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Using a Semi-supervised Learning Model for Recognition of Human Daily Activities from Wearable Sensor Data

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ABSTRACT

The application of Machine Learning (ML) and Artificial Intelligence (AI) is growing, and also becoming more important as the aging population increases. Smart support systems for distinguish Activities of Daily Living (ADL) can help the elders live more independently and safely. Many machine learning methods have been proposed for Human Activity Recognition (HAR), including complex networks containing convolutional, recurrent, and attentional layers. This study explores the application of ML techniques in ADL classification, leveraging wearable devices' time-series data capturing various parameters such as acceleration. The acceleration data obtained from sensors is so huge that it is difficult and expensive to accurately label every sample collected, so this study applies the Semi-supervised Learning model to unlabeled samples. Shuffling activity is a common symptom in the elderly, so the machine learning model in this study was designed to identify shuffling activity. Long Short-Term Memory (LSTM) has always been used for time series data such as acceleration, and recently, the Transformer model has emerged in many applications such as Natural Language Processing (NLP) or creating ChatGPT. In this study we proposed ADL classification method using the Self-Attention Transformer block and the Recurrent LSTM block and evaluated their results. After comparison, the model built with LSTM block gives better results than the model built with Transformer block, especially with LSTM's Macro average being 11% better than Transformer's.

1. Introduction

According to WHO, by 2050, the number of the world's elderly people over 60 years old population will reach 2.1 billion [1], placing a burden on the economy as well as making it difficult to provide adequate care for the elderly. Artificial intelligence (AI) has been applied and developed to support people's lives in the context of an increasing population aging rate [2]. Areas of support for the elderly where AI is applied include: fall prediction and prevention, daily living support, communication, etc. [3]-[6]. In particular, to effectively support daily activities and prevent falls, accurately identifying and distinguishing Activities of Daily Living (ADL) is essential.

The field of Fall Prediction and HAR belongs to the category of time series, there have been many studies using appropriate models for application such as LSTM, CNN-LSTM, CNN-RNN [7]-[10]. With the superiority of the Transformer model, many studies have been conducted to apply it to many different fields, including the fields of Fall Prediction and HAR, the Transformer model has been applied and compared with other classical LSTM models as in researches of Haben Yhdego [3],[4]. Haben Yhdego's research only uses a sensor mounted on the body to get input data to train models, the research in this article uses two sensors at different locations on the body to get more intuitive data about human gait. In this study, we use machine learning models to distinguish ADL of the elderly, using inputs data of Astrid Ustad's research [11]. That research only used classical LSTM, which doesn't have the Data Efficiency and Long-Term Dependencies as Transformer. Gabriela Augustinov's research used Transformer to analyze ADL for diverse activities that did not specifically revolve around the lower limbs, and showed better results than LSTM [6]. For those reason, this study also uses Transformer Model to see how good it is compared to LSTM in the field of Lower Limb ADL classification.

There are many types of input data for current HAR machine learning models, including video, images, acceleration, sound and so on [28]-[31], among them acceleration is one of the most used input data types. The amount of data captured in time series data is often extremely large, so labeling it all is often extremely laborious and expensive, most conventional HAR approaches that have shown promising results in the past have used supervised learning, requiring large amounts of expert-labelled user activity training data which is both difficult to obtain and not practical for real-world deployment [18]. Therefore, developing an unsupervised machine learning model, such as semi-supervised for semi-unlabeled data or self-supervised for unlabeled data, is necessary.

Without explicit named labels, subtle differences between signals of large range-of-motion ADLs cannot be classified by unsupervised algorithms [20]. Another study by Tang [21] built a self-supervised machine learning model, a variation of unsupervised machine learning. However, this model uses transfer learning to pass the parameters of the model trained with supervised data to Tang's model, so it is not completely self-supervised learning. Research by Liang Xi and Emadeldeen Eldele has also shown that semi-supervised machine learning with a small amount of labeled data gives better results than self-supervised learning with completely unlabeled data [13],[14]. For the above reasons, this study uses a semi-supervised machine learning model with a portion of the data labeled.

Recently, in the field of ADL classification, the integration of Semi-Supervised Learning into machine learning models is becoming increasingly popular, such as the research of Andrea Masciadri, Dongxin Liu and Hazar Zilelioglu [15]-[17]. However, Andrea Masciadri's research focuses more broadly on everyday states rather than the lower limbs ADLs presented in this study. Yuchen Zhao's literature [19] proposed a semi-supervised federated learning framework considering both privacy preservation problem and scarce labels problem, in which autoencoders were utilized for local models to learn representations and LSTM was for the global classifier. The machine learning model in Prankit's research [22] focuses on grouping repetitive actions within a short time frame to group unlabeled activities, this model works simultaneously to constantly learn activity patterns and evolve the user activity model on a short-term basis to account for any new or changing activities. Sungtae's DynaLAP model [23] uses input data measured over both short and long-time frames, having a highest F1 score of 80%. DynaLAP encodes data using a CNN-RNN network, calculates the relationship of the data, and finally decoders using an RNN-CNN network. The FedHAR model in HongZheng's study [24] uses federated servers to collect unlabeled data from online users, combined with offline labeled data, and has the highest F1 score of 82%. FedHAR calculates gradients from labeled and unlabeled input data through the model parameters, the processed data is passed to the federated server to adjust the model parameters, then new parameters are used to calculate the gradient. Dmitrijs's research [25] uses an adversarial autoencoder designed by him to extract features of input data for semi-supervised learning, which has the highest F1 score of 90.2%. As of this study, Dmitrijs's research shows the state-of-art of using a semi-supervised learning model to classify lower limb ADLs with acceleration as input data.

Elderly people are more likely to have symptoms such as trembling in place or shuffling with small steps [26], shuffling is a state of moving the legs, but the feet do not leave the ground, something that often happens to the elderly or people with lower limb injuries, making it essential to recognize shuffling in ADL. Scott's review of methods for detecting Parkinson's symptoms mentions shuffling detection [27]. However, most of the methods in the review do not use machine learning, only detect but do not distinguish shuffling from other ADLs, or have low discrimination efficiency. As far as this study is concerned, no study has attempted to distinguish shuffling activity from other lower limb ADLs with only two accelerometers as input, so this study attempts to include shuffling activity in its analysis and observe the results.

In this paper we use LSTM Model and Transformer Model as the basis, combined with Semi-supervised Learning so that the machine learning model can work with unlabeled samples. Then, compare the results of LSTM and Transformer, with Semi-Supervised Learning and without Semi-Supervised Learning in classifying the Lower Limb ADL of the elderly.

The contributions of our papers are summarized as follows:

- Our semi-supervised learning model produces better results when using accelerometer input to classify ADLs compared to the state-of-art models mentioned in the study.
- This study proposes for the first time a machine learning model to classify shuffling with other ADLs.
- The LSTM model demonstrated in this study is in many aspects better than Transformer model in classifying ADLs with acceleration as input data.

2. Method

2.1. Data Acquisition

To distinguish ADL of the elderly using Machine learning, data acquisition of ADL is required. In this study we decided to use acceleration values over time. Therefore, to build and train the models, we decided to use dataset of The Human Activity Recognition 70+ (HAR70+) dataset [12].

Two 3-axial accelerometers are mounted on the lower back and right thigh, the participants are elderly people over 70 years old. The frequency of each time step measured is 200Hz within 40 minutes during a semi-structured free-living protocol. Activities during measurement include: walking, shuffling, standing, sitting, lying. This study focuses on using data with many shuffling samples for training and validation.

2.2. Semi-Supervised Learning Model

Semi-supervised learning is a machine learning paradigm where a model is trained on a combination of labeled and unlabeled data. Unlike supervised learning, where the model is trained only on labeled data, and unsupervised learning, where the model learns patterns from unlabeled data alone, semi-supervised learning leverages both types of data to improve model performance. Overall, semi-supervised learning is a valuable approach for leveraging both labeled and unlabeled data to train models, especially in scenarios where labeled data is limited or expensive to obtain. The flow chart in Fig.1 below shows how Semi-supervised Learning works in this study.

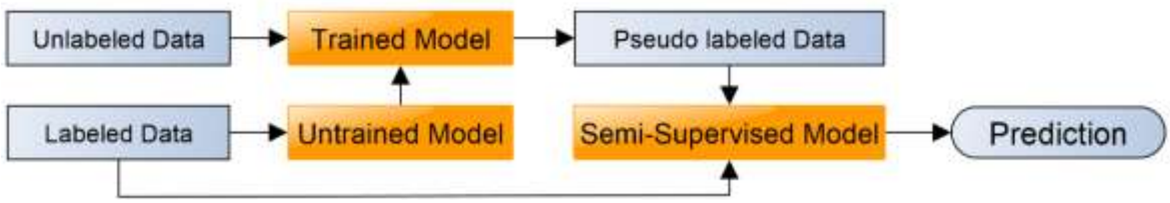

Fig. 1. Semi-Supervised Learning Flow Chart

2.3. LSTM Model and Transformer Model

LSTM Model is a specialized type of recurrent neural network (RNN) designed to address the challenges of capturing long-range dependencies in sequential data. LSTM excels at learning and remembering information across extended sequences. They achieve this through a unique architecture whose control mechanisms input, forget, and output gates regulate the flow of information in the network. These ports control what information is stored in the internal memory cells, ensuring relevant data is retained and less important data is forgotten. Overall, LSTMs have become foundational in sequence modeling, making them fundamental tools in many fields of artificial intelligence and machine learning. The structure of the LSTM Model in this study is shown through the characteristics shown in Fig.2 and Table 1.

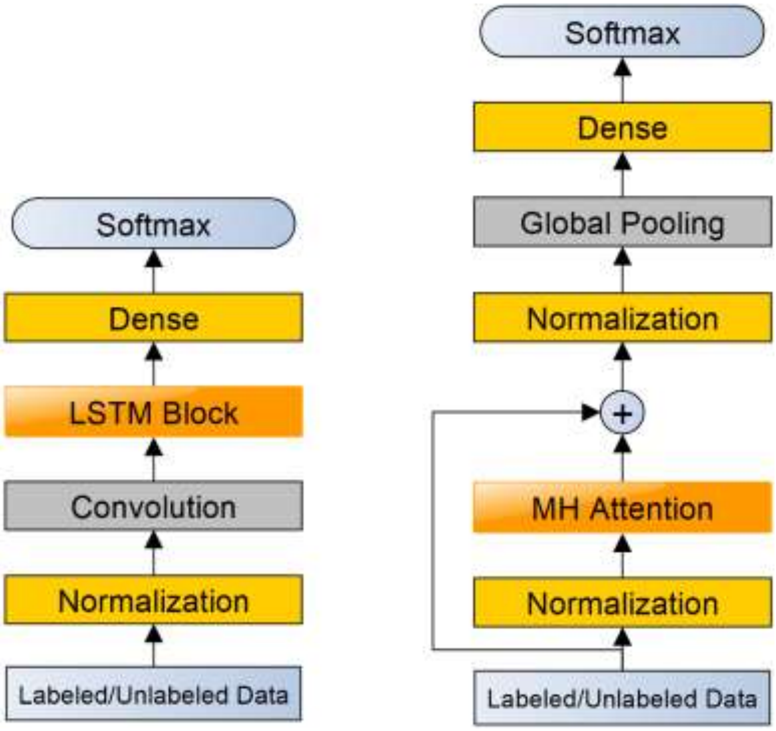

Fig. 2. Architecture of LSTM Model (left) and Transformer Model (right)

The Transformer model relies on the self-attention mechanism, allowing it to capture complex relationships and dependencies in data across distant positions effectively. Unlike recurrent models, Transformers process input sequences in parallel, enabling faster training and scalability to handle large datasets. Positional encoding is used to maintain sequential information without relying on recurrent connections. Multi-head attention enables the model to focus on different parts of the input simultaneously, enhancing its ability to understand context. The Transformer's stackable layers facilitate the modeling of hierarchical features and abstraction, making it adaptable to a wide range of tasks. These properties have made the Transformer a cornerstone in natural language processing, machine translation, and various other applications, consistently achieving state-of-the-art results and powering models like BERT and GPT-3, which have revolutionized language understanding and generation tasks. Its parallelizable structure, attention mechanism, and scalability make it a versatile choice for modern deep learning tasks. This study attempts to use the Attention feature of the Transformer Model for a Time Series task such as ADL classification. The structure of the Transformer Model in the study is shown in Fig.2 and Table 1.

Table 1. Specifications of Models

Specifications	**LSTM Model**	**Transformer Model**
Optimizer	Adam	Adam
Loss	Categorical Cross Entropy	Categorical Cross Entropy
Metrics	Categorical Accuracy	Categorical Accuracy
Epochs	20	20
Drop Out	0.1	0.2
Total Parameter	36497	128529

3. Results and Discussions

The results of our study indicate promising outcomes in using semi-supervised learning with LSTM and Transformer models for distinguishing Activities of Daily Living in the elderly people. We observed distinct patterns in the performance of these models, as well as their strengths and limitations. The overall F1-score accuracy of each model is shown in Table 2., and detailed information of other metrics such as Loss, Validation and Confusion Matrix are shown in the sections below.

Table 2. F1-Socre Accuracy of all Models

Indicators	F1 – Score			
	LSTM	*Semi-LSTM*	*Transformer*	*Semi-Transformer*
Micro average	0.93	**0.94**	0.91	**0.94**
Macro average	0.80	**0.82**	0.73	0.75
Weighted average	0.93	**0.94**	0.91	0.93
Samples average	0.93	**0.94**	0.91	**0.94**

3.1. Results of Semi-supervised + LSTM Model

Training results of the LSTM Model and Semi-LSTM Model through the Loss graphs are indicated in Fig.3 and Accuracy graphs in Fig.4. The ADL classification results, the Confusion Matrix of LSTM Model and Semi-LSTM Model are shown in Fig.5.

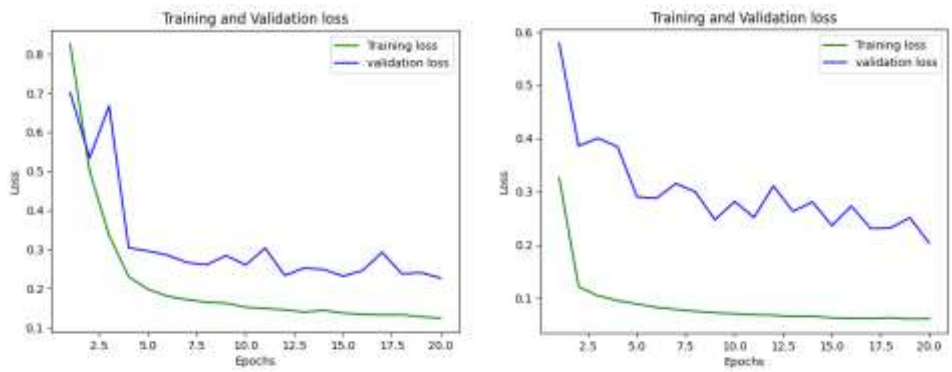

Fig. 3. Plot of the training and validation loss of LSTM Model (left) and Semi-LSTM Model (right)

In Fig.3, both LSTM Model and Semi-LSTM have a decreasing training loss and a decreasing validation loss that eventually stabilizes at a low value, it means both Models are Good Fit. In the last epoch, the training loss value of LSTM Model is 0.1234 and that of Semi-LSTM is 0.0613, the validation loss value of LSTM Model is 0.2267 and that of Semi-LSTM is 0.2023.

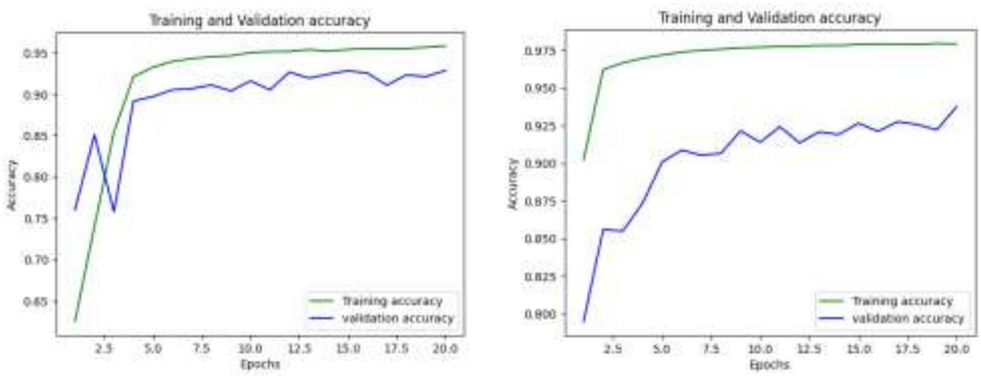

Fig. 4. Plot of the training and validation accuracy of LSTM Model (left) and Semi-LSTM Model (right)

In Fig.4, both LSTM Model and Semi-LSTM have a increasing training accuracy and a increasing validation accuracy that eventually stabilizes at a high value, it means both Models are Good Fit. In the last epoch, the training accuracy value of LSTM Model is 0.9585 and that of Semi-LSTM is 0.9769, the validation accuracy value of LSTM Model is 0.9287 and that of Semi-LSTM is 0.9376.

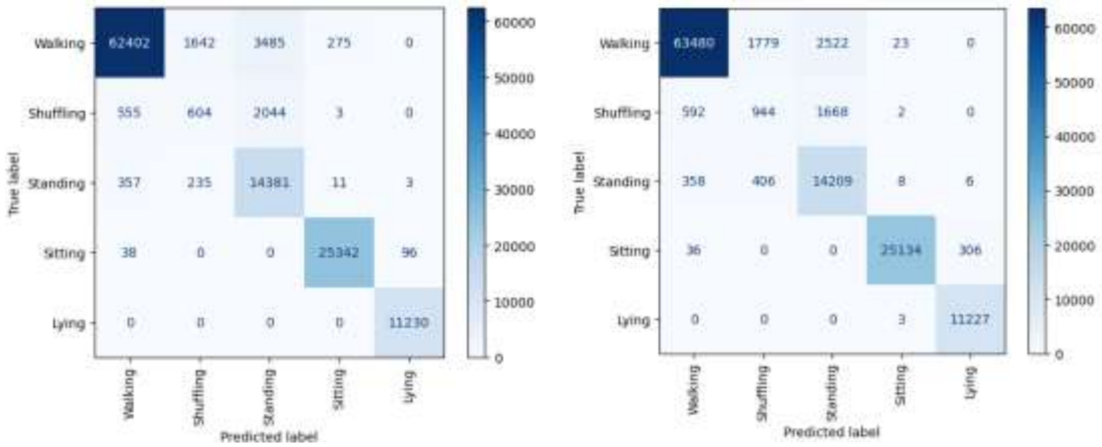

Fig. 5. Confusion matrix of LSTM Model (left) and Semi-LSTM Model (right)

Fig.5 shows that both LSTM Model and Semi-LSTM Model classify Sitting and Lying activities very well, classify Walking and Standing activities quite well, and classify Shuffling activities poorly. Semi-LSTM Model is slightly better than LSTM Model in every aspect. Detailed information about the accuracy indices of all 5 activities and average types of LSTM Model and Semi-LSTM Model are shown in Table 3.

The F1-score of Semi-LSTM Model in this study has the highest value of 94%, higher than the score of the LSTM Model and state-of-art models mentioned in the study: LSTM Model - 93%, DynaLAP Model - 80% [23], FedHAR - 82% [24], Dmitrijs's Model - 90.2% [25].

The F1-score of the Shuffling indicator in table 3 is very low, only 21% for LSTM Model and 30% for Semi-LSTM Model, this can be explained by two reasons:

- The training data is not balanced between labels, the ratio of Shuffling labels is the lowest. Specifically, the ratio of each label in the training data is: Walking - 55%, Shuffling - 3%, Standing - 12%, Sitting - 21%, Lying - 9%.
- The symptoms of Shuffling activity are extremely similar to Standing and Walking activities. This makes it more difficult for the model to classify Shuffling and easy to misclassify with the two neighboring activities.

Table 3. Accuracy of LSTM Model and Semi-LSTM Model

Indicator	**LSTM Model**			**Semi-LSTM Model**		
	Precision	***Recall***	***F1-score***	***Precision***	***Recall***	***F1-score***
Walking	0.99	0.92	0.95	0.98	0.94	0.96
Shuffling	0.24	0.19	0.21	0.30	0.29	0.30
Standing	0.72	0.96	0.82	0.77	0.95	0.85
Sitting	0.99	0.99	0.99	1.00	0.99	0.99
Lying	0.99	1.00	1.00	0.97	1.00	0.99
Micro average	0.93	0.93	0.93	0.94	0.94	0.94
Macro average	0.79	0.81	0.80	0.81	0.83	0.82
Weighted average	0.93	0.93	0.93	0.94	0.94	0.94
Samples average	0.93	0.93	0.93	0.94	0.94	0.94

3.2. Results of Semi-supervised + Transformer Model

Training results of the Transformer Model and Semi-Transformer Model through the Loss graphs are indicated in Fig.6 and Accuracy graphs in Fig.7. The ADL classification results, the Confusion Matrix of LSTM Model and Semi-LSTM Model are shown in Fig.8.

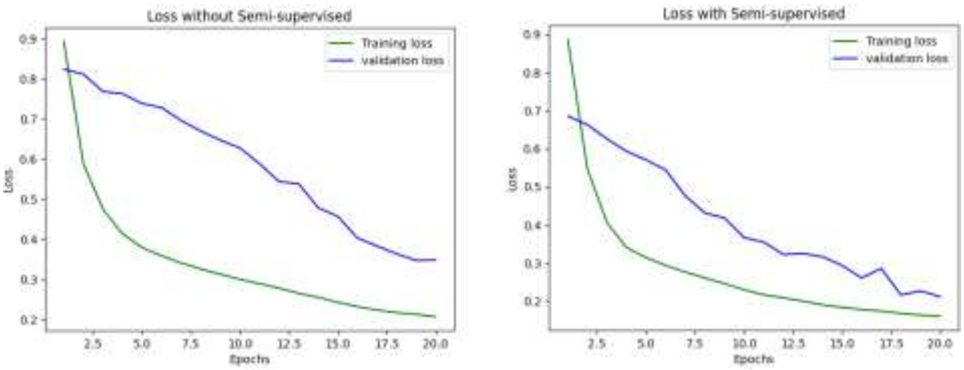

Fig. 6. Plot of the training and validation loss of Transformer Model (left) and Semi-Transformer Model (right)

In Fig.6, both Transformer Model and Semi-LSTM have a decreasing training loss and a decreasing validation loss that eventually stabilizes at a low value, it means both Models are Good Fit. In the last epoch, the training loss value of Transformer Model is 0.1234 and that of Semi-Transformer is 0.0613, the validation loss value of Transformer Model is 0.2267 and that of Semi-Transformer is 0.2023.

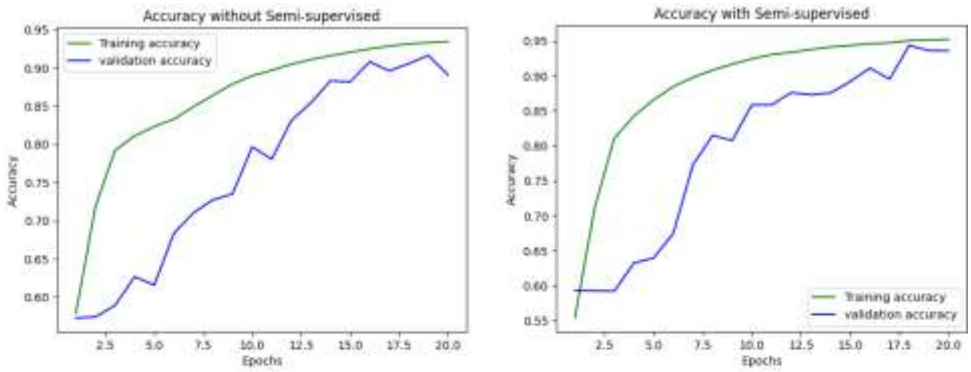

Fig. 7. Plot of the training and validation accuracy of Transformer Model (left) and Semi-Transformer Model (right)

In Fig.7, both Transformer Model and Semi-Transformer Model have a increasing training accuracy and a increasing validation accuracy that eventually stabilizes at a high value, it means both Models are Good Fit. In the last epoch, the training accuracy value of Transformer Model is 0.9585 and that of Semi- Transformer is 0.9769, the validation accuracy value of Transformer Model is 0.9287 and that of Semi- Transformer is 0.9376.

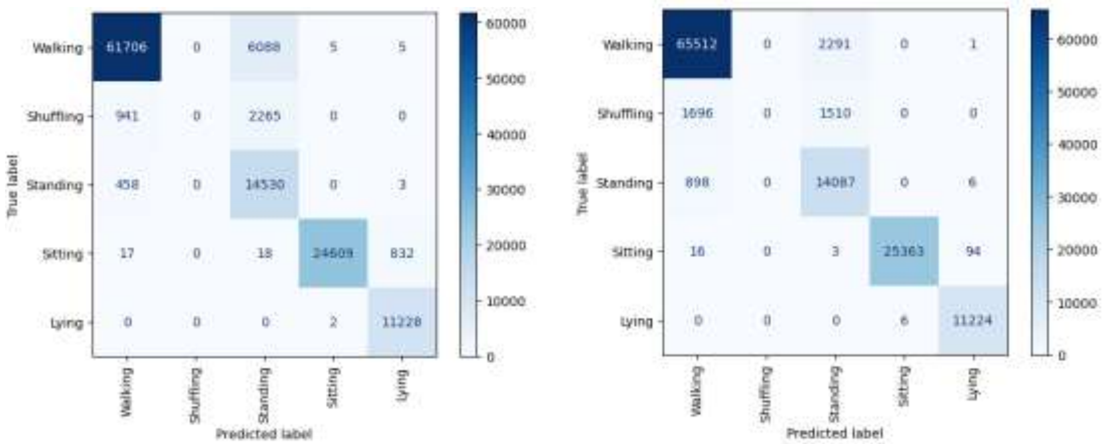

Fig. 8. Confusion matrix of Transformer Model (left) and Semi-Transformer Model (right)

Fig.8 shows that both Transformer Model and Semi-Transformer Model classify Sitting and Lying activities very well, classify Walking and Standing activities quite well, and unable to classify

Shuffling activities. Semi-Transformer Model is slightly better than Transformer Model in every aspect. Detailed information about the accuracy indices of all 5 activities and average types of Transformer Model and Semi-Transformer Model are shown in Table 4.

The F1-score of Semi-Transformer Model in this study has the highest value of 94%, which is also higher than the score of the Transformer Model and state-of-art models mentioned in the study: Transformer Model - 91%, DynaLAP Model - 80% [23], FedHAR - 82% [24], Dmitrijs's Model - 90.2% [25].

The F1-score of the Shuffling indicator in table 4 is 0%, this can be explained by three reasons:

- The training data is not balanced between labels, the ratio of Shuffling labels is the lowest.
- The symptoms of Shuffling activity are extremely similar to Standing and Walking activities.
- The Transformer structure is built on Attention connections to calculate the relevance and similarity between input data. This is further aggravated when the symptoms of Shuffling are extremely similar to those of Standing and Walking, the ratio of Shuffling label is only 3%, causing the model built with Transformer to completely misclassify Shuffling activity for the other two activities.

Table 4. Accuracy of Transformer Model and Semi-Transformer Model

Indicator	**Transformer Model**			**Semi-Transformer Model**		
	Precision	***Recall***	***F1-score***	***Precision***	***Recall***	***F1-score***
Walking	0.98	0.91	0.94	0.96	0.96	0.96
Shuffling	0.00	0.00	0.00	0.00	0.00	0.00
Standing	0.63	0.97	0.77	0.77	0.93	0.84
Sitting	1.00	0.97	0.98	1.00	0.97	0.99
Lying	0.93	1.00	0.96	0.94	1.00	0.97
Micro average	0.91	0.91	0.91	0.94	0.94	0.94
Macro average	0.71	0.77	0.73	0.73	0.77	0.75
Weighted average	0.91	0.91	0.91	0.92	0.94	0.93
Samples average	0.91	0.91	0.91	0.94	0.94	0.94

4. Conclusion

Although Transformer is superior to LSTM in areas such as NLP or Image Recognition, and even sometime ADL classification [6], this research show that Transformer is still not totally superior to LSTM in the field of Lower Limb ADL. Haben Yhdego's research shows similar results in ADL recognition and fall detection [4].

This research validated that combining Semi-Supervised Learning with LSTM Model and Transformer Model improved the classification capabilities of both models.

This research still has the following limitations:

- The ability to classify shuffling activity is still limited in both the LSTM and Transformer models, especially Transformer model.
- The number of samples of input data labels is unbalanced, there are too many samples with the label Walking and too few samples with the label Shuffling.

To address the limitations of current machine learning models, future research will focus on using data label balancing methods. The author of this study concluded that if we want to better identify activities that usually only occur in the elderly such as shuffling, there must be more than just two 3-axis accelerometers in different positions for better classification.

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