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Comparative Analysis of 1D – CNN, GRU, and LSTM for Classifying Step Duration in Elderly and Adolescents Using Computer Vision

Teng Hong Lee [a,1], Ezreen Farina Shair [a,2,*], Abdul Rahim Abdullah [a,3], Kazi Ashikur Rahman [a,4], Nursabillilah Mohd Ali [a,5], Nur Zawani Saharuddin [a.6], Nurhazimah Nazmi [b,1]

[a] Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
[b] Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100, Kuala Lumpur, Malaysia
[1] leetenghong06@gmail.com; [2] ezreen@utem.edu.my; [3] abdulr@utem.edu.my; [4] m112310040@student.utem.edu.my;
[5] nursabillilah@utem.edu.my; [6] nurzawani@utem.edu.my; [7] nurhazimah@utm.my
* Corresponding Author

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ABSTRACT

Developing a classification system that can predict the onset of neurodegenerative diseases or gait-related disorders in elders is vital for preventing incidents like falls. Early detection allows reduction in symptoms and treatment cost for the elderly. In this study, step duration data from five healthy adolescents with age range of 23 – 29 years old and five healthy elderly individuals with age range of 71 – 77 years old were sourced from PhysioNet. To ensure proper training of the deep learning models, synthetic data was generated from the original dataset using a noise jittering technique with random noise of a range between -0.01 and 0.01 added to the original data. Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and 1D Convolutional Neural Network (1D-CNN) are used for training the data since the data is available in the form time series data. LSTM and GRU are advanced forms of Recurrent Neural Network (RNN) while 1D – CNN can capture temporal dependencies in sequential data. 1D – CNN has the advantages over GRU and LSTM of being more robust to noise and can capture complex patterns behind the data. These methods will be compared in terms of processing time and accuracy. Results show that 1D – CNN outperforms both LSTM and GRU with accuracy of 1.000 in less than 60 seconds. The novelty and contribution of this research shows that healthy old people and healthy young people can be classified with deep learning. Further direction of the research can explore the deep learning in classification of Parkinson's disease.

1. Introduction

The study of human gait is extremely complex because there are many factors that involve coordination of multiple body systems and muscles that influence the way human walks [1], [2]. The musculoskeletal system that involves bones, muscles and joints working together, the nervous system that is responsible in coordinating muscle activation and movement patterns and finally, individual variability adds to the complexity of the human gait [3], [4]. The research into human gait uncovers various layers of complexity and encompasses many areas of sciences like biology, physics, physiotherapy, electrical engineering, mechanical engineering so on and so forth [5], [6]. Hence, there are many digital biomarkers that can be used for gait analysis like spatiotemporal parameters, kinematic parameters and muscle activity. One of the aspects of the spatiotemporal parameters is step duration.

The research scope of this research paper involves the comparative analysis of LSTM, GRU and 1D – CNN on the classification of the step duration of healthy young people and healthy old people. When a person ages, his or her gait deteriorates [7]. Early detection of gait deterioration is important to increase awareness for the people to live a healthier lifestyle to prevent the gait deterioration from advancing further into neurodegenerative diseases like Parkinson's disease [8]. Even though this research is only limited to the classification of youngsters and elderly, this research can open door for the classification of Parkinson's disease, Huntington's disease and many more. Reduction in symptoms and long – term treatment cost is possible if early detection of the abnormality of the adults' gait is done successfully [9], [10]. Adolescents and elders represent the opposite spectrum of gait where adolescents represent healthy and more active gait while elders represent a more deteriorating and more passive gait [11]. Elders suffer more from neurodegenerative diseases than adolescents and is often viewed as a starting point for progression of neurodegenerative diseases [12]. Hence, the research in the classification of the gait of adolescents and elders is very important because it allows the deterioration of gait in adults to be detected and allow early treatment to develop healthier gait in adults [13], [14].

Researchers come out with various features that can be used in the study of the gait analysis in which each has its own advantages or disadvantages and the suitability of the use of the feature depends on the specific cases [15], [16]. For example, Short – Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) can be used to derive the features from the data like root mean square (RMS) value [17], [18]. Besides, STFT and CWT can then be used to form the time – frequency images from the data. The images can then be fed into 2D – CNN for classification process. Nematallah et al conducted CWT on the signals form wearable sensors for human activity recognition [19]. Detrended Fluctuation Analysis (DFA) can be done on the data to determine if there is long – term correlation in the data [20], [21]. Di Bacco V et al studied the gait variability of treadmill and overground walking by performing DFA on the signals captured from accelerometer from the smartphone [22]. Furthermore, there are entropy methods like Shannon entropy to study the orderliness of the data [23], [24], [25]. Deep learning is a far easier method and prevails over machine learning because it does not require human intervention to generate features [26], [27]. There are many aspects of gait analysis which range from electromyography (EMG) signal, vertical Ground Reaction Force (vGRF) signal to the step duration [28], [29]. This research paper focuses on the step duration instead of EMG signal and vGRF signal because the data collection for EMG signal and vGRF signal requires a system that involves multiple sensor which makes it not convenient to be integrated with Internet – of – Things (IoT) due to patients' discomfort [30], [31]. Step duration which can be defined as time taken for consecutive footstep is easier to be implemented in the IoT because it can be captured easily using smartphone camera using computer vision with the utilization of OpenPose or MoveNet [32]-[34]. Computer vision allows objective and precise measurement which has the potential to replace the conventional system in analyzing the gait – related disorders which involves manual analysis by the physiotherapists. Computer vision has the advantage of being non – invasive [35], [36]. There are many researchers that are using the markerless computer vision method which require low only a camera that is readily available in smartphones in analyzing gait. For example, Wei V et al developed vision – based gait analysis using two smartphone cameras to analyze the normal subjects and Parkinson subjects [37]. Besides, Blasco – Garcia J et al incorporated RGB – D camera in robot to capture human motions [38]. The nature of step duration is time series data which makes LSTM, GRU and 1D – CNN suitable candidates for training the step duration data. LSTM and GRU can capture long – term dependencies in the data [39], [40] while 1D – CNN can capture the temporal

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features in the data [41]. 1D – CNN is the derivation of the conventional CNN method used to classify images to extract parameters of the data in the time series data [42], [43].

The contribution of this research paper is to analyze the efficacy of the GRU, LSTM and 1D – CNN to be used in the classification of the step duration of the young and the old people. The best deep learning method to be used in accordance with smartphone camera using computer vision in capturing and testing the stride interval will be identified.

2. Method

The flowchart of the research is shown in Fig. 1. Based on Fig. 1, the step duration data of the 5 healthy adolescents (23 – 29 years old) and 5 healthy elders (60 – 77 years old) have been collected from PhysioNet. Then, 20 synthetic data are generated from each original data using noise jittering. Noise jittering involves adding a noise which ranges from -0.01 to 0.01 to the data which replicates a new data for the original data. The combination of original data and synthetic data are fed into the deep learning system which are 1D – CNN, LSTM and GRU. The accuracy and the processing time of each deep learning method are then compared to identify the best deep learning method. There are a total of 210 data altogether after the synthetic data is combined with the original data. 80% of the 210 data will be used for training the system which is 168 data and the remaining 20% of the data will be used to test the system. The training data is selected to be 80% to ensure more data is used to train the deep learning while the testing is selected to be 20% to ensure there is enough data to be tested. Other than train – test split, cross – validation with 5 splits will also be conducted to be compared to the train – test split.

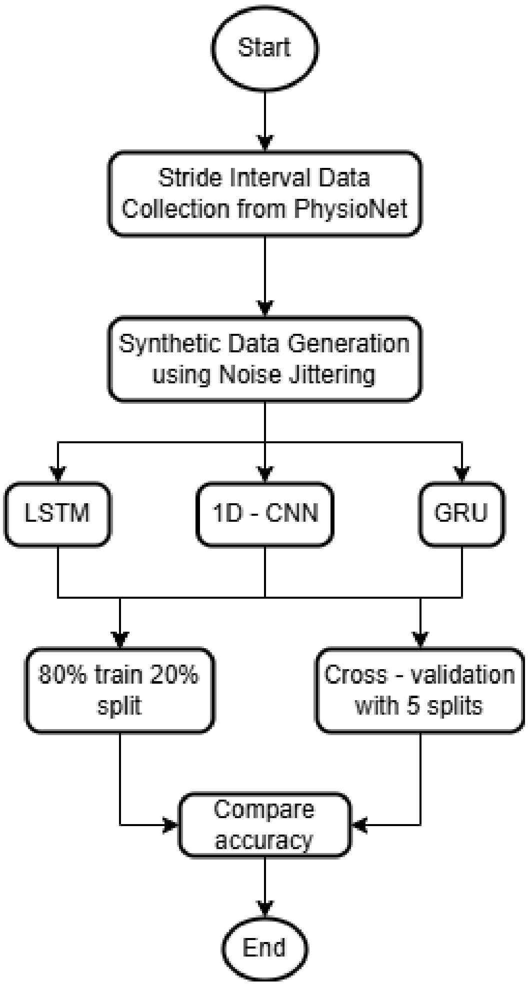

Fig. 1. The flowchart of the research

Since the step duration of the data have different timesteps, the maximum timesteps is identified which is 892. Then, this timestep will be used to train the system. If the data has less than 892 timesteps, then padded zero will be added so that maximum timestep will be 892. Other than padding zero, there is no normalization, scaling and preprocessing of the data and the raw data is left intact. In this research paper, it is hypothesized that the deep learning method is capable of handling complex data in complex environment which include noise for the classification. There is no hyperparameter tuning for the hyperparameters in this project. The best hyperparameters are identified by rigorous testing.

To train the 1D – CNN system, the format of the data to be fed into 1D – CNN will be (number of samples, timestep). Therefore, the shape of the training data will be (168, 892). Since GRU and LSTM only support data in 3D format which are (number of samples, timestep, feature), the training data will be converted to this format (168, 892, 1). The comparative analysis does not include the feature importance because deep learning does not require manual selection of feature. The deep learning project is run on TensorFlow by using a MSI laptop with 16 GB Random Access Memory (RAM), Intel Core i9 CPU and NVIDIA GeForce RTX 4070.

2.1. Deep Learning Method

2.1.1. 1D–CNN

The conventional CNN is designed for image processing tasks, applying convolutional operations on two – dimensional data to extract features. Image is two – dimensional data because it consists of height and width. 1D – CNN is then developed to work with one – dimensional data like time series data to extract features from sequential data. The operation behind the 1D – CNN is like the conventional CNN in the way that convolutional operation is applied too. One advantage of 1D – CNN over CNN is that 1D – CNN can capture temporal dependencies in sequential data more effectively. Other than that, 1D – CNN can result in shorter training time compared to CNN because few parameters are needed due to simplified architecture. The key principle behind the operation of 1D – CNN involves the convolution of a kernel with the input data in one dimension [44], [45]. Fig. 2 shows the construction of the 1D – CNN model for the classification system of the step duration of the elderly and the adolescents. The constructed 1D – CNN model consists of 3 layers of Conv1D with 64 filters with the kernel size of 3. The layers of Conv1D are followed by one flattening layer and finally, one dense layer.

```
model = Sequential()
model.add(Conv1D(64, 3, activation='relu', input_shape=(stride_interval_train.shape[1], 1)))
model.add(Conv1D(64, 3, activation='relu'))
model.add(Conv1D(64, 3, activation='relu'))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
```

Fig. 2. The construction of 1D – CNN model for the classification of the step duration of the elderly and the adolescents

The data is trained with the number of epochs set to 300 and the batch size set to 8. Fig. 3 shows the architecture of constructed 1D – CNN model in this research.

2.1.2. LSTM

LSTM is an improved RNN that was created to solve the problems traditional RNNs had identifying long-term dependencies in sequential data. Conventional RNNs have problems with vanishing and exploding gradients, which can make training the model difficult. RNNs also do not have specific memory cells, which makes it hard for them to remember important information over time. LSTMs, on the other hand, have specialized memory cells that are more resistant to disappearing and expanding gradient problems and can store information for longer periods of time. Information flow is controlled by input, forget, and output gates, which are components of the LSTM architecture [46], [47]. Fig. 4 shows the construction of the LSTM model for the classification of step duration of the elderly and the adolescents. The LSTM model starts with 256 LSTM cells, 128 cells, 128 cells, 64 cells, 32 cells and finally, there is a dense layer. Each LSTM cell is followed by dropout(0.2). Finally, dropout is included to prevent overfitting.

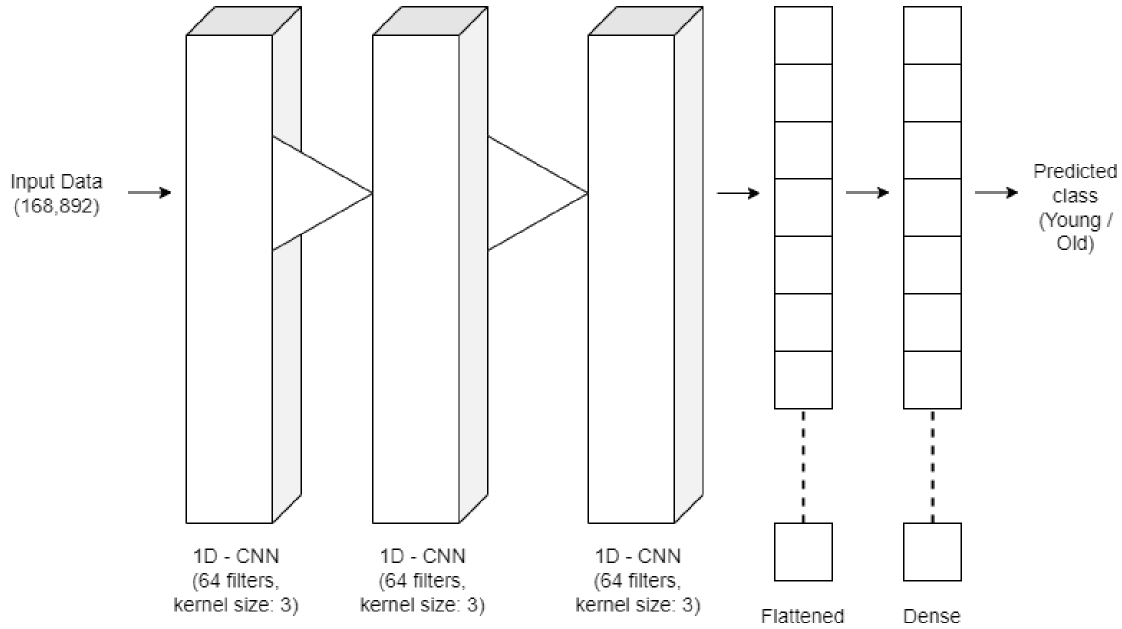

Fig. 3. The architecture of the constructed 1D – CNN model

```
model = Sequential()
model.add(LSTM(256, return_sequences=True, input_shape=(stride_interval_train.shape[1], stride_interval_train.shape[2])))
model.add(Dropout(0.2))
model.add(LSTM(128, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(128, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(64, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(32))
model.add(Dropout(0.2))
model.add(Dense(1))
model.summary()
```

Fig. 4. The construction of LSTM model for the classification of the step duration of the elderly and the adolescents

The data is trained with the number of epochs set to 300 and the batch size set to 8. Fig. 5 shows the architecture of the constructed LSTM model.

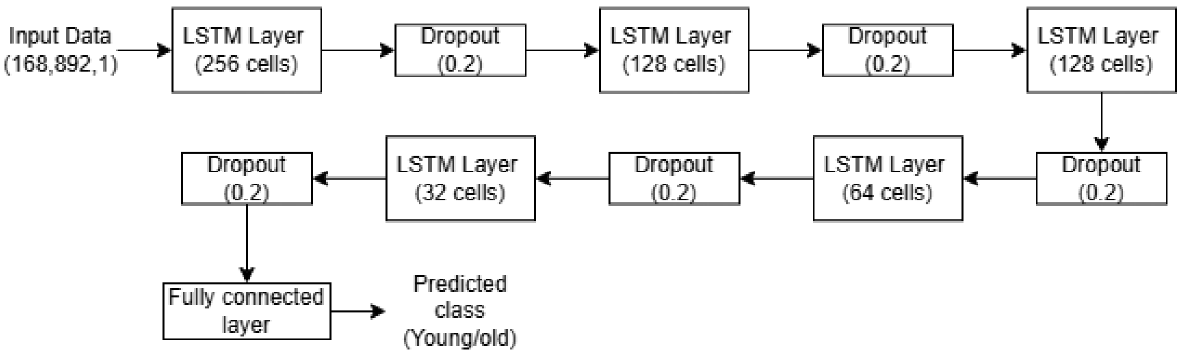

Fig. 5. The architecture of the constructed LSTM model

2.1.3. GRU

Like LSTM, GRU is an RNN variant created to get over some of its current drawbacks. With just two gates which are reset gate and an update gate, GRU has a more straightforward architecture than

LSTM. The reset gate controls how much previous data needs to be deleted, while the update gate controls how much needs to be combined with fresh input to update the memory. Each GRU and LSTM has benefits and drawbacks of their own. Compared to LSTM, GRU is more effective at capturing long-term dependencies in sequential data and is also more computationally economical. However, due to more straightforward architecture, GRU is less able to understand complex linkages and dependencies in the data and has less control over the flow of information [48], [49]. Fig. 6 shows the construction of the GRU model for classification of step duration of the elderly and adolescents. Like LSTM, the GRU model starts with 256 GRU cells, 128 cells, 128 cells, 64 cells, 32 cells and finally, there is a dense layer. Each GRU cell is followed by dropout(0.2). Finally, dropout is included to prevent overfitting.

```
model = Sequential()
model.add(GRU(256, return_sequences=True, input_shape=(stride_interval_train.shape[1], stride_interval_train.shape[2])))
model.add(Dropout(0.2))
model.add(GRU(128, return_sequences=True))
model.add(Dropout(0.2))
model.add(GRU(128, return_sequences=True))
model.add(Dropout(0.2))
model.add(GRU(64, return_sequences=True))
model.add(Dropout(0.2))
model.add(GRU(32))
model.add(Dropout(0.2))
model.add(Dense(1))
model.summary()
```

Fig. 6. The construction of GRU model for the classification of step duration of the elderly and the adolescents

The data is trained with the number of epochs set to 300 and the batch size set to 8. Fig. 7 shows the architecture of the constructed GRU model.

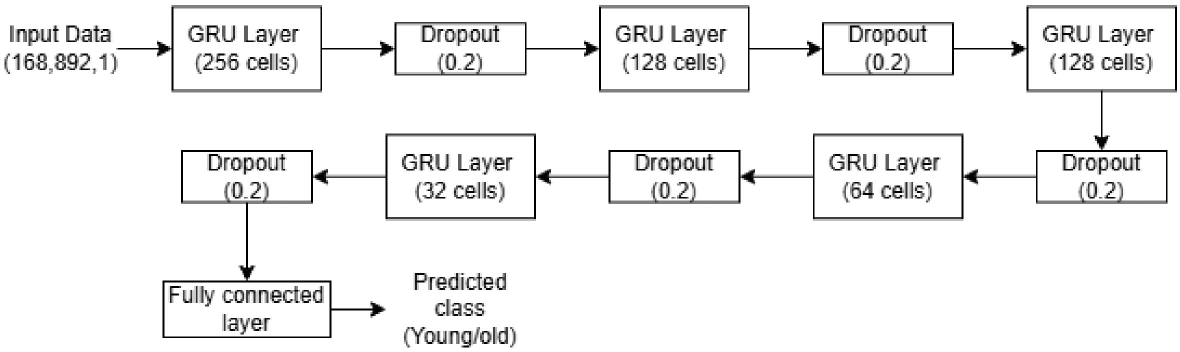

Fig. 7. The architecture of the constructed GRU model

3. Results and Discussion

Fig. 8 shows the parameters that are extracted from the constructed 1D – CNN model that is shown in Fig. 2 and Fig. 3, Fig. 8 shows the total number of parameters extracted are 81665. Fig. 9 shows the parameters that are extracted from the constructed LSTM model that is shown in Fig. 4 and Fig. 5, Fig. 9 shows the total number of parameters extracted are 654753. Fig. 10 shows the parameters that are extracted from the constructed GRU model that is shown in Fig. 6 and Fig. 7, Fig. 10 shows the total number of parameters extracted are 492897.

Based on Fig. 9 and Fig. 10, even though the constructed GRU and LSTM model have the same number of cells which go from 256, 128, 128, 64 and 32 and the same dense layer, GRU derives fewer parameters which are 492897 if compared to LSTM which are 654753. This is due to the simplified nature of GRU that causes it to learn less intricate relationships and dependencies in the data. Table 1 shows the test loss, test accuracy and processing time of 1D – CNN, LSTM and GRU. 1D – CNN has outperformed both LSTM and GRU in terms of test loss, test accuracy and processing time. Besides, the operation of 1D – CNN requires far less parameters which are 81665 compared to LSTM and

GRU. Therefore, the best deep learning method to be used in the classification of the step duration of the elderly and the adolescents is 1D – CNN. Table 1 also shows that the test loss and test accuracy of GRU and LSTM are roughly the same, which shows that the underlying operation of LSTM and GRU are also the same. According to literature review, LSTM does not work well with the highly irregular data, non – stationary data and data with high frequency noise [50]. This does show that the step duration data is highly irregular, non – stationary and has high frequency noise.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 890, 64)           256

 conv1d_1 (Conv1D)           (None, 888, 64)           12352

 conv1d_2 (Conv1D)           (None, 886, 64)           12352

 flatten (Flatten)           (None, 56704)             0

 dense (Dense)               (None, 1)                 56705

=================================================================
Total params: 81,665
Trainable params: 81,665
Non-trainable params: 0
```

Fig. 8. The parameters that are extracted from the constructed 1D – CNN model

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 892, 256)          264192

 dropout_5 (Dropout)         (None, 892, 256)          0

 lstm_1 (LSTM)               (None, 892, 128)          197120

 dropout_6 (Dropout)         (None, 892, 128)          0

 lstm_2 (LSTM)               (None, 892, 128)          131584

 dropout_7 (Dropout)         (None, 892, 128)          0

 lstm_3 (LSTM)               (None, 892, 64)           49408

 dropout_8 (Dropout)         (None, 892, 64)           0

 lstm_4 (LSTM)               (None, 32)                12416

 dropout_9 (Dropout)         (None, 32)                0

 dense_2 (Dense)             (None, 1)                 33
...
Total params: 654,753
Trainable params: 654,753
Non-trainable params: 0
```

Fig. 9. The parameters that are extracted from the constructed LSTM model

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 gru_5 (GRU)                 (None, 892, 256)          198912

 dropout (Dropout)           (None, 892, 256)          0

 gru_6 (GRU)                 (None, 892, 128)          148224

 dropout_1 (Dropout)         (None, 892, 128)          0

 gru_7 (GRU)                 (None, 892, 128)          99072

 dropout_2 (Dropout)         (None, 892, 128)          0

 gru_8 (GRU)                 (None, 892, 64)           37248

 dropout_3 (Dropout)         (None, 892, 64)           0

 gru_9 (GRU)                 (None, 32)                9408

 dropout_4 (Dropout)         (None, 32)                0

 dense_1 (Dense)             (None, 1)                 33

...
Total params: 492,897
Trainable params: 492,897
Non-trainable params: 0
```

Fig. 10. The parameters that are extracted from the constructed GRU model

Fig. 11 shows the plotting of the line graph of the stride interval against time (s). In this aspect, 1D – CNN prevails over LSTM and GRU because 1D – CNN is more robust to noise due to its ability to extract local patterns. 1D – CNN uses convolutional layers that apply filters across the input data that detect specific patterns by sliding over the data. These filters perform element – wise multiplications and summations. These filters suppress random noise by highlighting important features. The kernels operate on a fixed – size window of the input data and detect as well as amplify local features. In contrast, LSTM and GRU are not effective in detecting local patterns due to the wider focus on the entire sequence. Besides, the reason the processing time of 1D – CNN is shorter compared to LSTM and GRU because 1D – CNN process data in parallel while LSTM and GRU process data sequentially [51]. In 1D – CNN, convolutional layers that apply multiple layers across the input data simultaneously will be used. The parallel processing allows the network to extract features from different parts of the input at the same time which speeds up the computation and shortens the processing time. Fig. 12 and Fig. 13 show the bar chart of the parameter count and processing time versus the deep learning methods respectively.

Table 1. The test loss, test accuracy and processing time of 1D – CNN, LSTM and GRU

Deep Learning Methods	Test Loss	Test Accuracy
1D – CNN	2.6095×10^{-8}	1.0000
LSTM	9.5488	0.3810
GRU	9.5488	0.3810

Fig. 14, Fig. 15 and Fig. 16 show the classification report of 1D – CNN, LSTM and GRU respectively whether by cross – validation or 80% training and 20% testing. The train – test split and cross – validation produce the same result for 1D – CNN, LSTM and GRU. Fig. 14 shows that the classification using 1D – CNN has scored 100% for precision, recall and f1 – score both young group which is highlighted as 0 as well as elderly group which is highlighted as 1. Fig. 15 and Fig. 16 show that both LSTM and GRU produce similar classification result.

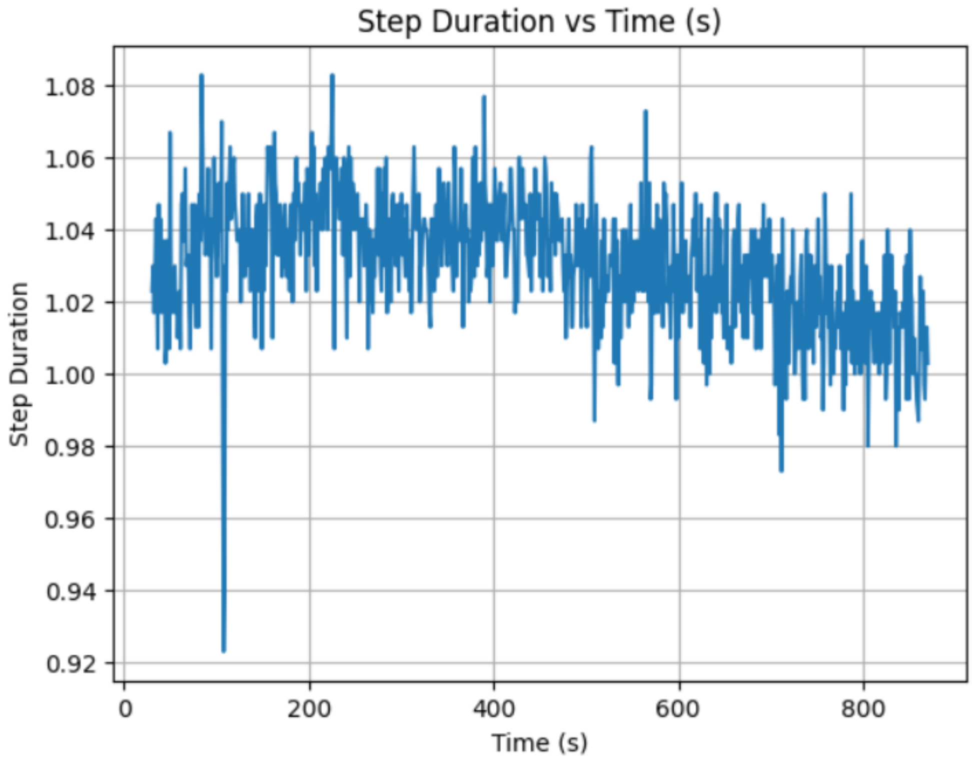

Fig. 11. The plotting of step duration against time (s) for a healthy old sample 1

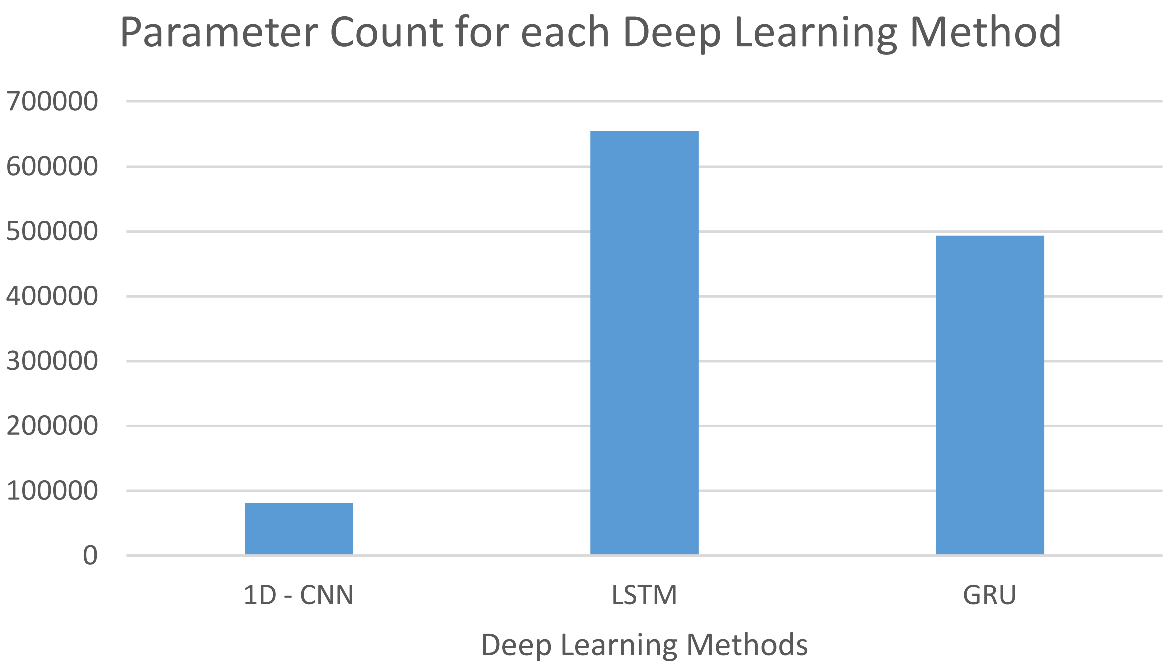

Fig. 12. The bar chart of parameter count versus the deep learning methods

The difference between GRU and LSTM is that due to simplified nature of GRU, GRU has fewer parameters extraction as shown in Fig. 12 and shorter processing times as shown in Fig. 13. This is because GRU has only two gates which are update gate and reset gate while LSTM has three gates which are input gates, forget gate and output gate. Even though GRU and LSTM derived a lot more parameters than 1D – CNN as shown in Fig. 12, 1D – CNN outperformed both GRU and LSTM with much shorter processing time as shown in Fig. 13 because of the ability to detect and amplify local features by using the filters which also suppress random noise while GRU and LSTM have a wider focus on the entire sequence. This suggests that the features that are relevant to the step duration for the classification of the young and elderly are not spread throughout the sequence but are locally concentrated in different distinct parts of the step duration. The research into distinct parts of the sequence of the step duration can be explored further to identify the parts of the step duration of the elderly that need to be rehabilitated to develop healthier gait.

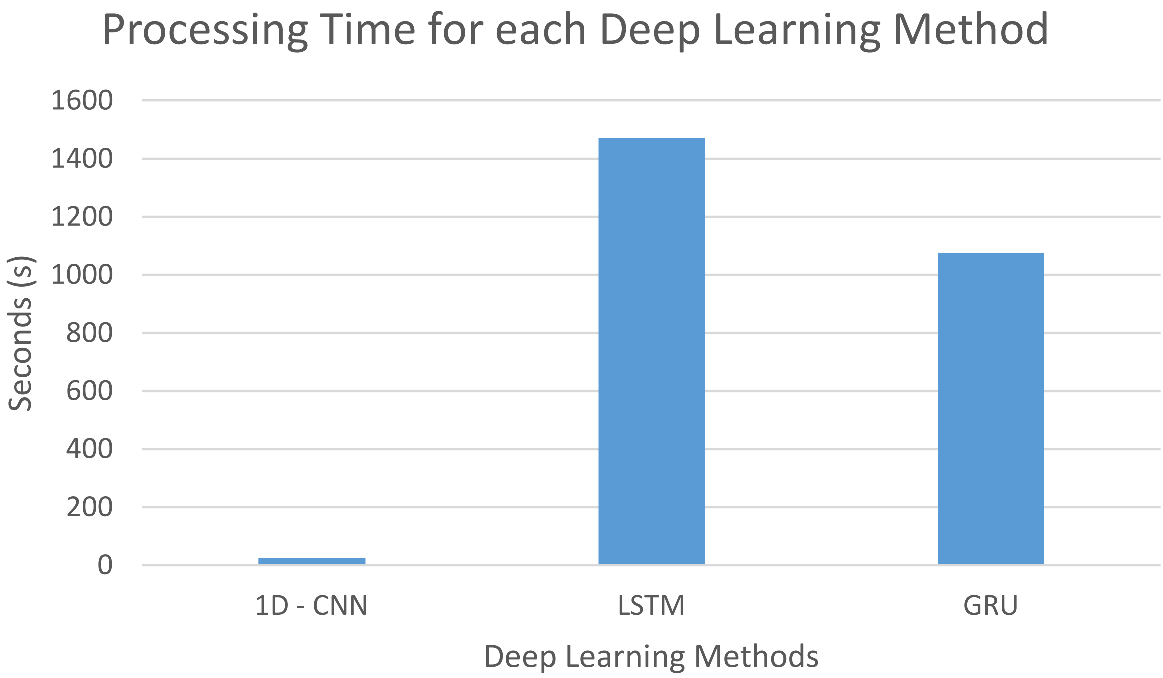

Fig. 13. The bar chart of processing time versus the deep learning methods

	precision	recall	f1-score	support
0	1.00	1.00	1.00	16
1	1.00	1.00	1.00	26
accuracy			1.00	42
macro avg	1.00	1.00	1.00	42
weighted avg	1.00	1.00	1.00	42

Fig. 14. The classification report of 1D – CNN

	precision	recall	f1-score	support
0	0.38	1.00	0.55	16
1	0.00	0.00	0.00	26
accuracy			0.38	42
macro avg	0.19	0.50	0.28	42
weighted avg	0.15	0.38	0.21	42

Fig. 15. The classification report of LSTM

	precision	recall	f1-score	support
0	0.38	1.00	0.55	16
1	0.00	0.00	0.00	26
accuracy			0.38	42
macro avg	0.19	0.50	0.28	42
weighted avg	0.15	0.38	0.21	42

Fig. 16. The classification report of GRU

4. Conclusion

1D - CNN is the best deep learning technique for classifying the step durations of adolescents and the elderly, which are easily accessible as time series data. The fact is that 1D- CNN outperformed LSTM and GRU in terms of test loss, test accuracy and processing time. The cross – validation with 5 splits and train – test split produces the same result for the 1D – CNN, LSTM and GRU. Besides, 1D – CNN required fewer parameters than LSTM and GRU. Furthermore, step duration data has high frequency noise, is highly irregular and non – stationary data which makes LSTM and GRU which are suited to capture long – term dependencies in sequential data unsuitable deep learning methods for the classification of the step duration data whereas, 1D – CNN is more robust to noise due to its ability to extract local pattern which render it a suitable deep learning method. This study demonstrates that, in comparison to LSTM and GRU, 1D – CNN is a more effective way to investigate how people's step duration declines with age, providing greater insight into individualized treatment for the elderly. Future work can also include combining the local pattern extraction abilities of 1D – CNN with the sequential learning capabilities of LSTM and GRU to enhance performance on time – series data with similar kind of noisiness and irregularity. Future work can also include the exploration of 1D – CNN, LSTM and GRU on the classification of neurodegenerative diseases like Parkinson’s disease, Huntington’s disease with different severity levels.

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References

[1] D. Nohelova, L. Bizovska, N. Vuillerme, and Z. Svoboda, “Gait Variability and Complexity during Single and Dual-Task Walking on Different Surfaces in Outdoor Environment,” *Sensors*, vol. 21, no. 14, p. 4792, 2021, https://doi.org/10.3390/s21144792.

[2] F. D. Groote and A. Falisse, “Perspective on musculoskeletal modelling and predictive simulations of human movement to assess the neuromechanics of gait,” *Proceedings of the Royal Society B*, vol. 288, no. 1946, pp. 1-10, 2021, https://doi.org/10.1098/rspb.2020.2432.

[3] J. S. Lora-Millan, J. C. Moreno, and E. Rocon, “Coordination Between Partial Robotic Exoskeletons and Human Gait: A Comprehensive Review on Control Strategies,” *Frontiers in Bioengineering and Biotechnology*, vol. 10, p. 842294, 2022, https://doi.org/10.3389/fbioe.2022.842294.

[4] M. K. MacLean and D. P. Ferris, “Human muscle activity and lower limb biomechanics of overground walking at varying levels of simulated reduced gravity and gait speeds,” *PLoS One*, vol. 16, no. 7, p. e0253467, 2021, https://doi.org/10.1371/journal.pone.0253467.

[5] S. Qin, J. Yan, X. Chen, W. Li, P. Li and Z. Liu, "Assessing the Stability of Human Gait Based on a Human Electrostatic Field Detection System," *IEEE Sensors Journal*, vol. 24, no. 7, pp. 11036-11047, 2024, https://doi.org/10.1109/JSEN.2024.3370301.

[6] S. Piergiovanni, P. Terrier, “Validity of Linear and Nonlinear Measures of Gait Variability to Characterize Aging Gait with a Single Lower Back Accelerometer,” *Sensors*, vol. 24, no. 23, p. 7427, 2024, https://doi.org/10.3390/s24237427.

[7] N. Nedović, F. Eminović, V. Marković, I. Stanković, and S. Radovanović, “Gait Characteristics during Dual-Task Walking in Elderly Subjects of Different Ages,” *Brain Sciences*, vol. 14, no. 2, p. 148, 2024, https://doi.org/10.3390/brainsci14020148.

[8] J. Silva, T. Atalaia, J. Abrantes, and P. Aleixo, “Gait Biomechanical Parameters Related to Falls in the Elderly: A Systematic Review,” *Biomechanics*, vol. 4, no. 1, pp. 165–218, 2024, https://doi.org/10.3390/biomechanics4010011.

[9] H. Kerminen, E. Marzetti, and E. D’Angelo, “Biological and Physical Performance Markers for Early Detection of Cognitive Impairment in Older Adults,” *Journal of Clinical Medicine*, vol. 13, no. 3, p. 806, 2024, https://doi.org/10.3390/jcm13030806.

[10] M. Sato, T. Yamashita, D. Okazaki, H. Asada, and K. Yamashita, “Valid Indicators for Predicting Falls in Community-Dwelling Older Adults Under Ongoing Exercise Intervention to Prevent Care Requirement,” *Sage Open Aging*, vol. 10, 2024, https://doi.org/10.1177/23337214241229328.

[11] M. Antonelli, E. Caselli, and L. Gastaldi, “Comparison of Gait Smoothness Metrics in Healthy Elderly and Young People,” *Applied Sciences*, vol. 14, no. 2, p. 911, 2024, https://doi.org/10.3390/app14020911.

[12] L. Delbes, N. Mascret, C. Goulon, and G. Montagne, “Differences of gait adaptability behavior between young and healthy older adults during a locomotor pointing task in virtual reality,” *Gait Posture*, vol. 109, pp. 233–239, 2024, https://doi.org/10.1016/j.gaitpost.2024.02.009.

[13] D. Commandeur, M. Klimstra, R. Brodie, and S. Hundza, “A Comparison of Bioelectric and Biomechanical EMG Normalization Techniques in Healthy Older and Young Adults during Walking Gait,” *Journal of Functional Morphology and Kinesiology*, vol. 9, no. 2, p. 90, 2024, https://doi.org/10.3390/jfmk9020090.

[14] A. Simonet, A. Delafontaine, P. Fourcade, and E. Yiou, “Vertical Center-of-Mass Braking and Motor Performance during Gait Initiation in Young Healthy Adults, Elderly Healthy Adults, and Patients with Parkinson’s Disease: A Comparison of Force-Plate and Markerless Motion Capture Systems,” *Sensors*, vol. 24, no. 4, p. 1302, 2024, https://doi.org/10.3390/s24041302.

[15] D. Sethi, C. Prakash, and S. Bharti, “Multi-feature gait analysis approach using deep learning in constraint-free environment,” *Expert System*, vol. 41, no. 7, p. e13274, 2024, https://doi.org/10.1111/exsy.13274.

[16] D. Łuczak, “Machine Fault Diagnosis through Vibration Analysis: Continuous Wavelet Transform with Complex Morlet Wavelet and Time–Frequency RGB Image Recognition via Convolutional Neural Network,” *Electronics*, vol. 13, no. 2, p. 452, 2024, https://doi.org/10.1111/exsy.13274.

[17] H. Kuduz and F. Kaçar, “A deep learning approach for human gait recognition from time-frequency analysis images of inertial measurement unit signal,” *International Journal of Applied Methods in Electronics and Computers*, vol. 11, no. 3, pp. 165–173, 2023, https://doi.org/10.58190/ijamec.2023.44.

[18] T. A. Mostafa, S. Soltaninejad, T. L. McIsaac, and I. Cheng, “A Comparative Study of Time Frequency Representation Techniques for Freeze of Gait Detection and Prediction,” *Sensors*, vol. 21, no. 19, p. 6446, 2021, https://doi.org/10.3390/s21196446.

[19] H. Nematallah and S. Rajan, "Quantitative Analysis of Mother Wavelet Function Selection for Wearable Sensors-Based Human Activity Recognition," *Sensors*, vol. 24, no. 7, p. 2119, 2024, https://doi.org/10.3390/s24072119.

[20] J. H. Hollman, W. D. Lee, D. C. Ringquist, C. Taisey, and D. K. Ness, "Comparing adaptive fractal and detrended fluctuation analyses of stride time variability: Tests of equivalence," *Gait Posture*, vol. 94, pp. 9–14, 2022, https://doi.org/10.1016/j.gaitpost.2022.02.019.

[21] D. A. Gadanayak, M. Mishra, and R. C. Bansal, "High impedance fault detection in distribution networks using randomness of zero-sequence current signal: A detrended fluctuation analysis approach," *Applied Energy*, vol. 368, p. 123452, 2024, https://doi.org/10.1016/j.apenergy.2024.123452.

[22] V. E. D. Bacco and W. H. Gage, "Gait variability, fractal dynamics, and statistical regularity of treadmill and overground walking recorded with a smartphone," *Gait Posture*, vol. 111, pp. 53–58, 2024, https://doi.org/10.1016/j.gaitpost.2024.04.002.

[23] H. P. Huang, C. F. Hsu, Y. C. Mao, and L. Hsu, "Gait Stability Measurement by Using Average Entropy," *Entropy*, vol. 23, no. 4, p. 412, 2021, https://doi.org/10.3390/e23040412.

[24] Y.-L. Hsieh, M. F. Abbod, G. Saggio, V. Errico, and I. Mazzetta, "Gait Analyses of Parkinson's Disease Patients Using Multiscale Entropy," *Electronics*, vol. 10, no. 21, p. 2604, 2021, https://doi.org/10.3390/electronics10212604.

[25] J. M. Yentes and P. C. Raffalt, "Entropy Analysis in Gait Research: Methodological Considerations and Recommendations," *Annals of Biomedical Engineering*, vol. 49, no. 3, pp. 979–990, 2021, https://doi.org/10.1007/s10439-020-02616-8.

[26] M. M. Taye, "Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions," *Computers*, vol. 12, no. 5, p. 91, 2023, https://doi.org/10.3390/computers12050091.

[27] S. Dargan, M. Kumar, M. R. Ayyagari, and G. Kumar, "A Survey of Deep Learning and Its Applications: A New Paradigm to Machine Learning," *Archives of Computational Methods in Engineering*, vol. 27, no. 4, pp. 1071–1092, 2020, https://doi.org/10.1007/s11831-019-09344-w.

[28] C. De Marchis *et al*., "Characterizing the Gait of People With Different Types of Amputation and Prosthetic Components Through Multimodal Measurements: A Methodological Perspective," *Frontiers in Rehabilitation Sciences*, vol. 3, p. 804746, 2022, https://doi.org/10.3389/fresc.2022.804746.

[29] E. F. Shair, N. A. Jamaluddin, and A. R. Abdullah, "Finger Movement Discrimination of EMG Signals Towards Improved Prosthetic Control using TFD," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 9, pp. 244–251, 2020, https://doi.org/10.14569/IJACSA.2020.0110928.

[30] M. Wang, W. Lee, L. Shu, Y. S. Kim, and C. H. Park, "Development and Analysis of an Origami-Based Elastomeric Actuator and Soft Gripper Control with Machine Learning and EMG Sensors," *Sensors*, vol. 24, no. 6, p. 1751, 2024, https://doi.org/10.3390/s24061751.

[31] İ. G. Özeloğlu and E. A. Aydin, "Combining features on vertical ground reaction force signal analysis for multiclass diagnosing neurodegenerative diseases," *International Journal of Medical Informatics*, vol. 191, p. 105542, 2024, https://doi.org/10.1016/j.ijmedinf.2024.105542.

[32] J. Stenum Id, M. M. Hsu, A. Y. Pantelyat, and R. T. Roemmich Id, "Clinical gait analysis using video-based pose estimation: Multiple perspectives, clinical populations, and measuring change," *PLOS Digital Health*, vol. 3, no. 3, p. e0000467, 2024, https://doi.org/10.1371/journal.pdig.0000467.

[33] T. Matsuda *et al*., "Validity Verification of Human Pose-Tracking Algorithms for Gait Analysis Capability," *Sensors*, vol. 24, no. 8, p. 2516, 2024, https://doi.org/10.3390/s24082516.

[34] C. Zhou, D. Feng, S. Chen, N. Ban, and J. Pan, "Portable vision-based gait assessment for post-stroke rehabilitation using an attention-based lightweight CNN," *Expert Systems with Applications*, vol. 238, p. 122074, 2024, https://doi.org/10.1016/j.eswa.2023.122074.

[35] H. Wang *et al*., "Markerless gait analysis through a single camera and computer vision," *Journal of Biomechanics*, vol. 165, p. 112027, 2024, https://doi.org/10.1016/j.jbiomech.2024.112027.

[36] R. Cedeno-Moreno, D. L. Malagon-Barillas, L. A. Morales-Hernandez, M. P. Gonzalez-Hernandez, and I. A. Cruz-Albarran, “Computer Vision System Based on the Analysis of Gait Features for Fall Risk Assessment in Elderly People,” *Applied Sciences*, vol. 14, no. 9, p. 3867, 2024, https://doi.org/10.3390/app14093867.

[37] V. W. S. Tan, W. X. Ooi, Y. F. Chan, T. Connie, M. K. O. Goh, “Vision-Based Gait Analysis for Neurodegenerative Disorders Detection,” *Journal of Informatics and Web Engineering*, vol. 3, no. 1, pp. 136–154, 2024, https://doi.org/10.33093/jiwe.2024.3.1.9.

[38] J. D. Blasco-García *et al*., “A Computer Vision-Based System to Help Health Professionals to Apply Tests for Fall Risk Assessment,” *Sensors*, vol. 24, no. 6, p. 2015, 2024, https://doi.org/10.3390/s24062015.

[39] L. Xiang *et al*., “Integrating an LSTM framework for predicting ankle joint biomechanics during gait using inertial sensors,” *Computers in Biology and Medicine*, vol. 170, p. 108016, 2024, https://doi.org/10.1016/j.compbiomed.2024.108016.

[40] M. Shayestegan, J. Kohout, L. Verešpejová, M. Chovanec and J. Mareš, "Comparison of Feature Selection and Supervised Methods for Classifying Gait Disorders," *IEEE Access*, vol. 12, pp. 17876-17894, 2024, https://doi.org/10.1109/ACCESS.2024.3360861.

[41] D. Martínez-Pascual, J. M. Catalán, A. Blanco-Ivorra, M. Sanchís, F. Arán-Ais and N. García-Aracil, "Gait Activity Classification With Convolutional Neural Network Using Lower Limb Angle Measurement From Inertial Sensors," *IEEE Sensors Journal*, vol. 24, no. 13, pp. 21479-21489, 2024, https://doi.org/10.1109/JSEN.2024.3400296.

[42] A. A. Ahmed *et al*., “Classifying Cardiac Arrhythmia from ECG Signal Using 1D CNN Deep Learning Model,” *Mathematics*, vol. 11, no. 3, p. 562, 2023, https://doi.org/10.3390/math11030562.

[43] J. Zhu, H. Chen and W. Ye, "Classification of Human Activities Based on Radar Signals using 1D-CNN and LSTM," *2020 IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 1-5, 2020, https://doi.org/10.1109/ISCAS45731.2020.9181233.

[44] A. K. Ozcanli and M. Baysal, “Islanding detection in microgrid using deep learning based on 1D CNN and CNN-LSTM networks,” *Sustainable Energy, Grids and Networks*, vol. 32, p. 100839, 2022, https://doi.org/10.1016/j.segan.2022.100839.

[45] S. Guessoum *et al*., “The Short-Term Prediction of Length of Day Using 1D Convolutional Neural Networks (1D CNN),” *Sensors*, vol. 22, no. 23, p. 9517, 2022, https://doi.org/10.3390/s22239517.

[46] G. V. Houdt, C. Mosquera, and G. Nápoles, “A review on the long short-term memory model,” *Artificial Intelligence Review*, vol. 53, no. 8, pp. 5929–5955, 2020, https://doi.org/10.1007/s10462-020-09838-1.

[47] H. Lin *et al*., “Time series-based groundwater level forecasting using gated recurrent unit deep neural networks,” *Engineering Applications of Computational Fluid Mechanics*, vol. 16, no. 1, pp. 1655–1672, 2022, https://doi.org/10.1080/19942060.2022.2104928.

[48] K. E. ArunKumar, D. V. Kalaga, C. M. S. Kumar, M. Kawaji, and T. M. Brenza, “Forecasting of COVID-19 using deep layer Recurrent Neural Networks (RNNs) with Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) cells,” *Chaos Solitons Fractals*, vol. 146, p. 110861, 2021, https://doi.org/10.1016/j.chaos.2021.110861.

[49] Y. Zhang *et al*., "Epileptic Seizure Detection Based on Bidirectional Gated Recurrent Unit Network," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 135-145, 2022, https://doi.org/10.1109/TNSRE.2022.3143540.

[50] S. Obeta, E. Grisan, and C. V. Kalu, “A Comparative Study of Long Short-Term Memory and Gated Recurrent Unit,” *SSRN Electronic Journal*, 2020, https://dx.doi.org/10.2139/ssrn.4442677.

[51] F. M. Shiri, T. Perumal, N. Mustapha, and R. Mohamed, “A Comprehensive Overview and Comparative Analysis on Deep Learning Models: CNN, RNN, LSTM, GRU,” *Machine Learning*, 2024, https://arxiv.org/abs/2305.17473.