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ORIGINAL ARTICLE

Deep learning based ankle–foot movement classification for prosthetic foot

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Abstract
The primary motivation behind this study is the aspiration to design a prosthetic foot that demonstrates enhanced functionality, enabling more active and prompt responses, particularly tailored for individuals with below-knee amputations. This goal underscores the intention to create a prosthetic foot with the capability to execute foot movements in a more natural and effective manner. A new 1D-ResCNN model has been proposed for the rapid and accurate classification of foot movements based on user intent in the context of a prosthetic limb. This research introduces an innovative approach by integrating inertial measurement units with deep learning algorithms to advance the development of more functional prosthetic feet, specifically tailored for below-knee amputees. Leveraging wearable technologies, this method allows for the prolonged monitoring of foot movements within the users' natural environments. The dual benefits of cost reduction and enhanced user experience are achieved through this combination of advanced technologies, providing a promising avenue for the evolution of prosthetic foot design and usage. The results obtained with this model are satisfying both in terms of speed and accuracy with 99.8% compared to other methods in the literature.

Keywords Deep learning · Inertial measurement unit · Convolutional neural network · Gyroscope · Accelerometer · Foot movement

Abbreviations

Wang[(a)]	Sitting, standing, walking on flat ground, climbing stairs, going downstairs
Feng[(b)], Su[(c)], Lu[(d)]	Climbing stairs, going downstairs, walking on flat ground, going up a ramp, going down ramp
Bijalwan[(e)]	Jogging, normal a walking, tiptoe walking, heel walking, climbing stairs, going down stairs, sit ups
Narayan[(f)]	16 Movement modes: Sitting, standing, climbing stairs, going down stairs, walking on flat ground, walking curved to the right, walking curved to the left, turning right, turning left, etc.
Vu[(g)]	Climbing stairs, going down stairs, walking on flat ground, standing.
Vakacherla[(h)]	Standing, walking on flat ground, walking on slopes, running, squatting
Aydin Fandakli[(i)]	Dorsiflexion, plantarflexion, inversion, eversion

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1 Introduction

Advancements in technology, particularly in sectors such as health, security, transportation, and education, are now contributing to the concept of smart living within our homes. This integration aims to enhance the quality of life and increase overall efficiency [1, 2]. As the cornerstone of smart living revolves around human activities and movements, researchers have increasingly focused on the field of human activity recognition in recent years, leading to numerous publications in the literature. Activity recognition technology enables individuals to analyze their daily routines by capturing and processing behavioral data. In human–human interactions and human–computer relationships, human activity recognition plays a pivotal role in

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offering insights into a person's identity and psychological state. This paper illustrates the application of human activity recognition within the healthcare domain. The objective is to develop a model capable of identifying a person's foot activity based on sensor-generated signals. This model is intended for use in designing smart prosthetics for individuals who have undergone below-the-knee amputations.

Amputation, the removal of part or the entire limb, stands as one of the oldest recorded surgical procedures. The incidence of lower extremity amputations is on the rise due to various uncertain and unexpected factors, including benign and malignant bone diseases, natural disasters, traffic accidents, birth defects, and peripheral vascular diseases [3]. Researchers have shown a heightened interest in deformations affecting the lower extremities, given their significant impact on both human movement and psychology, making research in this area particularly crucial [4]. Notably, the UK witnessed more than 42,000 lower extremity amputations between 2003 and 2013, highlighting substantial variations in human gait [5]. The cause of gait asymmetry in stable amputees is the increased strain on the healthy leg, leading to greater stress on the joints and muscles involved. Among the lower extremity amputations addressed in our study, below-knee (transtibial) and ankle-level amputations make up 12–32%, while partial foot amputations account for 15–26% of all amputations [6, 7]. Assessing mobility, a key indicator of quality of life, stands as a frequently used method to monitor the rehabilitation process in individuals with amputations. The necessity for prolonged monitoring of disabled individuals in their natural environments has spurred the development of wearable sensors. Identifying suitable sensors for smart prosthesis design is a prerequisite for understanding the complex movement of the lower extremities [8]. In the past, human activity recognition relied on data obtained in laboratory environments through videos and sensors. However, the high cost associated with laboratory setups, equipment, and the challenge of collecting data within confined spaces have led to a shift toward wearable sensor-based systems over video-based alternatives [9]. This review underscores that contemporary deep learning technologies, recognized as one of the most promising approaches, prove valuable in monitoring data through wearable sensor technologies.

Gait, being the most common human movement, plays a crucial role in enabling individuals to participate in various social activities. Any pathological issues related to gait necessitate prompt intervention [10, 11]. While passive prostheses and rehabilitation devices are often favored for their low cost and lightweight nature, they may prove insufficient in effectively regulating gait, potentially adding to the burden on individuals [12]. To address this challenge, there is a need for active prostheses that empower the ankle joint to execute diverse movements. Existing literature utilizes data collected during gait, where human movement predominantly occurs in the sagittal plane. However, this study takes a step further by classifying foot movements, examining motion in both the sagittal and frontal planes. To precisely ascertain the mode of movement and user intent, the researchers introduced a novel approach by initially detecting electromyography (EMG) signals from the muscles [13]. Factors such as sweating, temperature changes, and fatigue impact the electromyography (EMG) of muscles, hindering its practical use. Recently, attempts have been made to employ noninvasive active electrode scalp electroencephalography (EEG) signals for motion mode recognition [14]. However, these signals exhibit low robustness, and their heavy computing load diminishes performance, making their practical implementation challenging. The advent of the Internet of Things (IoT) has ushered in a new era, enabling the placement of sensors like accelerometers and gyroscopes on various devices, including portable ones like phones and watches, as well as non-portable entities like walls and cars. These sensors facilitate continuous data collection from individuals, contributing to the growing popularity and utilization of wearable micro-electromechanical systems and inertial measurement units [15, 16].

Existing solutions often fall short in providing a seamless user experience. This study introduces a groundbreaking approach by combining deep learning, specifically a novel 1D-ResCNN model with batch normalization, with inertial measurement units (IMUs). The aim is to address the inherent complexities associated with classifying foot movements based on user intent. Our original contributions lie in overcoming the challenges of capturing nuanced movements and ensuring real-world adaptability. The proposed model not only outperforms existing methods in accuracy but also offers a promising avenue for cost-effective and user-centric prosthetic foot design.

Following the Introduction section, the subsequent sections will include a detailed review of the literature, an explanation of the methodologies employed, an analysis of the findings, and conclusions drawn from the study. These sections will provide readers with a comprehensive understanding of the study's fundamental steps and the obtained results.

1.1 Related work

A human activity recognition study conducted by Vakacherla et al. explored various activities such as standing, walking on flat ground, walking on an incline, running, and squatting. The study utilized a single three-axis accelerometer attached to the chest of 10 subjects. Two methods were tested in real time: a one-dimensional convolutional neural network (CNN) and a hybrid model combining CNNs and long short-term memory (LSTM). The achieved accuracies were 96.6 and 97.2%, respectively [17]. In a related effort to enhance CNN models in sensor-based activity recognition, Tang et al. introduced a novel hierarchical split convolutional network approach. This approach was applied to four datasets, resulting in accuracies of 97.28% for the UCI-HAR dataset, 93.75% for the PAMAP2 dataset, 99.02% for the WISDM dataset, and 79.02% for the UniMiB SHAR dataset [18]. Hysenllari et al. conducted an experiment using a convolutional neural network (CNN) to recognize activities such as walking, jogging, cycling, sitting, standing, and lying. The purpose was to observe how neural network performance varies based on sensor location. Notably, the CNN achieved an accuracy of 96.57% when the sensor was placed on the ankle, while it demonstrated a higher accuracy of 99.28% when located on the thigh [19]. In a related study, Huang et al. proposed a shallower CNN model with cross-channel communication to eliminate unnecessary information accumulation between channels in a human activity recognition scenario. The evaluation and performance analysis were conducted on publicly available datasets, including UCI-HAR, OPPORTUNITY, PAMAP2, and UniMiB SHAR. The UCI-HAR dataset yielded the highest accuracy of 96.98% [20]. In addressing the challenge of limited labeled data, Nguyen et al. introduced a novel feature-based and feature-based learning approach employing support vector machines (SVM), *k*-nearest neighbor (*k*NN), and random forest (RF) classifiers for activity recognition. The method was tested on M health daily and sport and real disp datasets, showcasing superior performance, particularly with Random Forest [21]. For human activity recognition, six feed-forward and convolutional neural network (CNN) architectures were designed using leave one subject out cross-validation with four preprocessing scenarios. The 85.1% success achieved with a 2-convolution and one-dimensional filter CNN surged to an impressive 99.85% with the proposed approach [22]. Hassan et al. presented a deep belief network (DBN) approach using the publicly available UCI dataset to recognize 12 human activities such as standing, sitting, lying down, and walking. In comparison with support vector machines (SVM) and artificial neural network (ANN), DBN exhibited superior performance with a success rate of 95.85% [23]. Zebin et al. conducted a study involving 12 healthy volunteers, collecting accelerometer and gyroscope data for activities such as walking, walking upstairs, walking downstairs, sitting, standing, and lying down. The gathered data were input into support vector machines, multilayer perceptron, and deep convolutional neural network classifiers for activity recognition, and their performances were assessed. The results indicated that the convolutional neural network (CNN) exhibited higher accuracy and faster response times compared to other machine learning methods [24]. In a related effort, Ordonez et al. combined CNN and long short-term memory (LSTM) methods in their study, introducing a method named DeepConvLSTM. The proposed method's performance was tested on the Opportunity dataset and the Skoda dataset, showcasing satisfactory results compared to traditional machine learning methods [25]. Eyobu et al. conducted an analysis of human activity recognition performance using a deep long short-term memory (LSTM) neural network architecture. Their approach involved spectrogram-based feature extraction from raw Inertial Measurement Unit (IMU) sensor data and data augmentation to address data scarcity issues. Gyroscope and accelerometer data were collected from 5 subjects aged 25–40 years. The proposed method's performance was compared between their dataset and the publicly available UCI dataset [26]. In a study by Khera et al., 10 healthy subjects aged 20–33 were instructed to perform dorsiflexion, plantarflexion, inversion, and eversion movements, and electromyography (EMG) data were collected. Time and frequency features were extracted from the EMG signal, and support vector machine (SVM), neural networks (NN), and logistic regression algorithms were employed as classifiers. SVM outperformed the others, achieving an accuracy rate of 93.23% [27]. Negi et al. utilized EMG and force myography (FMG) signals from leg muscles to classify foot movements in the sagittal plane. Traditional machine learning methods, including linear discriminant analysis (LDA), logistic regression (LR), SVM, and *K*-nearest neighbors (KNN), were employed, with LDA achieving the highest accuracy [28].

Chaobankoh et al. collected EMG signals from five healthy volunteers and employed two-dimensional convolutional neural networks (2D-CNN) to classify human ankle movements such as dorsiflexion, neutral position, and plantarflexion. The 2D-CNN classifier achieved an average accuracy of 99% in training and 71.38% in testing [29].

In a previous study, foot movement recognition analysis with inertial measurement units (IMU) was performed using traditional machine learning methods and artificial neural network (ANN). The ANN achieved a classification accuracy of 93.66% [30].

The aim is to emulate the fluidity and efficiency of natural foot motions, enhancing the overall functionality and user experience for individuals with below-knee amputations.

2 Methods

2.1 Data set description

The foundation of deep learning approaches begins with acquiring raw data from wearable sensors. In this study, data were collected from 11 healthy subjects, comprising 8 males and 3 females, in the Biomechanics Laboratory of the Department of Mechanical Engineering at the Middle East Technical University. The subjects performed four movements (dorsiflexion, plantarflexion, inversion, and eversion) on a force plate named Bertec. A total of 2200 movement data points were collected, with 50 trials for each of the four movements for each individual. The raw data consist of three main signal types: total acceleration, total gyroscope, and total magnetometer, each with three axes of data. This results in a total of nine variables for each time step. As an example, Fig. 1 illustrates the gyroscope x-axis data from 50 trials of a subject's plantarflexion movement.

Utilizing an Inertial Measurement Unit (IMU) equipped with a 9-axis LSMD9DS1 module, incorporating a 3-axis gyroscope, 3-axis accelerometer, and 3-axis magnetometer, data from the foot metatarsal are transmitted to a laboratory computer interface. This interface, established with the USB-6212 Multifunction I/O device from National Instruments, enables data visualization. Subsequently, the data displayed in this interface are extracted with SQL and transferred to Excel for further processing. The Python programming language is then employed to manipulate and analyze the data. The collected data from the accelerometer, measuring the rate of acceleration in a single direction, the gyroscope, gauging spatial rotation, and the magnetometer, determining direction, are presented in Fig. 2. These data points were acquired within a 5 s interval from each subject.

In adherence to ethical standards, data collection from volunteers was conducted under the approval of the ethics committee. The study received approval with the certificate numbered 24,237,859–595 from the Karadeniz Technical University Faculty of Medicine Scientific Research Ethics Committee. Prior to participating in the measurements, eleven healthy volunteers aged 20–34 signed the informed consent form [29].

Figure 3 visually represents the foot movements that were collected in the laboratory for use in the classification process.

2.2 Feature scaling

2.2.1 Normalization

The preprocessing of data stands as a crucial step in achieving optimal classification performance before subjecting the data to evaluation. Among the various techniques employed during data preparation, data

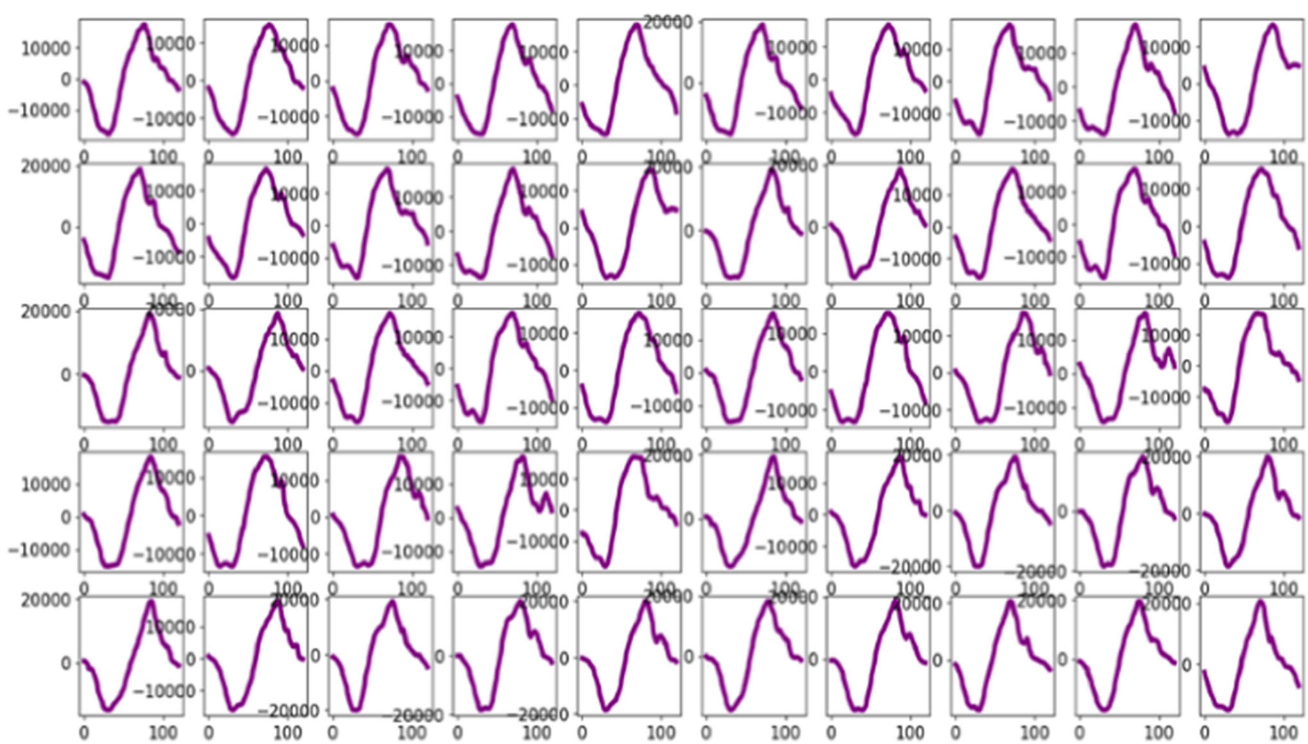

Fig. 1 6th subject 50 trial plantar flexion motion Gx data

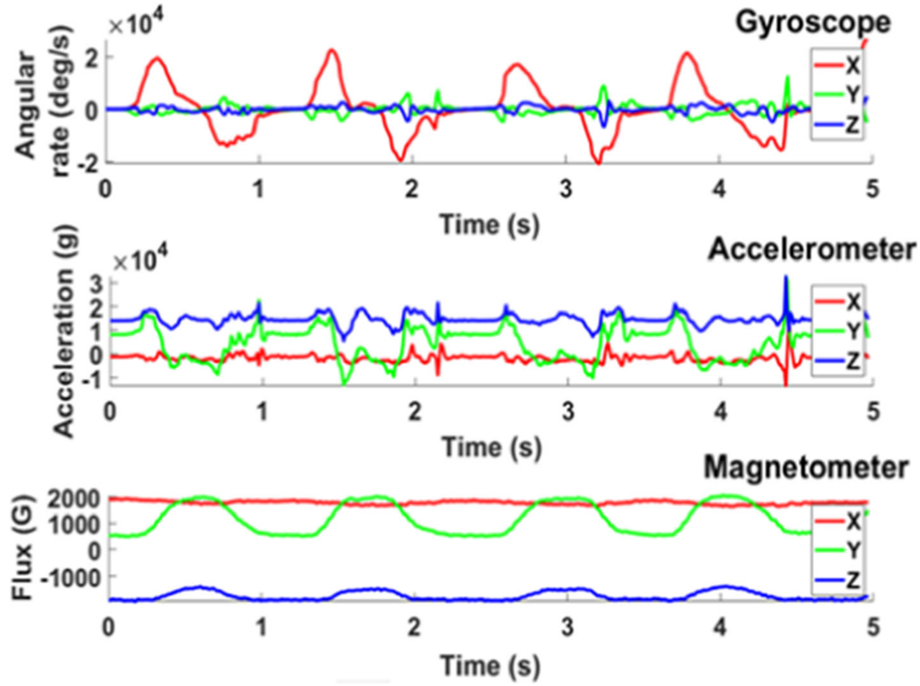

Fig. 2 5 s of gyroscope, accelerometer, and magnetometer data from a volunteer

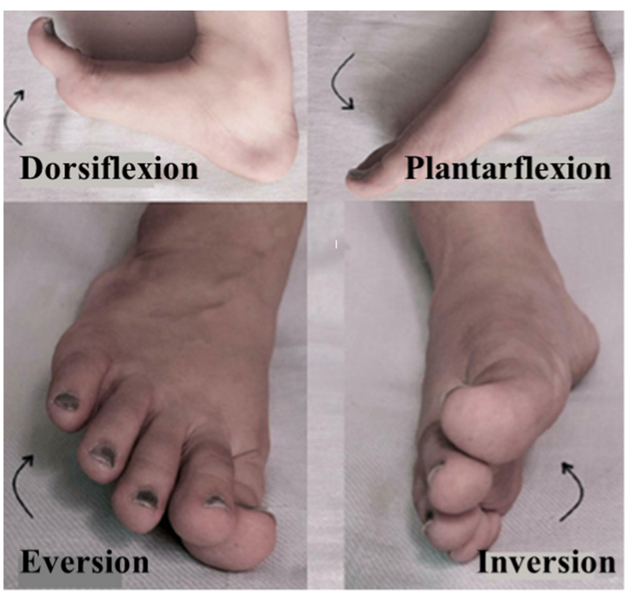

Fig. 3 Foot movements [27]

transformation plays a fundamental role in machine learning. One common technique is normalization, which involves transforming features to a similar scale. This practice enhances model performance and stability.

Normalization is particularly valuable as it ensures that features are on a comparable scale, preventing numerical values of different features from disproportionately influencing the model. By providing equal weight to all features, normalization contributes to the creation of more effective models [31]. Therefore, all data in this study underwent normalization, with the numbers in the dataset scaled to the [0, 1] interval. This process was executed through min–max normalization, as depicted in Eq. (1).

$$\mathrm{Normalized}(X_i) = \frac{x_i - x_{\min}}{x_{\max} + x_{\min}} \tag{1}$$

where i is the rank of the dataset, $x_{\min}$ is the minimum value of the dataset, $x_{\max}$ is the max value of the dataset, and normalized X_{i} is normalized data of the i_{th} row.

2.3 Classification

2.3.1 Convolutional neural networks

In recent times, time series data collected from body-worn sensors have become a focal point, with deep architectures employed for processing to detect complex features in human movements [32]. The seamless recognition of a volunteer's foot movements from raw data prompted our exploration into deep architectures [33].

Deep learning, an advanced iteration of machine learning, represents the cutting edge in intelligent systems within the realm of artificial intelligence. Its primary advantage lies in its capacity to swiftly process vast amounts of data, yielding meaningful outputs in record time [34]. In the domain of human activity recognition with sensors, while real-time predictions can be achieved using traditional machine learning methods such as *k*NN and SVM, the reliance on manual features obtained through these methods may lead to suboptimal performance. This challenge has directed researchers toward the adoption of convolutional neural networks (CNNs), which autonomously learn intricate human features [35].

While deep CNN models have demonstrated superior performance, a deliberate decision was made to opt for a shallower model. The rationale behind this choice stems from the resource constraints inherent in wearable devices. Deep models, while powerful, demand more computational cost and memory power. CNNs stand as one of the most prevalent deep learning algorithms, accepting raw data as input, autonomously learning features at various levels. They have proven particularly effective in the analysis of signals with time series data. However, the decision to employ a shallower model in our context arises from the necessity to streamline the model for efficient operation within the limited resources of wearable devices [36].

The inspiration for CNNs dates back to Hubel and Wiesel's 1959 discovery that cells in the animal's visual cortex recognize light in a small receptive field. Kunihiko Fukusima proposed the first theoretical model of CNN in 1980 [37]. The initial success of CNNs materialized with the introduction of the 7-layer CNN algorithm LeNet5 in 1998 by LeCun et al., albeit on a small dataset with 10 classes [38].

CNNs are beneficial in the classification of foot movements for prosthetic feet due to their ability to learn spatial hierarchies, automatically extract relevant features, handle time-series data, leverage transfer learning, adapt to varied input sensors, and support real-time inference. These characteristics contribute to the effectiveness of CNNs in accurately classifying different foot movements for improved prosthetic control and user experience. In the context of foot movements, this is crucial because different movements may involve intricate spatial patterns in the input data. The ability to capture spatial relationships allows CNNs to discern subtle variations in foot movements, enabling more accurate classification.

3 Results

The data collected from volunteers underwent preparation for utilization in the proposed deep learning algorithm, a process conducted using the Python programming language within the Spider editor. Performance analysis studies employing the prepared dataset were conducted through various platforms, including Spider, Jupiter editors, and Google Colab. Key libraries such as Keras, TensorFlow, and PyTorch were preferred for these studies.

In the data preparation phase for the model, a series of steps were executed. Initially, the data were loaded, followed by normalization and one-hot encoding for labeling. Subsequently, the data were partitioned into training, testing, and validation datasets to facilitate effective model training and evaluation.

In our study, we configured the PyTorch framework with 2200 samples, 9 channels, and a sequence length of 100. For the task at hand, we identified 4 classes corresponding to 4 distinct movements, ensuring an equitable distribution of data for balanced training and testing. Specifically, we allocated 80% of the data for training and 20% for testing, with an additional 20% of the training set reserved for validation purposes. To facilitate seamless integration with PyTorch, the data underwent translation into a format compatible with the framework. The training, testing, and validation datasets were converted into torch data and transformed into tensors, ensuring their compatibility with PyTorch for subsequent processing.

In the initial step, the 1D-ResCNN model executes convolution operations, multiplying the input time data with a filter matrix to extract features from the data with 9 channels and a length of 100. Subsequently, batch normalization is applied to prevent the data from becoming excessively large. The third step involves subjecting the data to the ReLU activation function. Following this, the data are fed into a Res-Block in the fourth stage, where valuable features are extracted. This process is repeated through the fifth to the ninth stages, encompassing feature extraction processes leading up to the classification stage.

In these eight layers, raw data are taken, features are extracted, and the model classifies these features. At the classification stage, the data go through a linear layer, ReLU activation function, another linear layer, ReLU activation function, and finally, a final linear layer. The convolutional neural network model is configured as illustrated in Fig. 4 to model the movements of individuals participating in the experiment. Detailed information about the 1D-ResCNN model is outlined in Table 1, with numerical values of the parameters provided in Table 2.

The CNN model is composed of two 1D convolution layers featuring 16 and 32 filters with a kernel size of 3, accompanied by a batch normalization (BN) layer, rectified linear unit (ReLU) activation function, fully connected layers, and Res-Blocks. The convolution layer serves as the fundamental and principal building block of the CNN.

Batch normalization, a key component, addresses overfitting concerns by enabling layers to learn concurrently, eliminating the need for layers to wait for prior ones to learn. This enhances network organization, stability, and speed [39]. The ReLU activation function, chosen for its ability to introduce nonlinearity to the network, stands as the most widely used activation function in deep neural networks. ReLU converts all input values to positive numbers, resulting in an output of 0 when $x < 0$ [40].

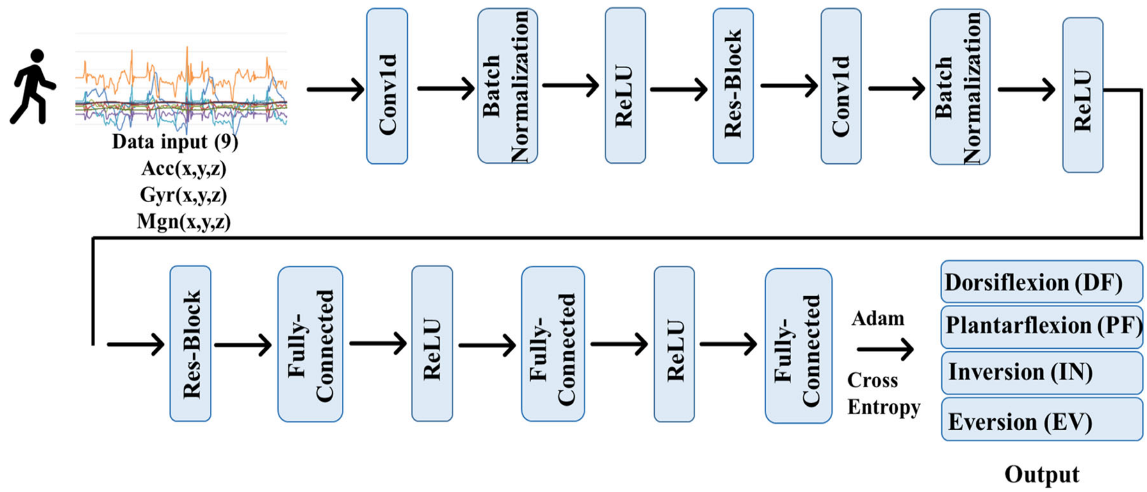

Fig. 4 The architecture of the proposed 1D-ResCNN model. The inputs to the network are created by nine signal channels of one IMU. The outputs are classified into four-foot movements: DF, PF, IN, and EV

Table 1 Detailed 1D-ResCNN architecture

Layer name	Input shape	Output shape	Param #
CNN model	[100, 9, 100]	[100, 4]	–
Conv1d	[100, 9, 100]	[100, 16, 100]	448
BatchNorm1d	[100, 16, 100]	[100, 16, 100]	32
ReLU	[100, 16, 100]	[100, 16, 100]	–
Res-Block	[100, 16, 100]	[100, 16, 100]	–
Sequential	[100, 16, 100]	[100, 16, 100]	–
Conv1d	[100, 16, 100]	[100, 16, 100]	784
BatchNorm1d	[100, 16, 100]	[100, 16, 100]	32
Conv1d	[100, 16, 100]	[100, 16, 100]	784
BatchNorm1d	[100, 16, 100]	[100, 16, 100]	32
Conv1d	[100, 16, 100]	[100, 32, 100]	1,568
BatchNorm1d	[100, 32, 100]	[100, 32, 100]	64
ReLU	[100,32,100]	[100, 32, 100]	–
Res-Block	[100, 32, 100]	[100, 32, 100]	–
Sequential	[100, 32, 100]	[100, 32, 100]	–
Conv1d	[100, 32, 100]	[100, 32, 100]	3,104
BatchNorm1d	[100, 32, 100]	[100, 32, 100]	64
Conv1d	[100, 32, 100]	[100, 32, 100]	3,104
BatchNorm1d	[100, 32, 100]	[100, 32, 100]	64
Linear	[100, 3200]	[100, 2048]	6,555,648
ReLU	[100, 2048]	[100, 2048]	–
Linear	[100, 2048]	[100, 1024]	2,098,176
ReLU	[100, 1024]	[100, 1024]	–
Linear	[100, 1024]	[100, 4]	4,100

The Res-Block significantly fortifies the model by minimizing information loss and reducing training error. This enhancement contributes to the model's robustness and overall effectiveness.

Table 2 Numerical values of parameters

Number of trainable parameters	8.668.004
Training data	1408, 9, 100
Test data	440, 9, 100
Validation data	352, 9, 100
Batch size	100
Epoch	50

The Res-Block structure was employed to mitigate challenges related to reduced features and to streamline the training of CNNs. The proposed Res-Block architecture is visually depicted in Fig. 5. This Res-Block configuration incorporates two convolutional layers with 3×3 filters, complemented by two batch normalization layers and the ReLU activation function.

For optimization purposes, the ADAM optimizer was employed as the chosen method in the model. This optimizer plays a crucial role in enhancing the convergence speed and overall performance of the neural network during the training process.

The study utilized various performance metrics, including accuracy, precision, recall, and F1 score, as defined in Eqs. (2), (3), (4), and (5), respectively.

Table 3 illustrates the examination of epoch values during result acquisition to achieve the highest accuracy. Through this analysis, the optimal epoch value was determined to be 50, demonstrating the least error and the quickest response time.

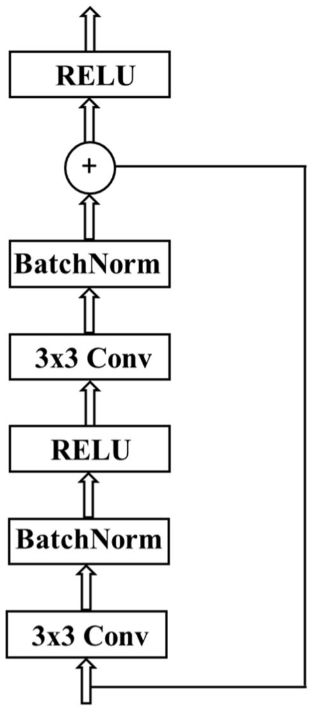

Fig. 5 Res-Block layers

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (2)$$

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (3)$$

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (4)$$

$$\text{F}_1\ \text{score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (5)$$

In the context of the study, the terms true positive (TP), false positive (FP), true negative (TN), and false negative (FN) are defined as follows:

True positive (TP): The number of positive class predictions that correctly belong to the positive class. False positive (FP): The number of instances that were predicted as positive but actually belong to the negative class. True negative (TN): the number of negative class predictions that correctly belong to the negative class. False negative (FN): the number of instances that were predicted as negative but actually belong to the positive class.

Table 4 Comparison of traditional machine learning methods and artificial neural networks used in our previous studies with the proposed deep learning model

	Classification accuracy
Linear SVM	90
Fine KNN	90.92
Gaussian naïve Bayes	92.74
Wide neural network	93.66
1D-ResCNN	99.8

Precision is a metric that measures the accuracy of positive class predictions, recall measures the proportion of actual positive instances correctly predicted, and the F1 score is the harmonic mean of precision and recall.

As the most optimum results in terms of response time and accuracy were achieved at epoch 50, the subsequent results presented are based on this epoch value. Table 4 provides a comparison of the proposed model in this study with the methods utilized in our previous study [29].

As illustrated in Table 4, the proposed method demonstrates exceptional success with notably high accuracy, surpassing classical machine learning methods and artificial neural networks.

4 Discussions

Table 5 illustrates the types of sensors used in various motion recognition systems, the number of participants, the methods employed, and the reported accuracy rates. Generally, IMU sensors and CNN-based methods are frequently utilized. Additionally, the proposed method achieved a high accuracy of 99.8% using 1D-ResCNN, which is a notably high success rate. In the study conducted by Vu et al., walking modes such as walking on a flat surface, standing, and stair ascending/descending were identified using IMU data. The highest success rates were achieved with CNN at 99.6% and with LSTM at 98.68%. In comparison with our study, their approach exhibits lower robustness due to its focus solely on recognizing foot

Table 3 Effect of different epoch values on error and accuracy of training and validation

	Training error	Training accuracy	Validation error	Validation accuracy
Epoch = 10	0.00252	1	0.0134	0.995
Epoch = 50	8.13e−5	1	0.0012	1
Epoch = 100	1.7e−5	1	0.0415	0.993
Epoch = 500	5.01e−8	1	0.0157	0.995
Epoch = 1000	1.59e−10	1	0.0279	0.993

Table 5 Comparison of the proposed model with other deep learning models

References	Sensors	Number of Subject	Method	Motion	Accuracy (%)
Wang et al [41]	Joint angle sensor	1	LSTM	Wang[(a)]	98.3
Feng et al [42]	Strain gauge angle sensor	3	CNN	Feng[(b)]	93.1
Su et al [43]	IMU	11	CNN	Su[(c)]	94.15
Lu et al [44]	IMU	10	CNN	Lu[(d)]	98.06
Bijalwan et al [45]	IMU	30	CNN-LSTM	Bijalwan[(e)]	90
Narayan et al [46]	IMU	8	CNN	Narayan[(f)]	94.34
Vu et al [47]	IMU	4	CNN	Vu[(g)]	99.6
Vakacherla et al [48]	Accelerometer	5	CNN	Vakacherla[(h)]	98.1
Our proposed method	IMU	11	1D-ResCNN	Aydin Fandakli[(i)]	99.8

movements in the sagittal plane and conducting experiments with fewer participants.

This article introduces a novel application of convolutional neural networks for the classification of foot movements with inertial measurement units (IMU). The 1D-ResCNN model, based on the architecture of 1D convolutional neural networks (ConvNet), adeptly processes and classifies motion data from prosthetic feet. The integration of 'Res' (residual) blocks in the architecture aids in the training of deep networks, contributing to superior performance. Through the inclusion of Res-Blocks and batch normalization layers in the convolutional neural network, the proposed model exhibits commendable performance in terms of speed, robustness, and accuracy when compared to existing methods in the literature. The uniqueness of this study arises from the utilization of a novel dataset, the introduction of a new modeling approach, and the demonstrated superior performance of this model compared to other methods in the literature.

5 Conclusions

We utilized raw accelerometer, gyroscope, and magnetometer data as inputs for the convolutional neural network (CNN). The network autonomously extracts valuable feature information from the raw data, enabling accurate predictions of corresponding motions. The one-dimensional CNN architecture, incorporating two convolutional Res-Blocks, demonstrates superior performance compared to alternative architectures. It is noteworthy that while the proposed system exhibits encouraging performance in classifying human ankle–foot movements, the study involved only healthy volunteers. Future investigations aim to explore the effectiveness of the proposed system in individuals with below-knee amputations. The study has an additional limitation concerning the utilization of data collected in a laboratory setting. Future efforts aim to gather and process data in individuals' natural environments. This model marks a significant stride in improving user experience in prosthetic technology, presenting an artificial intelligence-based system capable of effectively responding to user intent. Nevertheless, further experimental studies and validation are essential to evaluate the model's performance under real-world conditions.

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Data availability The dataset was prepared by the corresponding author. It has not yet been published publicly. It will be shared if requested.

Declarations

Conflict of interest The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Diraco G, Rescio G, Siciliano P, Leone A (2023) Review on human action recognition in smart living: sensing technology multimodality, real-time processing, interoperability, and resource-constrained processing. Sensors 23(11):5281. https://doi.org/10.3390/s23115281
2. Diraco G, Rescio G, Caroppo A, Manni A, Leone A (2023) Human action recognition in smart living services and applications: context awareness data availability, personalization and privacy. Sensors 23(13):6040. https://doi.org/10.3390/s23136040
3. Batzianoulis I, Krausz NE, Simon AM, Hargrove L, Billard A (2018) Decoding the grasping intention from electromyography during reaching motions". J Neuro Eng Rehabilit 15(1):57. https://doi.org/10.1186/s12984-018-0396-5
4. Yang D, Yang W, Huang Q, Liu H (2017) Classification of multiple finger motions during dynamic upper limb movements. IEEE J Biomed Health Inform 21(1):134–141. https://doi.org/10.1109/JBHI.2015.2490718
5. Ahmad N, Thomas GN, Gill P et al (2016) The prevalence of major lower limb amputation in the diabetic and non-diabetic population of England 2003–2013. Diabetes Vasc Dis Res 13(5):348–353. https://doi.org/10.1177/1479164116651390
6. Spoden M, Nimptsch U, Mansky T (2019) Amputation rates of the lower limb by amputation level—observational study using German national hospital discharge data from 2005 to 2015. BMC Health Serv Res 19(1):8. https://doi.org/10.1186/s12913-018-3759-5
7. Imam B, Miller WC, Finlayson HC et al (2017) Incidence of lower limb amputation in Canada. Can J Public Health 108(4):e374–e380. https://doi.org/10.17269/cjph.108.6093
8. Gong W, Chen H, Zhang Z et al (2019) A novel deep learning method for intelligent fault diagnosis of rotating machinery based on improved CNN-SVM and multichannel data fusion. Sensors 19(7):1693. https://doi.org/10.3390/s19071693
9. V B Semwal, S A Katiyar, P Chakraborty, G Nandi (2013). Biped model based on human gait pattern parameters for sagittal plane movement. In: Proceedings of the 2013 international conference on control, automation, robotics and embedded systems (CARE), Jabalpur, India, IEEE: New York, NY, USA, 1–5
10. H A Hansen, A N Eric (2013). Ankle-foot prosthesis for automatic adaptation to sloped walking surfaces. U.S. Patent application, 14/022,645
11. LaPre AK, Umberger BR, Sup F (2016) A robotic ankle-foot prosthesis with active alignment. ASME J Mech Des 10(2):025001
12. Colborne GR, Naumann S, Longmuir PE, Berbrayer D (1992) Analysis of mechanical and metabolic factors in the gait of congenital below knee amputees: a comparison of the SACH and Seattle feet. Amer J Phys Med Rehabil 71(5):272–278. https://doi.org/10.1097/00002060-199210000-00004
13. Peeraer L, Aeyels B, Van der Perre G (1990) Development of EMG-based mode and intent recognition algorithms for a computer-controlled above-knee prosthesis. J Biomed Eng 12(3):169–182
14. Luu TP, Brantley JA, Nakagome S, Zhu F, Contreras-Vidal JL (2017) Electrocortical correlates of human level-ground, slope, and stair walking. PLoS ONE 12(11):1–15
15. Chen PZ, Li J, Luo M, Zhu NH (2015) Real-time human motion capture driven by a wireless sensor network. Int J Comput Games Technol 2015:14. https://doi.org/10.1155/2015/695874
16. Ravì D, Wong C, Lo B, Yang GZ (2017) A deep learning approach to on-node sensor data analytics for mobile or wearable devices. IEEE J Biomed Health Inform 21(1):56–64. https://doi.org/10.1109/JBHI.2016.2633287
17. Vakacherla SS, Kantharaju P, Mevada M, Kim M (2023) Single accelerometer to recognize human activities using neural networks. J Biomech Eng 145(6):1–11
18. Tang Y, Zhang L, Min F, He J (2022) Multi-scale deep feature learning for human activity recognition using wearable sensors. IEEE Trans Industr Electron 70(2):2106–2116. https://doi.org/10.1109/TIE.2022.3161812
19. Hysenllari E, Ottenbacher J, McLennan D (2022) Validation of human activity recognition using a Convolutional neural network on accelerometer and gyroscope data. German J Exerc Sport Res 52(2):248–252
20. Huang W, Zhang L, Gao W, Min F, He J (2021) Shallow Convolutional neural networks for human activity recognition using wearable sensors. IEEE Trans Instrum Meas 70:1–11
21. L T Nguyen, M Zeng, P Tague, J Zhang (2015). Recognizing new activities with limited training data. In: Proceedings of the 2015 ACM International symposium on wearable computers, 67–74
22. Gholamiangonabadi D, Kiselov N, Grolinger K (2020) Deep neural networks for human activity recognition with wearable sensors: leave-one-subject-out cross validation for model selection. IEEE Access 99:1–1
23. Hassan MM, Uddin MdZ, Mohamed A, Almogren A (2018) A robust human activity recognition system using smartphone sensors and deep learning. Futur Gener Comput Syst 81:307–313
24. T Zebin, P J Scully, K B Ozanyan (2016) Human activity recognition with inertial sensors using deep learning approach. In: 2016 IEEE Sensors, Orlando, FL, USA, 1–3. https://doi.org/10.1109/ICSENS.2016.7808590
25. Ordóñez F, Roggen D (2016) Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition. Sensors 16(1):115
26. Eyobu OS, Han D (2018) Feature representation and data augmentation for human activity classification based on wearable IMU sensor data using a deep LSTM neural network. Sensors 18(9):28–92
27. Khera P, Kumar N, Ahuja P (2020) Machine learning based electromyography signal classification feature selection for foot movements. J Sci Ind Res 79:1011–1016
28. Negi S, Sharma N (2022) A standalone computing system to classify human foot movements using machine learning techniques for ankle-foot prosthesis control. Comput Methods Biomech Biomed Engin 25(12):1370–1380
29. Chaobankoh N, Jumphoo T, Uthansakul M, Phapatanaburi K, Sindhupakorn B, Rooppakhun S, Uthansakul P (2022) Lower limb motion based ankle foot movement classification using 2D-CNN. Comput Mater Continua 73:1269–1282
30. Aydın Fandaklı S, Okumuş H (2023) Comparison of artificial neural networks with other machine learning methods in foot movement classification. Karadeniz Fen Bilimleri Dergisi 13(1):153–171
31. Singh D, Singh B (2020) İnvestigating the impact of data normalization on classification performance. Appl Soft Comput 97:1–23
32. Rueda FM, Grzeszick R, Fink GA, Sascha F, Hompel M (2018) Convolutional neural networks for human activity recognition using body worn sensors. Informatics 5(26):1–17
33. Jain A, Kanhangad V (2018) Human activity classification in smartphones using accelerometer and gyroscope sensors. IEEE Sens J 18(3):1169–1177
34. Arora V, Yin-Kwee Ng E, Singh A (2022) Smart Electrical and Mechanical Systems, Chapter one—Machine learning and its applications. Academic Press, Cambrige, pp 1–37
35. K Simonyan, A Zisserman (2014). Very deep convolutional networks for scale image recoginition, arXiv :1409.1556, computer science, computer vision and pattern recognition

36. Y Tang, Q Teng, L Zhang, F Min, J He (2020). Layer-wise training convolutinal neural networks with smaller filters for human activity recognition using wearable sensors. arXiv :2005.03948. Computer science, computer vision and pattern recognition
37. Ghosh A, Sufian A, Sultana F, Chakrabarti A, De D (2020) Fundamental concepts of Convolutional neural network. In: Balas V, Kumar R, Srivastava R (eds) Recent trends and advances in artificial intelligence and Internet of Things. Intelligent systems reference library, vol 172. Springer, Cham. https://doi.org/10.1007/978-3-030-32644-9_36
38. LeCun Y, Bottou L, Bengio Y, Haffner P (1998) Gradient-based learning applied to document recognition. Proc IEEE 86(11):2278–2324
39. Rehman, Y.A.U., Tariq, M. (2022). Internet of Multimedia Things (IoMT), Techniques and Applications, Intelligent Data Centric Systems, Chapter 3-Visual information processing and transmission in Wireless Multimedia Sensor Networks : a deep learning based practical approach, 47–66.
40. A F Agarap (2019) Deep learning using rectified linear units (ReLU), computer science, neural and evolutionary computing, arXiv. 1803.08375
41. Wang C, Wu X, Ma Y, Wu G, Luo Y (2018) A flexible lower extremity exoskeleton robot with deep locomotion mode identification. Complexity 2018:5712108. https://doi.org/10.1155/2018/5712108
42. Feng Y, Chen W, Wang Q (2019) A strain gauge based locomotionmode recognition method using Convolutional neural network. Adv Rob 33:254–263. https://doi.org/10.1080/01691864.2018.1563500
43. Su B-Y, Wang J, Liu S-Q, Sheng M, Jiang J, Xiang K (2019) A cnn-based method for intent recognition using inertial measurement units and intelligent lower limb prosthesis. IEEE Trans Neural Syst Rehabil Eng 27:1032–1042. https://doi.org/10.1109/TNSRE.2019.2909585
44. Z Lu, A Narayan, H Yu (2020). A deep learning based end-to-end locomotionmode detectionmethod for lower limb wearable robot control In : 2020 IEEE/RSJ International conference on Intelligent Robots and Systems (IROS) (Las Vegas: IEEE), 4091–4097
45. Narayan A, Reyes FA, Ren M, Haoyong Y (2021) Realtime hierarchical classification of time series data for locomotion mode detection. IEEE J Biomed Health Inform 26:1749–1760. https://doi.org/10.1109/JBHI.2021.3106110
46. Vu HTT, Cao H-L, Dong D, Verstraten T, Geeroms J, Vanderborght B (2022) Comparison of machine learning and deep learning based methods for locomotion mode recognition using a single inertial measurement unit. Front Neurorobot 16:1–15
47. Bijalwan V, Senwal VB, Gupta V (2021) Wearable-sensor based pattern mining for human activity recognition: deep learning approach. Ind Robot 49:21–33
48. Vakacherla SS, Kantharaju P, Mevada M, Kim M (2023) Single accelerometer to recognize human activities using neural networks. J Biomech Eng 145(6):1–11

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