\mu}^{(l)} = \frac{1}{N} \sum_{i=1}^N m_j \boldsymbol{\mu}_j^{(l)}$ at l th modular unit. The final feature vector is the nonlinear learned features of each modular layer,

$$\tilde{\mathbf{x}}_i^{final} = [\tilde{\mathbf{x}}_i^{(1)}, \tilde{\mathbf{x}}_i^{(2)}, \tilde{\mathbf{x}}_i^{(3)}] \quad (8)$$

Results

We scrutinized how well SDFL could analyse the inertial data and correctly classify those activities. The experimental hardware platform was constructed on a desktop with an Intel® Core™ i7-7700 processor with 4.20 GHz and 48.0 GB main memory; whereas the experimental software platform was a 64-bit operating system of Windows 10 with **Matlab R2018a** (MATLAB, RRID:SCR_001622) software (An open-access alternative that provides an equivalent function is **GNU Octave** (GNU Octave, RRID:SCR_014398)).

We used the **UCI HAR** dataset¹²: There were 30 subjects with 7352 training samples and 2947 testing samples. Each subject was required to carry a smartphone (Samsung Galaxy SII) on the waist and perform six different activities. The activities were “walking”, “walking_upstairs”, “walking_downstairs”, “sitting”, “standing” and “laying”.

The generalization level of SDFL was evaluated in a user-independent scenario. SDFL was trained using training samples from a group of users. Then, the model was applied to new users without the necessity of collecting additional samples of these new users to retrain the model. In this experiment, the UCI HAR dataset was partitioned into two sets: 70% of the volunteers were selected to generate the training data and the remaining 30% of the volunteers' data was used as the testing data. There was no subject overlapping between the training and test data sets. **Table 2** records the performance of SDFL and **Table 3** records the performance comparison with other approaches.

Table 4 tabulates the computational time. The computational time of SDFL is benchmarked with that of the ordinary methodology, which is directly performing classification on the pre-processed data. Instead of using a multiclass support

Table 2. Performance of Stacked Discriminant Feature Learning (SDFL).

Metric	Performance
True Positive (TP) rate	0.963
False Positive (FP) rate	0.008
Precision	0.964
Recall	0.963
F-score	0.963
Area Under the Curve	0.977
Accuracy (%)	96.2674

Table 3. Performance comparison of Stacked Discriminant Feature Learning (SDFL) with alternative approaches.

Method	Accuracy (%)
Dynamic Time Warping ²⁴	89.00
Hierarchical Continuous Hidden Markov Model ²⁵	93.18
Deep Belief Network (as reported in ⁴)	95.80
Group-based Context-aware method for human activity recognition (GCHAR) ³	94.16
Handcrafted Cascade Ensemble Learning model (CELearning) ²⁰	96.88
Automated Cascade Ensemble Learning model (CELearning) ²⁰	95.93
Convolutional Neural Network (CNN) ¹⁴	95.75
Artificial Neural Network (ANN) (as reported in ¹⁴)	91.08
Stacked Discriminant Feature Learning (SDFL)	96.27

Table 4. Computational time of Stacked Discriminant Feature Learning (SDFL) compared with directly performing classification on the pre-processed data. Classifier = Nearest Neighbour (NN) classifier.

System phase		Computational time (s)	
		Pre-processed data + classifier	SDFL + classifier
Training (7352 instances)	Model training	-	0.468258
	Classification	53.7	2.67
	Total training	53.7	3.138258
Testing (2947 instances)	Data learning	-	0.017416
	Classification	40.42	1.22
	Total testing	40.42	1.237416

vector machine as in,¹² we adopt Nearest Neighbour (NN) classifier for classification because the focus of this work is the feature extraction capability and the classification is standardized with the simplest classifier, i.e. NN.

Discussion

From the empirical results, we observed that the proposed SDFL was able to demonstrate superior classification performance compared to most of the existing techniques, even though a simple classifier was adopted in the system. The exceptional performance of SDFL explains the capability of SDFL in capturing the essence of the inertial data without heavily depending on the classifier. Furthermore, SDFL also exhibited its superiority to most of the existing approaches, including deep learning models. To be specific, SDFL obtained an accuracy of 96.3%, whilst Deep Belief Network's accuracy was 95.8%,⁴ CNN achieved 95.75% accuracy¹⁴ and ANN's accuracy was 91.08%.

Last but not least, it was discerned that the performance of SDFL is on a par with the Cascade Ensemble Learning model (CELearning).²⁰ Both approaches are ensemble learning methods with multiple layers for data learning. The key difference between these approaches is the analysis algorithms in each layer. CEEarning is comprised of four different classifiers, i.e. Random Forest, Extremely Gradient Boosting Trees, Softmax Regression and Extremely Randomized Trees and the final classification result is obtained through the last layer via the score-level fusion of the four complex classifiers. On the other hand, in SDFL, merely Rayleigh coefficient optimization is implemented to extract the low-to-higher level of discriminant features. Further, a simple classifier, i.e. NN classifier, is adopted in SDFL. This deduces that the discrimination capability of SDFL primarily depends on the SDFL modular model to extract discriminant features demanding no complex classifier.

From Table 4, we can notice that the overall training and testing time of SDFL are much lesser than those of the benchmark method. On average, SDFL just needs $\sim 4.3 \times 10^{-4}$ seconds per sample (sps) for the training phase and $\sim 4.2 \times 10^{-4}$ sps for the testing phase. The fast feature learning of SDFL and the dimensionality reduction in SDFL to project the data onto a lower-dimensional subspace are the main reasons for having such an efficient computation.

Conclusions

A cascading learning network for human activity recognition using smartphones is proposed. In this network, a chain of independent discriminant learning modules is aggregated, layer by layer in a stackable framework. Each layer is constituted by a discriminant analysis function and a nonlinear activation function to effectively extract the rich features from the inertial data. This proposed SDFL network possesses characteristics of good performance even on small-scale training sample sets, as well as less hyper-parameter fine-tuning, and fast computation compared with the other deep learning networks. Despite showing computational efficiency, the proposed network also demonstrated its classification superiority to most of the state-of-the-art approaches with an accuracy score of ~97% in differentiating human activity classes.

Data availability

All data underlying the results are available as part of the article and no additional source data are required.

References

1. Poppe R: **A survey on vision-based human action recognition.** *Image Vis. Comput.* 2010; **28**(6): 976–990.
[Publisher Full Text](#)
2. Ahmed N, Rafiq JI, Islam MR: **Enhanced Human Activity Recognition Based on Smartphone Sensor Data Using Hybrid Feature Selection Model.** *Sensors.* Jan. 2020; **20**(1): 317.
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
3. Cao L, Wang Y, Zhang B, et al.: **GCHAR: An efficient Group-based Context—aware human activity recognition on smartphone.** *J. Parallel Distrib. Comput.* Aug. 2018; **118**: 67–80.
[Publisher Full Text](#)
4. Li H, Trocan M: **Deep learning of smartphone sensor data for personal health assistance.** *Microelectronics J.* Jun. 2019; **88**: 164–172.
[Publisher Full Text](#)
5. Hernández F, Suárez LF, Villamizar J, et al.: **Human Activity Recognition on Smartphones Using a Bidirectional LSTM Network.** 2019 22nd Symp. Image, Signal Process. Artif. Vision, STSIVA 2019 - Conf. Proc. 2019: 1–5.
[Publisher Full Text](#)
6. Yang Z, Raymond OI, Zhang C, et al.: **DFTerNet: Towards 2-bit Dynamic Fusion Networks for Accurate Human Activity Recognition.** *IEEE Access.* Jul. 2018; **6**: 56750–56764.
[Publisher Full Text](#)
7. Yang J, MN N, PP S, et al.: **Deep Convolutional Neural Networks on Multichannel Time Series for Human Activity Recognition.** *IJCAI.* 2015.
8. Sun J, Fu Y, Li S, et al.: **Sequential Human Activity Recognition Based on Deep Convolutional Network and Extreme Learning Machine Using Wearable Sensors.** *J. Sensors.* 2018; **2018**: 8580959.
[Publisher Full Text](#)
9. Nweke HF, Teh YW, Al-garadi MA, et al.: **Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges.** *Expert Systems with Applications.* Elsevier Ltd; Sep. 01, 2018; vol. **105**. pp. 233–261.
[Publisher Full Text](#)
10. Kwapisz JR, Weiss GM, Moore SA: **Activity recognition using cell phone accelerometers.** *ACM SIGKDD Explor. Newsl.* 2011; **12**(2): 74–82.
[Publisher Full Text](#)
11. Wu W, Dasgupta S, Ramirez EE, et al.: **Classification accuracies of physical activities using smartphone motion sensors.** *J. Med. Internet Res.* Sep. 2012; **14**(5): e130.
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
12. Anguita D, Ghio A, Oneto L, et al.: **A public domain dataset for human activity recognition using smartphones.** 2013.
[Publisher Full Text](#)
13. Temitope Yekeen S, Balogun AL, Wan Yusof KB: **A novel deep learning instance segmentation model for automated marine oil spill detection.** *ISPRS J. Photogramm. Remote Sens.* Sep. 2020; **167**: 190–200.
[Publisher Full Text](#)
14. Ronao CA, Cho SB: **Human activity recognition with smartphone sensors using deep learning neural networks.** *Expert Syst. Appl.* 2016; **59**: 235–244.
[Publisher Full Text](#)
15. Lee SM, S M, Cho H, et al.: **Human Activity Recognition From Accelerometer Data Using Convolutional Neural Network.** *IEEE Int. Conf. Big Data Smart Comput. (BigComp).* 2017; vol. **62**. pp. 131–134.
[Publisher Full Text](#)
16. Ignatov A: **Real-time human activity recognition from accelerometer data using Convolutional Neural Networks.** *Appl. Soft Comput. J.* 2018; **62**: 915–922.
[Publisher Full Text](#)
17. Zeng M, et al.: **Convolutional Neural Networks for human activity recognition using mobile sensors Article.** 2014: 381–388.
[Publisher Full Text](#)
18. Chen Y, Zhong K, Zhang J, et al.: **LSTM Networks for Mobile Human Activity Recognition.** *no. Icaita.* 2016; pp. 50–53.
[Publisher Full Text](#)
19. Yu S, Qin L: **Human activity recognition with smartphone inertial sensors using bidir-LSTM networks.** *Proc. - 2018 3rd Int. Conf. Mech. Control Comput. Eng. ICMCCE 2018.* 2018: 219–224.
[Publisher Full Text](#)
20. Xu S, Tang Q, Jin L, et al.: **A cascade ensemble learning model for human activity recognition with smartphones.** *Sensors (Switzerland).* May 2019; **19**(10).
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
21. Zhang X, Wong Y, Kankanhalli MS, et al.: **Hierarchical multi-view aggregation network for sensor-based human activity recognition.** *PLoS One.* 2019; **14**(9): e0221390.
[PubMed Abstract](#) | [Publisher Full Text](#) | [Free Full Text](#)
22. Lecun Y, Bengio Y, Hinton G: **Deep learning.** *Nature.* 2015; **521**: 436–444.
23. Fukunaga K: *Introduction to Statistical Pattern Recognition.* Elsevier; 1990.
24. Seto S, Zhang W, Zhou Y: **Multivariate time series classification using dynamic time warping template selection for human activity recognition.** *Proc. - 2015 IEEE Symposium Series on Computational Intelligence, SSCI 2015.* 2015: 1399–1406.
[Publisher Full Text](#)
25. Ronao CA, Cho SB: **Recognizing human activities from smartphone sensors using hierarchical continuous hidden Markov models.** *Int. J. Distrib. Sens. Networks.* 2017; **13**(1).
[Publisher Full Text](#)

Open Peer Review

Current Peer Review Status: ? ?

Version 1

Reviewer Report 30 November 2021

<https://doi.org/10.5256/f1000research.76806.r99185>

© 2021 Samraj A. This is an open access peer review report distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Andrews Samraj

Department of Computer Science and Engineering, Mahendra Engineering College, Namakkal, Tamil Nadu, India

1. The motivation and contributions may be rewritten to make it simpler to understand the purpose and achievements of the work (purpose of deep features have to be mentioned).
2. Any chances of an Intra personal scatter matrix with any other inter personal scattermatrix? How was the threshold or borderline decided? There needs to be explanations with sample values.
3. The used hardware and software details, and details about dataset should be shifted from result to any other section in methodology.
4. Slight corrections on technical writings need to be carried out. (eg: Table 4 tabulates: can be changed as either: Table4 presents or it is tabulated in table 4)
5. A sample subject wise (Personnel) data table would be nice if presented to know the inter personnel differences.

Is the work clearly and accurately presented and does it cite the current literature?

Yes

Is the study design appropriate and is the work technically sound?

Yes

Are sufficient details of methods and analysis provided to allow replication by others?

Partly

If applicable, is the statistical analysis and its interpretation appropriate?

I cannot comment. A qualified statistician is required.

Are all the source data underlying the results available to ensure full reproducibility?

Partly

Are the conclusions drawn adequately supported by the results?

Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: AI, Patterns, Bionics, ML and DEEP Learning, signals,sensors

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 15 Feb 2022

Ying Han Pang, Multimedia University, Ayer Keroh, Malaysia

First of all, we would like to express our heartiest thanks to the Editor-in-Chief and Reviewers who have provided us with many insightful comments and a chance to improve our works.

1. The motivation and contributions may be rewritten to make it simpler to understand the purpose and achievements of the work (purpose of deep features have to be mentioned).

Response: The motivation and contribution have been revised for better clarification.

2. Any chances of an Intra personal scatter matrix with any other inter personal scattermatrix? How was the threshold or borderline decided? There needs to be explanations with sample values.

Response: The Method section has been revised for better clarification. The optimal projection in SDFL is computed by optimizing the Rayleigh coefficient for modelling the difference between the classes of data through maximizing the ratio of the inter-personal scatter matrix and intra-personal scatter matrix. The variability between data is contained in a subspace spanned by the eigenvectors corresponding to the number of class -1 largest eigenvalues. Hence, the threshold is C-1 in this work.

3. The used hardware and software details, and details about dataset should be shifted from result to any other section in methodology.

Response: The amendment has been done and the details have been shifted to the Method section.

4. Slight corrections on technical writings need to be carried out. (eg: Table 4 tabulates: can be changed as either: Table4 presents or it is tabulated in table 4)

Response: The correction has been done.

5. A sample subject wise (Personnel) data table would be nice if presented to know the inter personnel differences.

Response: Figure 3 is added to illustrate the inter-personnel inertial signal differences of standing activity

Competing Interests: No competing interests were disclosed.

Reviewer Report 25 November 2021

<https://doi.org/10.5256/f1000research.76806.r97058>

© 2021 Low C. This is an open access peer review report distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Cheng-Yaw Low

¹ Yonsei University, Seoul, South Korea

² Institute for Basic Science, Daejeon, South Korea

This manuscript proposes a stacked deep analytic model, dubbed stacked discriminant feature learning (SDFL), for mobile-platform human activity recognition (HAR). Based on the reported experimental results, the layer-wise SDFL trained with small-scale training data outperforms the SOTAs, including the conventional (end-to-end-trained) deep neural networks.

My concerns are as follows:

1. Objective 2: The authors claim that SDFL learns low-level to higher-level feature representation. This hypothesis should be demonstrated, if possible. Otherwise, I think this objective should be revised accordingly.
2. Objective 3: The authors should elaborate the subject-independent protocol from the motivation section as a problem statement to be resolved. In addition to that, the advantages of the subject-independent protocol should also be revealed.
3. The methodology section is ambiguous.
 - a) For clarity, the data/feature dimensionalities for all mathematical equations should be indicated accordingly.
 - b) The SDFL hyper-parameters are unknown?
4. The experiment section may not be convincing as it is reliant on only a single dataset, and there is no comprehensive analysis conducted.

- a) For reproducibility, the parameter configurations should be disclosed.
- b) It would be better if an ablation study is presented, e.g., exploration of the number of SDFL layers, etc. (refer to [14¹]). Furthermore, the baseline performance, the accuracy for the preprocessed data prior to SDFL learning, is not presented.
- c) I suggest the authors include additional small-scale HAR datasets for more extensive experiments.
- d) I think cross-validation should also be performed.
- e) I suggest the authors double-check the results reported for precision, recall, f-score, and accuracy. It is rare that these varying matrices give the same value, approximately 96.3%. Alternatively, the confusion matrices for these evaluation matrices should be disclosed.
- f) In Table 4, I think the inference time should be computed for the SDFL and other conventional models, in place of the pre-processed data? Otherwise, this comparison may not be meaningful.
- g) In Table 3, the authors compare SDFL with [24], [25], [4], [3], etc., however, not all are reviewed in the related work section.

References

1. Ronao C, Cho S: Human activity recognition with smartphone sensors using deep learning neural networks. *Expert Systems with Applications*. 2016; **59**: 235-244 [Publisher Full Text](#)

Is the work clearly and accurately presented and does it cite the current literature?

Partly

Is the study design appropriate and is the work technically sound?

Partly

Are sufficient details of methods and analysis provided to allow replication by others?

Partly

If applicable, is the statistical analysis and its interpretation appropriate?

Partly

Are all the source data underlying the results available to ensure full reproducibility?

Partly

Are the conclusions drawn adequately supported by the results?

Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Stacked neural networks, deep neural networks

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 15 Feb 2022

Ying Han Pang, Multimedia University, Ayer Keroh, Malaysia

First of all, we would like to express our heartiest thanks to the Editor-in-Chief and Reviewers who have provided us with many insightful comments and a chance to improve our works.

1. Objective 2: The authors claim that SDFL learns low-level to higher-level feature representation. This hypothesis should be demonstrated, if possible. Otherwise, I think this objective should be revised accordingly.

Response: Thanks for the feedback. Authors have revised Objective 2 for better clarification.

2. Objective 3: The authors should elaborate the subject-independent protocol from the motivation section as a problem statement to be resolved. In addition to that, the advantages of the subject-independent protocol should also be revealed.

Response: Authors have included the preference of subject-independent solution in real-time applications in the Motivation section for better relating the motivation and the Objective 3.

3. a) For clarity, the data/feature dimensionalities for all mathematical equations should be indicated accordingly. b) The SDFL hyper-parameters are unknown?

Response: Authors have included dimensionalities of data/feature, number of training classes C and the generated final feature vector in the Methods section for better clarification. Parameters of SDFL are the number of stacking layers, nonlinear activation function, dimensions of intermediate feature vectors and dimensions of the final feature vector. The Method section has been revised to include the information of these parameters for better clarification.

4. a) For reproducibility, the parameter configurations should be disclosed. b) It would be better if an ablation study is presented, e.g., exploration of the number of SDFL layers, etc. (refer to [14¹]). Furthermore, the baseline performance, the accuracy for the preprocessed data prior to SDFL learning, is not presented. c) I suggest the authors include additional small-scale HAR datasets for more extensive experiments. d) I think cross-validation should also be performed. e) I suggest the authors double-check the results reported for precision, recall, f-score, and accuracy. It is rare that these varying matrices give the same value, approximately 96.3%. Alternatively, the confusion matrices for these evaluation matrices should be disclosed. (f) In Table 4, I think the inference time should be computed for the SDFL and other conventional

models, in place of the pre-processed data? Otherwise, this comparison may not be meaningful. (g) In Table 3, the authors compare SDFL with [24], [25], [4], [3], etc., however, not all are reviewed in the related work section.

Response: The information of these parameters has been included in the Methods section for better clarification. Table 3 has been revised to include the benchmark method, that is Multiclass Support Vector Machine, proposed by the original author of the UCI database. This baseline performance which is the accuracy of the preprocessed data with Support Vector Machine has been included in the table. In order to have a better performance comparison with the existing methods, the testing protocol of this study follows the train-test split protocol defined by the database provider, i.e. this database has a version that is already split into training and test sets that contain data from different participants. This paper is using this version of the database. The results have been double-checked and the confusion matrix of SDFL has been included. Table 4 has been revised by just presenting the computational time of SDFL. With this, readers can have a picture of the training and inference time of the proposed SDFL. The Related Work section has been revised to include the reference in Table 3.

Competing Interests: No competing interests were disclosed.

The benefits of publishing with F1000Research:

- Your article is published within days, with no editorial bias
- You can publish traditional articles, null/negative results, case reports, data notes and more
- The peer review process is transparent and collaborative
- Your article is indexed in PubMed after passing peer review
- Dedicated customer support at every stage

For pre-submission enquiries, contact research@f1000.com

F1000Research