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Classification Of Walking Patterns From sEMG Using Hybrid CNN-LSTM Model

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Abstract: Advanced technologies help in the analysis of the surface electromyogram (sEMG) signals to recognize the pattern of the gait and provides the mechanism to control the prosthetics. EMG signals used for the diagnosis of neuromuscular diseases, human-machine interaction as they reflect human intensions. In this study an attempt has been made with novel approach for the classification of walking activity using a hybrid CNN-LSTM model based on the sEMG and goniometer (GM) signals from healthy and knee abnormal subjects. This study utilizes the dataset from UC Irvine Machine Learning Repository (UCI) on lower limb sEMG signals of 11 normal and 11 abnormal subjects with knee abnormality while performing the walking activity. A hybrid CNN-LSTM effectively captures the temporal and spatial features from sEMG signals and provides the average accuracy and average precision of 82.10%, 72.69%. This performance suggests that the proposed model successfully classifies the sEMG signals during walking and thereby leading to more precise control of the prosthetics using the hybrid model.

Keywords: CNN-LSTM, Gait, Prosthetics, sEMG

1 Introduction

In rehabilitation, gait analysis is important since it provides the information about the lower limb movement and the walking pattern. Gait also enables the clinicians to give optimised treatment which results in the good outcomes. Limb amputation and injury like osteoarthritis, meniscus and anterior cruciate ligament affects the movement and the physical functioning across the world [1] [2]. Assistive devices like passive prosthesis to enhance or compensate the function by particularly tracking the gait. They only provide the support to the beneficiary and doesn't have any sensory feedback [3] [4] [5]. Gait analysis act as diagnostic tool [6] for the design of the powered prostheses which achieves the optimal performance and also helps in the classification of the movement [7]. Human gait is the coordinated complex cyclic interaction of muscles, nervous system and the bone. Acquisition of the EMG signals can be either Invasive or non-invasive technique from the muscles and non-invasive techniques are far better since there is no supervision of the clinician are required [8]. Applications of the upper limb using the sEMg is focused more on the past years compared to the lower limb. The acquisition of the sEMG signals from the lower extremity is complex due to the neuromuscular activity, physiological and anatomical properties and the numerous motor unit contribution at a time. Human activities such as sitting, standing, walking, staircase ascent, staircase descent and squatting provides the extremity information. Neuromuscular and skeletal disorder are diagnosed by evaluating and classifying by the movement of the leg [9] [10]. Previous studies have deployed a transfer learning – based LRCN model on the UCI dataset to classify and predict the joint angles of the lower extremity activities [11]. The authors in [12] used Mivrosoft Kinect V2 sensor for the acquisition of the different human activities and used hybrid deep learning models for the classification of the activity. Myopathy and neuropathy classification based on neural network is proposed in [13]. Six different movements of lower limb are classified using Machine Learning (ML) and worked on identifying the knee abnormality [14] [15]. In [16] a hybrid model of wavelet Denoising – Ensemble Empirical Mode Decomposition (WD - EEMD) is proposed for the recognition of the activity with and without knee abnormality. Another study [17] proposes a hybrid ensemble deep learning model for the classifying the movement of the lower extremity during the different activities.

In this study, an attempt has been made to classify the walking pattern using the hybrid CNN-LSTM model using the sEMG data from the quadriceps and the hamstrings.

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2 Materials and Methods

2.1 Participants

The dataset [18] comprises sEMG signals collected from 22 male volunteers aged 18 and older, including 11 fit individuals and 11 with knee disorders such as sciatica, meniscal rupture, and ACL injury. The data acquisition setup utilized four sEMG channels and one goniometer measurement channel, recorded with Biometrics Ltd. and Datalog MWX8, while knee joint angles were captured using an SG150B goniometer.

2.2 Experimental Protocol

sEMG electrodes were placed on the rectus femoris (RF), semitendinosus (ST), vastus medialis (VM), and biceps femoris (BF) muscles, maintaining a 20 mm spacing and an input impedance greater than 10 MΩ. The signals were sampled at 1000 Hz and filtered within a range of 20–460 Hz. Participants performed three key activities: standing with knee flexion, walking on ground level, and sitting with knee extension. To ensure consistency, the sEMG signals underwent standardization to achieve zero mean and unit variance. Additionally, the ADASYN algorithm was applied to address class imbalance by generating synthetic samples for underrepresented classes.

2.3 Data Preparation

The data was segmented into 256 milliseconds (ms) windows with a 64 ms overlap using a sliding window approach, allowing for detailed temporal analysis. For validation, a 3-fold cross-validation technique was employed to assess model performance. These preprocessing steps ensured high-quality data for subsequent feature extraction and classification tasks.

2.4 Deep Learning Model

The proposed methodology deploys a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model to classify the walking pattern using sEMG signals. CNN component captures the spatial features and LSTM component extracts that help in the gait classification.

$$h_t^l = f\left(\sum_{i=0}^{k-1} w_i^l \cdot x_{t+i}^l + b^l\right) \quad (1)$$

EMG signals collected undergoes the Z-score normalization and the spatial patterns from EMG signals are extracted using 1 Dimensional (1D) is given by equation (1). h_t^l represents the feature at position t in the layer l, w_i^l are kernel weights, kernel size. Further the temporal features are extracted by LSTM layers, and it maintains a memory cell and hidden state which helps in refining the temporal representations. For the binary classification the output of the LSTM is given to the fully connected dense layer follow through a sigmoid activation. This model uses binary cross-entropy to optimize the loss, and it is defined in equation 2.

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)\right] \quad (2)$$

y_i is the actual label, $\hat{y}_i$ is the predicted label. The architectural of the proposed CNN-LSTM model is shown in Fig. 2.

3 Results and discussion

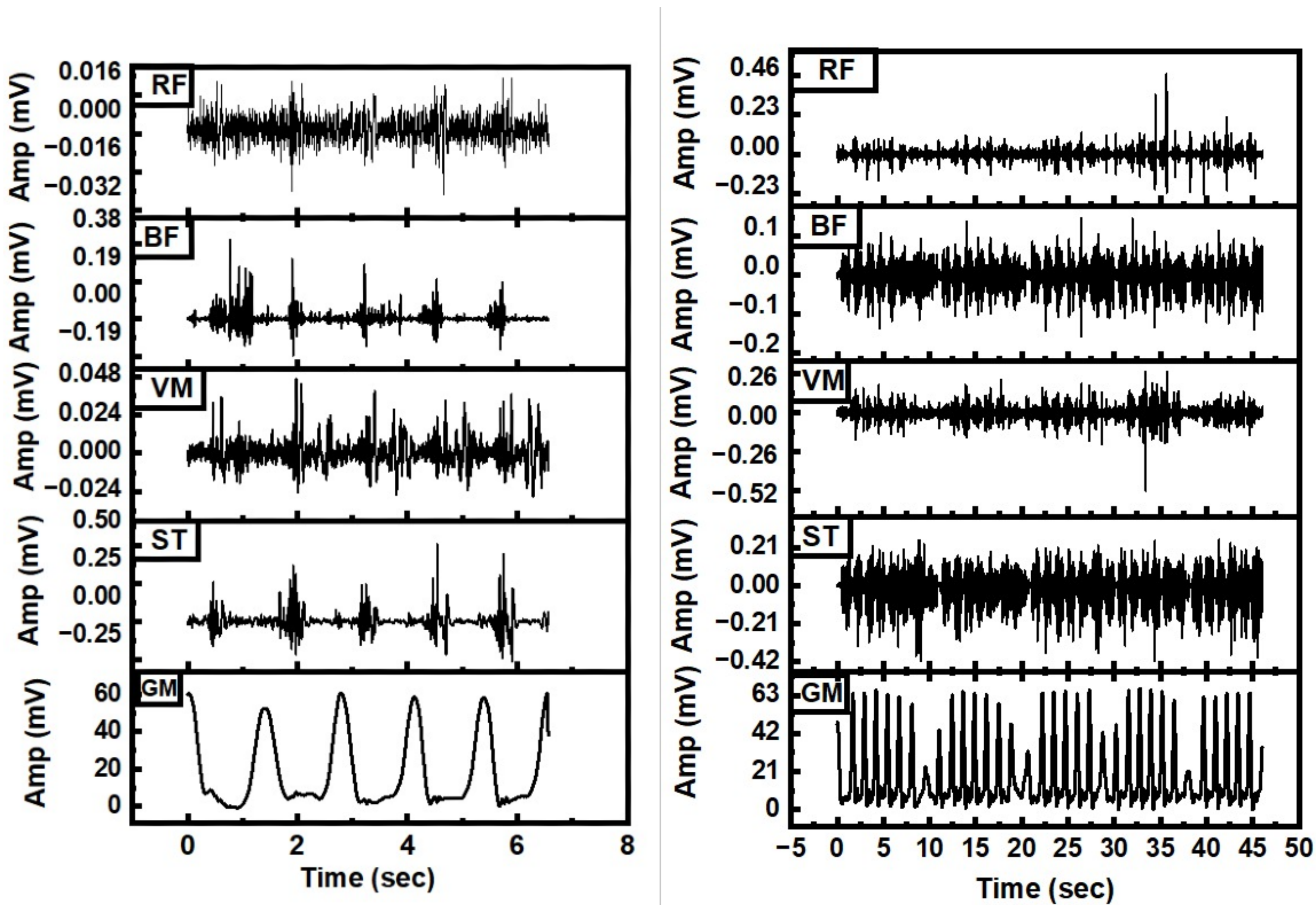
The performance of the CNN-LSTM model for the evaluation the normal and abnormal walking pattern using the sEMG is proposed. The model achieves the accuracy of 82.10% in recognising the walking abnormalities.

3.1 Performance Analysis

The result of the classification attains the precision of 82.72% and recall of 98.58% for the walking in normal subjects and results in 89.96% F1-score. With the high recall value provides that model is with minimal of the false positives and highly sensitive in detecting the normal walking pattern. Similarly for the abnormal walking it achieves the precision of 72.66% followed by recall of 80.66% that correspondingly yields the F1-score of 74.24% can be illustrated in Table 1. The precision is comparatively low than normal walking as some abnormal patterns may have been misclassified because of the overlapping of the gait features in the sEMG signals.

3.2 Feature Representation

CNN layers effectively capture the spatial patterns from the sEMG signals that can be illustrated from the Figure 1A, 1B in which the EMG signals variations for the different muscle channel can be visualised. LSTM layer captures the temporal (time) dependencies in gait as the same can be seen in Figure 2 architecture diagram. The batch normalisation and max pooling layer reduces the overfitting, improve feature stability.



A) B)

Figure 1: A) Representative signal of quadriceps and Hamstring muscle for normal walking pattern B) Representative signal of quadriceps and Hamstring muscle for abnormal walking pattern

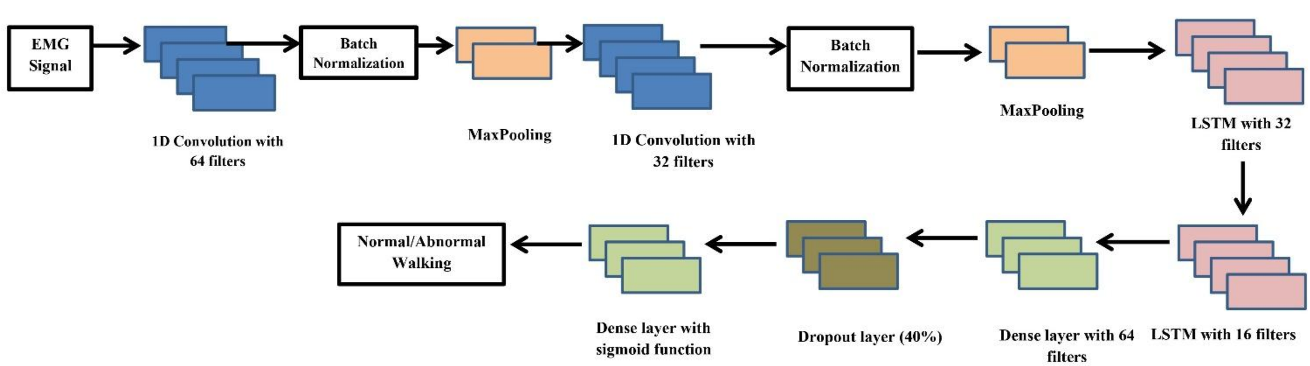


Figure 2: Architectural diagram of the proposed CNN-LSTM model

Normal walking muscle activation is periodic while in the abnormal walking exhibits the inconsistent patterns of the activation across the different muscle channels. The spatial difference is captured by the CNN layers and LSTM layers.

Table 1: Performance metrics of CNN-LSTM model

Class	Precision (%)	Recall (%)	F1-Score (%)
Normal	82.72	98.58	89.96
Abnormal	72.66	80.66	74.24
Accuracy (%)	-	-	82.10

Overall, the model achieves the strong performance and in the precision of abnormal walking needs some improvement. Further the misclassification is because in certain conditions it has the similar walking conditions. Despite that models paves way for the improves diagnosis and provide the strong potential for application of real-time gait analysis.

4 Conclusion

This study explores the use of the hybrid CNN -LSTM model for classifying normal and abnormal walking patterns. The findings highlight the effectiveness of the CNN-LSTM model in classifying the gait pattern by attaining an accuracy of 82.10%. Utilizing the hybrid model leverages the CNN layers and LSTM layers for the spatial feature extraction and temporal sequence modelling makes effective for classification based on muscle activity. Furthermore, studies could explore the different models and feature extraction technique to support the classification and the performance of the model. Larger dataset with different gait abnormalities can further enhance the model robustness.

Author Statement

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