ICIC Express Letters
Part B: Applications
Volume **14**, Number **6**, June **2023**

pp. **579–586**

PERFORMANCE ENHANCEMENT OF MULTIPLE SOURCES FOR ACTIVITY RECOGNITION USING DEEP NEURAL NETWORK RETRAINING

Sujittra Sarakon[1] and Kreangsak Tamee[1,2,*]

[1]Department of Computer Science and Information Technology
[2]Research Center for Academic Excellence in Nonlinear Analysis and Optimization
Faculty of Science
Naresuan University
Tha Pho Sub-District, Mueang Phitsanulok District, Phitsanulok 65000, Thailand
sujittras61@nu.ac.th; *Corresponding author: kreangsakt@nu.ac.th

Received November 2022; accepted February 2023

Abstract. *Deep learning enhances the ability of multiple machine learning to provide a more comprehensive insight into movements. This technique was designed to learn new patterns of data regarding previously trained models. Our researchers focused on an experimental design approach in which a retraining networking model effectiveness of the deep learning from multiple sources was practical. To recognize a deep neuron network, the model was reconstructed for each multiple sources. We used the varied 3-axis accelerometer sensor data to identify two states, Move and Still. The model tested the data using Wireless Sensor Data Mining (WISDM). The data was tested using Motion sensors; however, it was impractical when attempting to improve the performance. WISDM and Motion sensors were combined to form a trained model and then evaluated. These findings showed that this process was significantly higher at monitoring human movement than traditional machine learning.*
Keywords: Activity recognition, Retraining network, Accelerometer sensor, Machine learning

1. **Introduction.** Deep learning provides effective knowledge for the modern learning [1,2] and prediction, a process which involves pattern recognition. Pattern recognition provides a more precise investigation of deep learning, a multi-layer perceptron [3], is a mathematical process used to compute data patterns that makes it possible to predict future patterns from existing data. This approach provides the most accurate and efficient answers to shifting patterns of dissimilar data sources. LeCun and Bengio [4] developed a prototype model derived from several artificial neural networks, such as the convolutional neural networks and the recurrent neural networks. In many cases, the problem with research is that existing data may not be sufficient for comprehensive learning as new data emerges [5,6]. There are more missing values than in any other classes, i.e., noise and incomplete data fluctuate. The data used to learn the model may be inefficient for other models to coherently reformulating varied data, for the systems inhibit further development of the learning patterns [7]. The advantage of using multiple sources reinforces the model's ability to learn more features. Using knowledge transfer techniques to retrain a small part of the information allows the model to recognize new samples with the same attributes that can be combined with previously trained.

This research will focus on using human motion sensors from 3-axis of accelerometer sensors from two public datasets. To solve the problem of traditional machine learning, this study clearly demonstrates the ability of modern machine learning in the classification recognition task. The wearable devices have become the most used source of detecting

DOI: 10.24507/icicelb.14.06.579

human behaviors such as standing, walking, sitting, running, going up, ascending and descending stairs (an activity considered to be a basic human activities). The researchers designed an experiment to illustrate and resolve this issue using sensory data from two different sources in a human activity recognition task. To represent various sets of data with the same measurements, the proof of traditional and modern machine learning is illustrated in this work. Our research provides an alternative approach for improving the pathway for retraining in Deep Neural Networks (DNN) from new functioning multiple sources.

The research paper is organized as follows. The DNN model building utilized in this investigation is detailed in Section 2. Section 3 provides the datasets and study framework approaches. Section 4 additionally illustrates the performance and research results. We review the results and discuss future work in Section 5.

2. Proposed Method.

In the work of [8], we found a problem that traditional machine learning can no longer perform its tasks when data source emerges or acquire from other sources. Because a large volume of raw data must be initiated in process of learning and developing new models, it takes a long time to compute.

2.1. Model architecture.

The model uses a DNN structured as demonstrated in Figure 1. By randomly rearranging the accelerometer sensor of the x, y, and z axis features in this study, every 80 rows have been rearranged vertically as one dimension. Each order has a data input to the model that is calculated as $80 \times 3 = 240$ units until the whole dataset is complete. Figure 1 shows where each layer in our structural config may use the same or different activation functions. In this research, two activation functions are used for computation in the Rectified Linear Unit (ReLU) function which is found in the hidden layer because the data is non-linear. A model needs to be retrieved if the classification of activities is to occur. In cases of overlaps between classes of Move and Still, the researchers use a statistical value (Mode) to implement a small percentage of excess classes of observed interpolations. The output layer used the sigmoid function, fitting for resolving the result in the range 0 and 1, suitable for the class value in this research and explained more significantly experimental in Section 3.

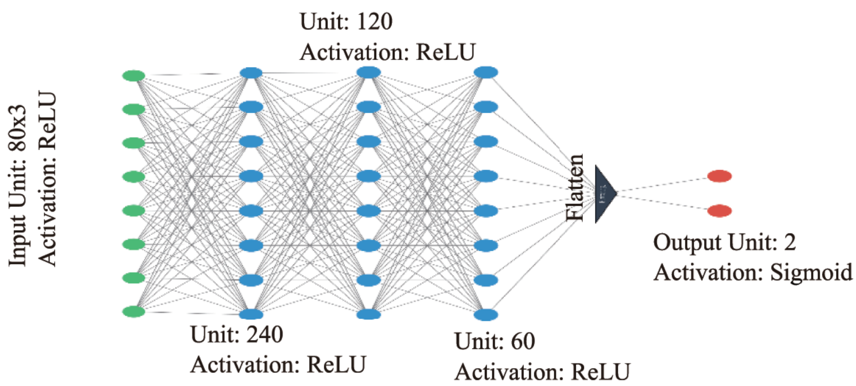

FIGURE 1. Our effective DNN structure

The ReLU is an activation function that shows outputs (x) directly from the ReLU if it is positive the output is also x; otherwise, the output is 0. It is defined as $f(x) = \max(x, 0)$, and requires less computing time. It has become the default activation function for many types of DNNs. Agarap [9] updated the models that were used to train system to perform faster and more effectively, requiring less computational power. The sigmoid function was the default activation used on output layer. The input to the function has transformed a value between 0 and 1, which is relevant to this work.

2.2. **Retraining network.** Data mining techniques related to machine learning and algorithms are based on the principle that training and future data are distributed similarly within the same attributes. However, in many practical applications, this traditional learning method may not be relevant; for example, when a classification task is exceptional in one domain, while inadequate training data is available in another domain. The data source may contain different feature areas or originate from different distributions. Over the years, transfer learning or retraining has emerged as a new learning framework to tackle this problem [10]. Collections of research and reviews provide an overview of the current progress of the broad application of transfer learning methods for classification, regression, and clustering of machine learning and algorithms challenges. The DNN has Multiple Layers Perceptron (MLP) and connects to an output layer. Our model was freeze parameter (weight, bias) values appropriately for retraining network a new domain as added hidden layer or fully connected before classified on the output layer. Figure 2 depicts a diagram that illustrates the process of transfer learning, which involves utilizing a source domain (Ds_i) to retrain a model in a target domain (Dt_i). To accomplish this, only a small portion of the available data was utilized for model retraining.

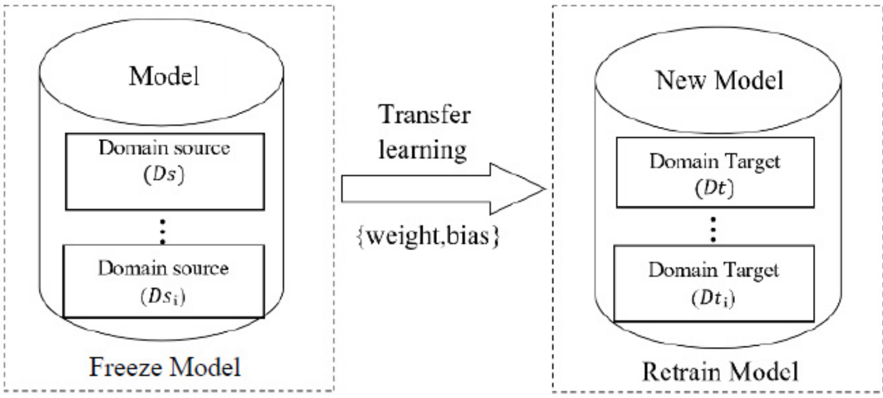

Figure 2. Transfer learning and retraining model

3. **Materials and Research Framework.** Our study retrieved the data from two research sources for this experiment; dataset A: WISDM [11] and dataset B: Motion Sense [12]. The sensory data measurements from the accelerometer sensors, which have three attributes: values from the x, y, and z axes, are used to recognize human activity. The two public available datasets are collected from variously sources across a device using data distinctive tester, the location of the devices relative of the position on the body, and the specific points of time that the test is administered. This paper will concentrate on a specific accelerometer sensor from both sources that apply the retraining network approach to the test utilizing data from various sources.

The experiment illustrated the difference between traditional and modern machine learning. One effective learning process developed from multiple sources approaches is shown in Figure 3, an overview of the experimental design and dataset. The first phase in our process, Step 1 in Figure 3, shows the data source in the experiment as datasets A and B. The datasets represent an accelerometer sensor, and an electromechanical accelerometer sensor. To measure the acceleration acting on the x, y, and z axes, many researchers, [13,14] have created specialized sensors related to the field of health that are able to recognize abnormal response in people [15]. These sensors are nowadays the primary intelligence devices that humans use in their daily life. Dataset A consists of 1,098,205 rows of raw data, while dataset B raw data includes 331,420 rows.

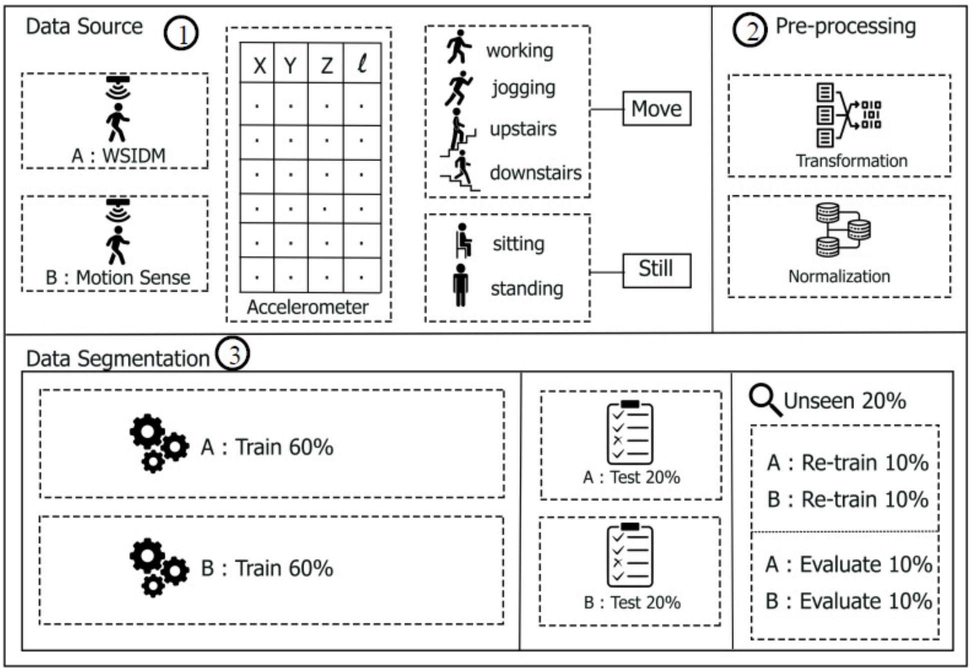

FIGURE 3. Experimental research framework

3.1. **Datasets and data preprocessing.** In Step 2 (Data preprocessing), the data is divided into two datasets while maintaining the same range values. And finally in Step 3, the process splits the data into proportions that correspond with the practical applications of the experiment.

In the pie graph in Figure 4 (left), the result shows that the division of data in the Move and Still classifications in dataset A are unequal or imbalanced. However, as shown in Figure 4 (right), there is a reasonably balance-grouping of the categories found in Dataset B. Therefore, it is advantageous to use a dataset that is complete, one that complements the data of Dataset A that consists of imbalanced classes.

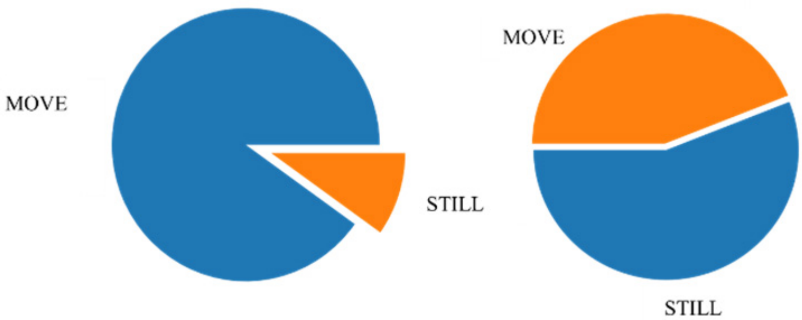

FIGURE 4. Move, Still dataset ratios of A (left) and B (right)

Our findings used the Z-score that were applied to the datasets $A = \{x_i, y_i, z_i\}$, and dataset $B = \{x_i, y_i, z_i\}$. If defined X as a data point in $X \in A$ and B, which was determined by using the scalar transformation in both of datasets, the mean (μ) and standard deviation (σ) were computed accordingly, along with the frequency range of each axis in both datasets. The data ranges for both datasets in the x, y, and z axes must be taken into data point of datasets A and B. Once the data was analyzed, findings showed a higher error rate because the data ranges were too heterogeneous when relating to data provided. Before learning is to help our model recognize previously inputted more accurately and efficiently, a more precise dataset must be formed. There were six activity datasets:

walking, jogging, ascending stairs, and descending stairs categories that represent physical movements (Move), while sitting and standing denoted stillness (Still). These variables were used that form the weighting parameter values. These variables, however, were inconsistent, so parameters were needed to meticulously be developed.

Computing in all cycles of a deep network was complicated, so the appropriate were needed to be meticulously developed; however, it required a longer processing time. Kappal's research [16] computed the new data from various sample sizes, and the result correlated with a new range of algorithms produced. These algorithms were appropriate for the import of data into the new model used for the recognition task.

3.2. **Data segmentation and model.** This research is designed to provide an effective and comprehensive model learning process across all datasets. Researchers test all viewpoints of data training, both in Model A and Model B. Single training and testing including both of A and B datasets were combined to train. The datasets were divided into sections for training 60%, testing 20%, while the remaining sets were unseen data 20% which were evaluation 10% and retraining 10% of the model. Several testing scenarios were essential to this study as shown in Figure 5.

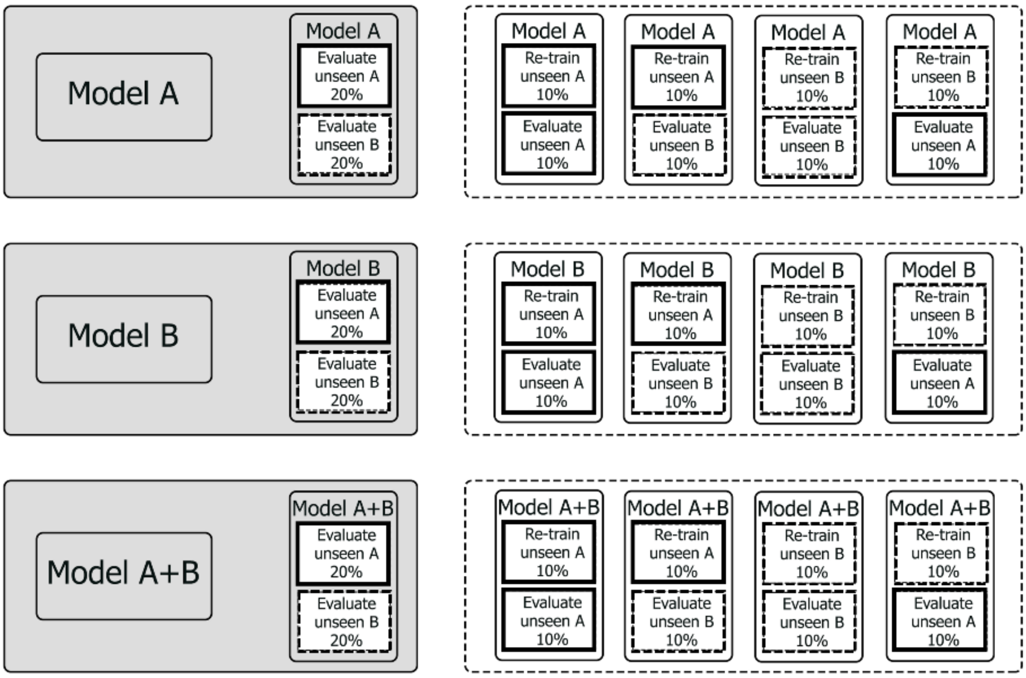

Figure 5. Experimental research

4. **Results and Discussion.** Figure 5 illustrates a typical model in six tests as a grey square. The developed model was retrained using unseen data for eight investigations under the whole thick dotted line. An unseen dataset A is given by an ultra-thick solid square, and an unseen dataset B is shown by an ultra-thick dash square, along with performance measurements with the accuracy and error values of all operations displayed in Table 1.

4.1. **Evaluation.** The classification performance was measured by precision and recall using the accuracy metric, a usual measurement used to evaluate the model classifier [17]. Furthermore, the error or loss metric proceeds on the binary cross-entropy. The binary cross entropy needed to be computed. The logarithms of predicted yield were between 0 and 1 that matched the properties found in Move and Still groupings which calculated the error or loss of an instance as the value of the class probability.

TABLE 1. Overall accuracy and loss of the traditional machine learning

Experiment	Model	Evaluate dataset	Accuracy	Loss
1	A	Unseen A 20	0.9627	0.0731
2	A	Unseen B 20	0.9896	0.2157
3	B	Unseen B 20	0.9960	0.0353
4	B	Unseen A 20	0.8760	0.8854
5	A+B	Unseen A 20	0.9890	0.4901
6	A+B	Unseen B 20	0.9749	0.4603

4.2. **Discussion.** The results encouraged researchers to inquire about the performance of classical machine learning of DNNs in Model A, Model B, and Model A+B presented in Figures 6(a)-6(c), respectively. When evaluated with the same datasets as shown in Table 1, experiments 1 and 3 showed that the loss rate was minimum, and the model learned effectively. However, at the same time, when taking the two evaluated by crossing the dataset, according to experiments 2 and 4, the model reduced the accuracy, and the loss value was higher than in other experiments. Because the model trained and evaluated the datasets from separate sources, the model never experienced an effective recognition when handling test set from the same data source. Therefore, we are interested in producing two datasets to study in the same learning process. The experiment results are shown in Figure 6(c) where the drastic raising and falling lines on the graph signify a powerfully independent source. This model illustrates the problem of consolidating data from multiple sources into training using traditional machine learning.

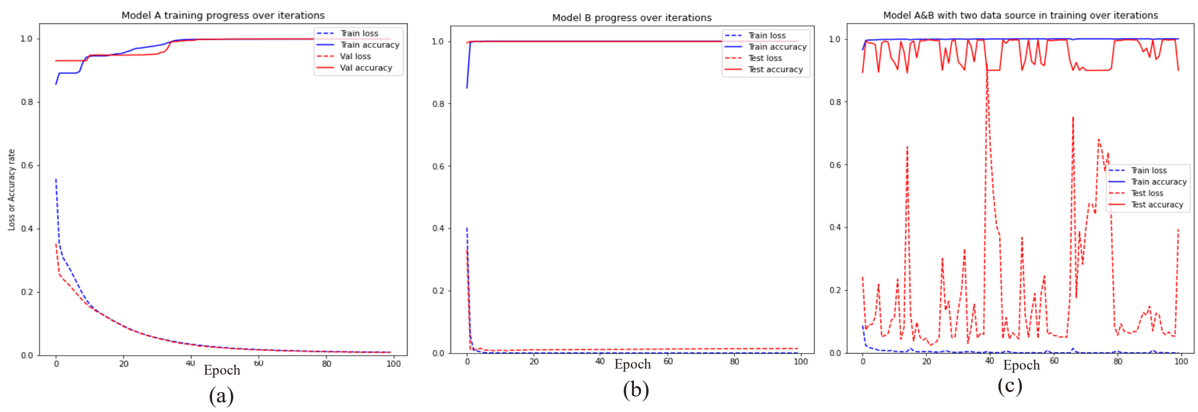

FIGURE 6. Experimental result of traditional machine learning

As a result, trials 5 and 6 in Table 1 are worse than findings of trials 1 and 3, but only slightly greater than outcomes in trails 2 and 4 where the training was ineffective inside multiple sources of pattern recognition.

From the discovery in Table 1, researchers were determined to investigate further, and additional studies were initiated to reveal the impacts of future machine learning problems. With that being said, the modern machine learning commonly used in DNN is transfer learning, and we are building a unique retraining network resulting task that will change the way researchers and practitioners use machine learning algorithms, as shown in Table 2.

The model learns with only a tiny portion of unseen data 10% and use the remaining data 10% to evaluate. In Table 2, the experiments during this phase showed that trials 1 and 3 were evaluated with the same data source as the model with satisfactory results. In reference to trials 2 and 4, the retraining phase, there were signs of improved machine learning performance compared to the results in Table 1 of trials 2 and 4, which

Table 2. Overall accuracy and loss of the retraining model

Experiment	Model	Retrain dataset	Evaluate dataset	Accuracy	Loss
1	A	Unseen A 10	Unseen A 10	0.9751	0.0870
2	A	Unseen B 10	Unseen B 10	0.9948	0.0312
3	B	Unseen B 10	Unseen B 10	0.9969	0.0376
4	B	Unseen A 10	Unseen A 10	0.9861	0.0812
5	A+B	Unseen A 10	Unseen A 10	0.9978	0.0110
6	A+B	Unseen A 10	Unseen B 10	0.9333	0.4349
7	A+B	Unseen B 10	Unseen B 10	0.9917	0.1364
8	A+B	Unseen B 10	Unseen A 10	0.9495	0.3884

showed a significant reduction in the error value, even though the model acquires data from different sources. This approach has shown to provide the necessary assistance for problematic resolutions. In Table 1, trails 5 and 6, we find that there were learning inefficiency problems. The retraining network solved this by designing an experiment in the modeling phase, as in Table 2. Trails 5 and 7 demonstrate the strength of learning new models by transferring significant parameter values. In Table 2, focus on the experiments 6 and 8 that demonstrate an increase in loss rate; nonetheless, the overall performance is substantially higher than the traditional machine learning in Table 1.

5. **Conclusions and Future Work.** The increasing use of data has produced a demand for more effective machine learning approaches. Our research is aimed at discovering patterns hidden within various data sources when they have merged. Researchers focused on an accelerometer sensor that identifies human motions from various sources rather than data formats that are exclusive to each source.

The aim was to develop a model that could recognize patterns more diversely than learning from a single data source. Because of experiments 6 and 8 in Table 2, the researchers utilized the partial datasets when feeding data into the new model(s), because the process of evaluating the remaining unseen data is preferred over various unreliable sources. This creative alternative strategy proved to achieve excellent performance.

For future study, researchers are interested in performing a multimodal sensor data analysis to construct multimodal classifiers that include addition locations on the human body, such as the chest, and knees. Moreover, researchers are focused on developing the multivariate characteristics that might include structural design that increase the performance of other structures in deep learning algorithms.

Acknowledgment. The research was partially supported by The Royal Golden Jubilee (RGJ) Ph.D. Programme under the supervision of the National Research Council of Thailand (NRCT). Materials or dataset for this research comes from the WISDM Lab under the Department of Computer and Information Science, Fordham University, Bronx, NY.; and the Motion Sense Dataset: Sensor-Based Human Activity and Attribute Recognition by the Queen Mary University of London. We wish to thank the Division of International Affairs and Language Development (DIALD) for proofreading this paper.

REFERENCES

[1] Magnimind, Deep learning and its 5 advantages, *Medium*, 2020, https://becominghuman.ai/deep-learning-and-its-5-advantages-eaeee1f31c86, Accessed on Sep. 18, 2021.

[2] Y. Liu, J. Wang, J. Li, S. Niu and H. Song, Machine learning for the detection and identification of internet of things devices: A survey, *IEEE Internet Things J.*, vol.9, no.1, pp.298-320, 2021.

[3] G. Nguyen et al., Machine learning and deep learning frameworks and libraries for large-scale data mining: A survey, *Artif. Intell. Rev.*, vol.52, no.1, pp.77-124, DOI: 10.1007/s10462-018-09679-z, 2019.

[4] Y. LeCun and Y. Bengio, Pattern recognition and neural networks, *Handb. Brain Theory Neural Netw.*, MIT Press Camb. MA, 1995.

[5] S. Dash, S. K. Shakyawar, M. Sharma and S. Kaushik, Big data in healthcare: Management, analysis and future prospects, *J. Big Data*, vol.6, no.1, p.54, DOI: 10.1186/s40537-019-0217-0, 2019.

[6] M. H. Ramadhan, T. N. Adi, H. Bae and H. Kim, Obtaining lightweight human activity recognition model through knowledge distillation of deep neural network, *ICIC Express Letters, Part B: Applications*, vol.13, no.5, pp.519-526, DOI: 10.24507/icicelb.13.05.519, 2022.

[7] J. Li, W. Wu, D. Xue and P. Gao, Multi-source deep transfer neural network algorithm, *Sensors*, vol.19, no.18, 3992, DOI: 10.3390/s19183992, 2019.

[8] H. D. Nguyen, K. P. Tran, X. Zeng, L. Koehl and G. Tartare, Wearable sensor data based human activity recognition using machine learning: A new approach, *arXiv*, 2019, http://arxiv.org/abs/1905.03809, Accessed on Jun. 14, 2022.

[9] A. F. Agarap, Deep learning using rectified linear units (ReLU), *arXiv180308375 Cs Stat*, 2019, http://arxiv.org/abs/1803.08375, Accessed on Nov. 30, 2021.

[10] S. J. Pan and Q. Yang, A survey on transfer learning, *IEEE Trans. Knowl. Data Eng.*, vol.22, no.10, pp.1345-1359, DOI: 10.1109/TKDE.2009.191, 2010.

[11] G. M. Weiss, K. Yoneda and T. Hayajneh, Smartphone and smartwatch-based biometrics using activities of daily living, *IEEE Access*, vol.7, pp.133190-133202, DOI: 10.1109/ACCESS.2019.2940729, 2019.

[12] M. Malekzadeh, R. G. Clegg, A. Cavallaro and H. Haddadi, Privacy and utility preserving sensor-data transformations, *arXiv191105996 Cs Eess Stat*, 2019, http://arxiv.org/abs/1911.05996, Accessed on Dec. 01, 2021.

[13] I. Tobore et al., Deep learning intervention for health care challenges: Some biomedical domain considerations, *JMIR MHealth UHealth*, vol.7, no.8, e11966, DOI: 10.2196/11966, 2019.

[14] F. Ali et al., A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion, *Inf. Fusion*, vol.63, pp.208-222, 2020.

[15] D. D. Mehta, M. Zañartu, S. W. Feng, H. A. Cheyne II and R. E. Hillman, Mobile voice health monitoring using a wearable accelerometer sensor and a smartphone platform, *IEEE Trans. Biomed. Eng.*, vol.59, no.11, pp.3090-3096, DOI: 10.1109/TBME.2012.2207896, 2012.

[16] S. Kappal, Data normalization using median median absolute deviation MMAD based Z-score for robust predictions vs. min-max normalization, *Lond. J. Res. Sci. Nat. Form.*, 2019, https://research.journalspress.com/index.php/science/article/view/444, Accessed on Dec. 03, 2021.

[17] D. Lu and Q. Weng, A survey of image classification methods and techniques for improving classification performance, *Int. J. Remote Sens.*, vol.28, no.5, pp.823-870, 2007.