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Deep Autoencoder for Identification of Abnormal Gait Patterns Based on Multimodal Biosignals

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Abstract: Gait abnormality is a common problem in humans after any lower limb injury or a stroke attack. The detection of abnormal gait is an important measure for designing and following appropriate rehabilitation protocol. This study presents a model for identifying the abnormal gait patterns for knee injured subjects based on a deep autoencoder neural network. The model employed micro-electro-mechanical motion sensors (MEMS) and electromyography (EMG) system to collect the joints motion and neuromuscular signals, respectively. The important kinematics and EMG features were extracted from the collected data and autoencoder models (single and multilayer) were trained using the features of normal gait data. Various parameters and hyperparameters for the models were explored and fine-tuned during the training phase. Later, the best trained models along with a thresholding method were used to detect the abnormal gait patterns. The performance of the single and multilayer (deep) autoencoder models have been compared and reported for the data sets. The deep autoencoder model was able to identify the abnormal gait patterns with higher accuracy (98.3%) and area under curve (99.2%) values as compared to existing models. The proposed model can serve as a decision support system for clinicians, physiatrists and physiotherapists for detecting abnormal gait automatically.

Keywords: Deep Learning, Abnormal Gait, Autoencoder, Knee Injury, Kinematics, Electromyography

1. Introduction

Human gait analysis has various applications in the fields of surveillance, biometrics and medicine [1-3]. For security applications, the purpose of gait analysis is to differentiate among individuals or identify a person based on his/her walking style. While for clinical applications, the focus of gait analysis is more on the recovery of the patients to the normal gait movements. Gait impairments are common in humans after lower limb or brain injuries [4,5]. These injuries result in kinematics and musculoskeletal changes which may persist and permanently alter the gait patterns if appropriate rehabilitation procedures are not followed. Before taking any action and suggesting relevant exercises by the physiatrists or physiotherapists, the detection of an abnormal gait is crucial for patients' recuperation. In most of the cases the gait is adapted after lower limb injuries or surgeries [6]. However, in the absence of proper monitoring and rehabilitation, long term problems can be noticed in the subjects having these injuries or surgeries. Dynamic joint instability, neuromuscular impairments, cartilage degeneration, early onset of osteoarthritis and progressive arthritic changes have been observed in subjects having knee injuries and surgeries [3,6].

Automation of abnormal gait identification is very useful for developing a decision support system for clinicians, physiatrists and physiotherapists. Various statistical and machine learning based techniques have been proposed previously for identification of abnormal gait patterns in literature [7-12]. These techniques employ mainly either statistical comparison of normal and abnormal gait patterns or use supervised learning methods to train/test the model based on a collection of normal and abnormal gait patterns. The statistical and supervised learning models generally require a large amount of data from both classes (normal/abnormal) to train and validate the results. Moreover, most of the existing studies have used kinematics data (collected through optical cameras) for developing such models.

In this study we propose an unsupervised non-linear model, namely autoencoder neural network to identify the abnormal gait patterns. Since, the lower limb injuries alter the joint kinematics as well as the muscle movements so the proposed model has been developed using integrated

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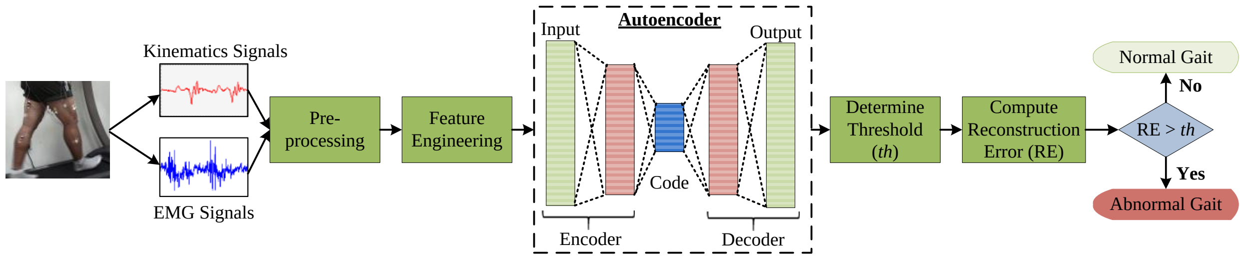

Figure 1. Steps for abnormal gait identification using deep autoencoder and thresholding method

kinematics and electromyography (EMG) signals as compared to only kinematics features used in the previous studies. This model is trained using the features from the normal gait data and later the trained model along with a thresholding method is used to detect the abnormal gait patterns. Experiments have been conducted on a dataset of healthy and knee injured subjects and the results show the effectiveness of the proposed method for identifying the abnormal gait patterns.

The rest of the paper is organized as follows: Section 2 presents a brief review of the previous works in the field. Section 3 describes the proposed model along with the details of data acquisition, feature extraction and autoencoder neural network. The results and discussion of are elaborated in section 4 followed by conclusions in section 5.

2. Literature Review

The design of an abnormal gait identification system depends on the type of equipment used for data acquisition, selection of signals/data to be monitored and the techniques applied for differentiating normal and abnormal gaits. A common practice for human activity monitoring is to use either an optical/camera system or wearable micro-electro-mechanical motion sensors (MEMS). Optical motion capture systems (e.g. Vicon, Qualisys etc.) have been found very reliable and accurate in providing joints motion but these systems are light sensitive, expensive and as well as require longer setup time [13]. As a low cost alternative to these systems, Kinect has been used in many recent studies which provides quite reliable information about the joint movements for gait classification [7]. Further, the RGB image based gait classification system has also been proposed previously [8]. In contrast to optical/camera systems, wearable wireless MEMS have also gained a lot of attention for human activity analysis due to their small size and easy setup in any kind of environment [3]. Multiple sensors' integration in wearable systems provide different signals at the same time which makes such a low-cost system very suitable for gait monitoring [5,9].

In recent studies, mostly kinematics, kinetics and/or spatio-temporal data have been collected during the walking activity and models have been proposed based on the features extracted from these signals [9-12]. Further, since the lower limb injuries cause muscle atrophy and neuromuscular disorders so the electromyography signals have also been evaluated to monitor the changes in the gait patterns in few studies [14]. However, most of the existing studies focus on individual kinematics or sptio-temporal or electromyography signals and there exists only few studies which have integrated these biosignals to analyze the gait patterns in subjects [3,5,15].

Based on the selected signals and extracted features the gait analysis is performed either by statically comparing the parameters or some machine learning techniques are used to train/test the model. In statistical models, mostly the abnormality in the gait is detected by comparing the spatio-temporal and kinematics parameters or leg movement symmetry of healthy and injured subjects [9-12]. On the other hand, the machine learning model uses the selected features (e.g. joint angles/positions) to build a classification model for normal and abnormal gaits. Supervised machine learning techniques such as support vector machine (SVM), k-nearest neighbor (KNN) and artificial neural network (ANN) have been used previously for identifying abnormal gait [7,8,12,16,17]. The supervised learning techniques generally require ample training data for both classes (normal/abnormal) which may not be readily available for patients having specific type of injuries or surgeries. In most of the previous studies, the training data have been collected through pretended abnormality in the gait; for example by attaching a load to one of the feet or simulating the restricted movements of joints, which do not truly represent the changes in gait patterns after injuries [7-12]. Recently, the recognition of human activities and gait analysis through unsupervised learning have gained attention by few researchers [7,18,19]. The use of deep learning based unsupervised models such as auto-encoder and generative adversarial network have been applied on the image or video data to recognize human activities or perform gait analysis. However, these studies do not take into consideration the multimodal kinematics and EMG data. Hence, this study proposes the use of unsupervised machine learning technique along with multimodal kinematics and EMG data which can be useful in situations where less amount of abnormal gait data are available from the real subjects having knee data are available from the real subjects having knee injury or surgery.

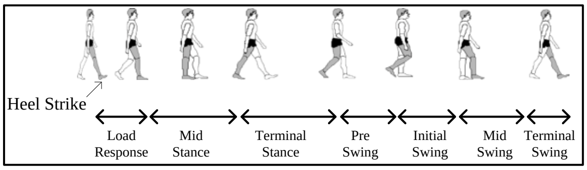

Figure 2. Seven phase of a human gait cycle

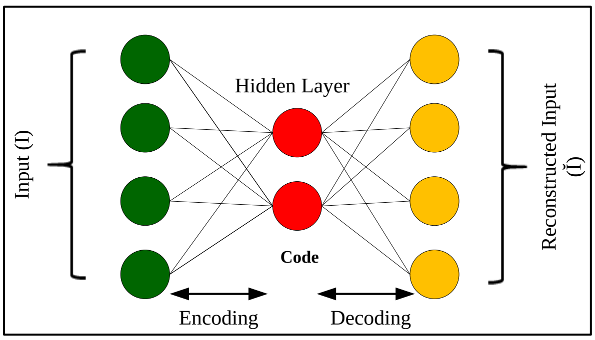

Figure 3. Autoencoder architecture with one hidden layer (code)

3. Proposed Methodology

Fig. 1 shows the flow of the proposed model for identifying the abnormal gait patterns based on the kinematics and neuromuscular signals using the autoencoder architecture. The details of the each step are provided below.

A. Data Acquisition and Pre-processing

Since the knee injuries result in changes in both kinematics and neuromuscular signals so both type of data were simultaneously recorded during walking activity for this study. The wireless MEMS were attached to the shank on halfway up the surface of the tibia and thigh at two thirds up the tensor fascia latae for each subject in order to collect 3-D angular rates (in x, y and z planes) and 3-D linear acceleration data (in x, y and z planes) from knee joint movements. The motion sensor data were sampled at 128Hz with 12 bit Analog/Digital resolution within a frequency range 0-20Hz. These signals were captured and wirelessly transferred to the laptop where the KinetiSense software stored all the data as a comma separated value (CSV) file for filtering and extracting required features for the 3-D knee joint rotational movements. The neuromuscular data were recorded using a physiological monitoring system (BioCapture) from the four relevant muscles around knee joint i.e. (1) vastus lateralis, (2) vastus medialis, (3) biceps femoris and (4) semitendinosus. The changes in these muscles have been reported in previous studies after knee injuries [3]. The EMG data were recorded at a sampling rate of 960Hz with 12 bit Analog/Digital conversion. The EMG signals captured through surface electrodes were wirelessly transmitted to the laptop using USB receiver and stored in CSV file format for further processing. Both kinematics and EMG systems were synchronized and data were segmented by detecting the heel strike event during the gait cycles [3,5].

The angular rate and acceleration measurements obtained from the MEMS were filtered using 6th order Butterworth filter before computing the joint orientations in order to minimize noise due to human movements and external sources. Moreover, the raw EMG data with zero mean were band-pass filtered (20-450Hz) using 4th order Butterworth filter. More details about the hardware setup, synchronization of MEMS and EMG data, coordinate transformation and preparation of subjects were followed as mentioned in [3,5].

B. Data Acquisition and Pre-processing

During the feature engineering phase, the important features were extracted from kinematics and EMG data based on the knowledge about the gait patterns changes after knee injuries. Each gait cycle consists of seven phases namely load response, mid-stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing (Fig. 2). The kinematics and EMG features were extracted for each of these seven phases.

In order to generate the kinematics feature set, first the trapezoidal integration was applied on the angular rate data for the seven gait phases and the flexion/extension, internal/external rotations and abduction/adduction knee joint movements were computed [5]. Then the mean, standard deviation and maximum values for these 3-D movements were calculated and thus a kinematics feature set consisting of a total of 63 values (3 knee joint movements × 7 gait phases × 3 statistics) was formed.

$$KIN = \bigcup_{i=1}^{63} k_i \qquad (1)$$

The EMG features were extracted by employing the multilevel discrete wavelet transform (DWT). Daubechies 05 (db05) wavelet was applied to the EMG signals from four muscles and six coefficients (5 detailed and one approximate) were extracted with a five level decomposition of these signals. The mean value and power of the six wavelet coefficients were computed for each gait cycle for each muscle. Thus, an EMG feature set consisting of 336 values (4 muscles × 6 coefficients × 7 gait phases × 2 statistics) was formed.

$$EMG = \bigcup_{i=1}^{336} e_i \qquad (2)$$

A total of 512 gait cycles data were collected from a group of 10 healthy and 6 knee injured/operated subjects. The distribution of normal and abnormal gait patterns was 87.5% and 12.5%, respectively. Two sets from this data were formed as follows: the first data set consisted of only kinematics features (512 × 63) while the second data set combined the kinematics and EMG features having a dimension of 512 × 399 (3).

TABLE I. PARAMETERS/HYPERPARAMETERS INVESTIGATED

Parameters/Hyperparameters	Value
Type of autoencoder	Single and Multilayer
No. of middle hidden layer neurons	3 - 10
Activation function	relu, sigmoid, tanh
Optimization algorithm	Adam, RMSProp, Adadelta
Loss function	Mean squared error, L2 regularization
Weight initialization	glorot_uniform, he_normal
Number of epochs	500, 1000, 2000
Learning rate	0.001, 0.0005, 0.0001
Batch size	1, 2, and 5

TABLE II. EMPIRICALLY SELECTED HYPERPARAMETERS FOR KINEMATICS DATA SET

Parameters/Hyperparameters	Value
Type of autoencoder	Multilayer
No. of middle hidden layer neurons	5
Activation function	relu for all layers
Optimization algorithm	Adam/RMSProp
Loss function	Mean squared error, L2 regularization
Weight initialization	glorot_uniform
Number of epochs	1000
Learning rate	0.0001
Batch size	5

TABLE III. EMPIRICALLY SELECTED HYPERPARAMETERS FOR MULTIMODAL DATA SET

Parameters/Hyperparameters	Value
Type of autoencoder	Single/Multilayer
No. of middle hidden layer neurons	6/8
Activation function	relu for all layers
Optimization algorithm	Adam
Loss function	Mean squared error, L2 regularization
Weight initialization	glorot_uniform
Number of epochs	500
Learning rate	0.0001
Batch size	5

$$Multimodal\_Dataset = \{ KIN, EMG \} \tag{3}$$

The autoencoder networks were trained and tested for these two data sets separately and the results were compared.

C. Autoencoder Neural Network and Thresholding

An autoencoder is a type of neural network which can represent and reconstruct the input data with a reduced amount of information (coding) employing unsupervised learning mechanism. A simple autoencoder consists of three layers: input layer (encoder) → hidden layer (code) → output layer (decoder) as shown in Fig. 3. The number of input and output neurons are same while the neurons in the hidden layers are smaller in number to compress the data or reduce the input dimensions. The network receives input 'I' and tries to produce the output '$\hat{I}$' as much similar to the input as possible by a compressed representation 'C' of data using the hidden layer 'H' as shown below in (4) and (5).

$$H = C(I) \tag{4}$$

$$\hat{I} = f(C(I)) \tag{5}$$

The training of the network is performed using the feedforward backpropagation algorithm minimizing the loss function 'L' (6).

$$L = Loss\ (I, f(C(I))) \tag{6}$$

For a deep autoencoder, the number of hidden layers can be more than one such that the middle layer (code) has the fewest neurons.

Identifying an abnormal gait pattern using autoencoder can be considered as detecting an anomaly in the data. The autoencoder network learns the patterns of a normal gait and the gait data which do not follow this pattern is classified as abnormal gait. The steps to develop the model are as follows:

- Divide the data set into normal and abnormal gait classes
- Train the autoencoder network on only normal gait data with a very small reconstruction error
- Determine the anomaly threshold by using the distribution of the reconstruction loss for normal gait data
- Evaluate the trained model on test data (abnormal/normal gait data) by calculating the reconstruction loss
- Mark all those gait pattern as abnormal for which the reconstruction loss is more than the threshold value

There are various parameters and hyperparameters (e.g. activation functions, optimization functions, number epochs, size of the network, number of hidden layers etc.) which can be optimized during the training phase to find the best possible combination for a given data set. In this study, both single and multilayer autoencoder networks were developed and evaluated for the data sets. The number of input and output layers neurons were 63 for the kinematics data set and 399 for multimodal data set. Different number of neurons (3 to 10) were tested for the middle hidden layer. Various activation functions and optimization algorithms were explored to find the optimal results. Table I summarizes the parameters and hyperparmeters investigated during this study for developing the abnormal gait patterns detection model. The final selection of the parameters and hyperparameters was based on the best performance of the models as explained in the next section.

4. Results And Discussion

In this section we'll present and compare the results of autoencoder models for both kinematics and multimodal data sets. Before developing the models, normal and abnormal gait data were separated for each of the data set. The distribution of normal and abnormal gait patterns was 87.5% and 12.5%, respectively. Further, around 60% of normal gait data were used to train the autoencoder and rest of the data (i.e. 40% of normal gait and all of the abnormal gait data) were used to test the models. The training and testing data were standardized with a zero mean and a standard deviation of one.

For evaluation of the models, different performance metrics were computed namely Area Under Curve of the Receiver Operating Characteristics (ROC) curve, accuracy, sensitivity, specificity, precision and F1-score. The model having higher values of AUC and F1-score were preferred over the others as these metrics balance the performance of the model for both positive and negative classes.

First, the single and multilayer autoencoder models were trained and tested for kinematics data set with various parameters/hyperparameters settings as presented in Table I. The best empirically selected values for these parameters/hyperparameters are shown in Table II for this data set. After performing various experiments, it was found that multilayer autoencoder model performed better in detecting the abnormal gait patterns as compared to single layer model (Table IV). The multilayer model was trained using the normal gait data and it converged with a loss (MSE) of around 0.6 using 'relu' activation function for all layers (Fig. 4). The threshold value of loss function for abnormal gait was determined as 0.8 based on the distribution of loss function (Fig. 5 and Fig. 6) and the model was evaluated using various performance metrics. Based on the AUC value, the multilayer model trained with 'Adam' optimization algorithm was found better while the model trained with 'RMSProp' optimization algorithm had higher accuracy and F1-score values (Fig. 7).

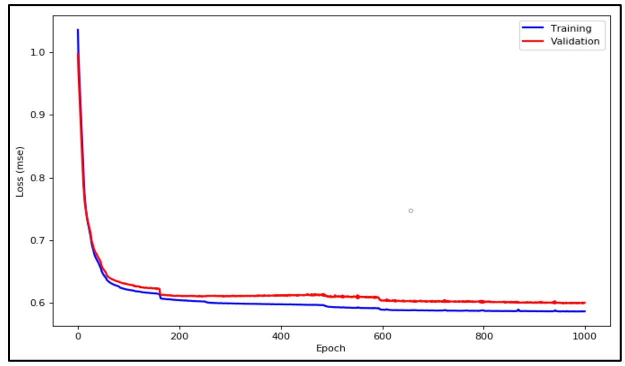

Figure 4. Training-Validation loss value for the multilayer autoencoder for kinematics data set

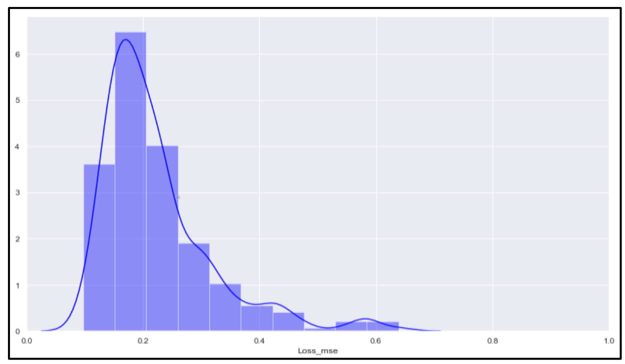

Figure 5. Distribution of the reconstruction loss for the multilayer autoencoder for kinematics data set

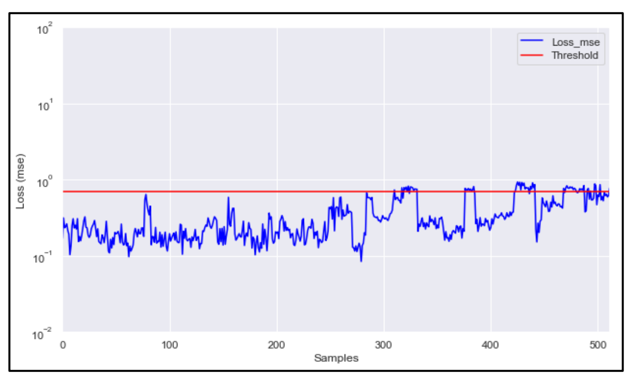

Figure 6. Abnormal gait detection with a threshold > 0.8 using the multilayer autoencoder for multimodal data set

Next, the multimodal data set consisting of integrated kinematics and EMG features was used to train and test the single and multilayer autoencoder networks. Similar to the kinematics models, various parameters and hyperparameters were explored and their optimal values were determined empirically as shown in Table III.

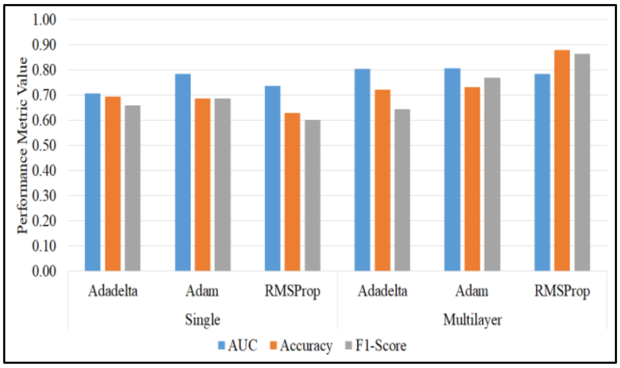

Figure 7. Comparison of single and multilayer autoencoder performance with different optimization algorithms for kinematics data set

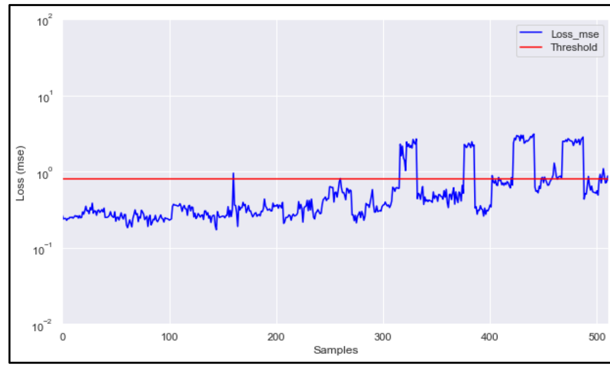

Figure 10. Abnormal gait detection with a threshold > 0.8 using the multilayer autoencoder for multimodal data set

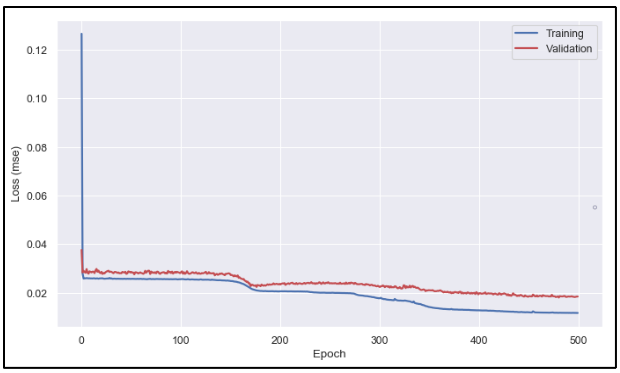

Figure 8. Training-Validation loss for the multilayer autoencoder for multimodal data set

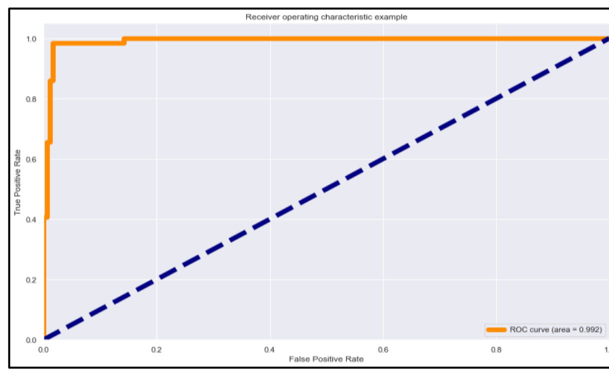

Figure 11. ROC curve for the multilayer autoencoder for multimodal data set

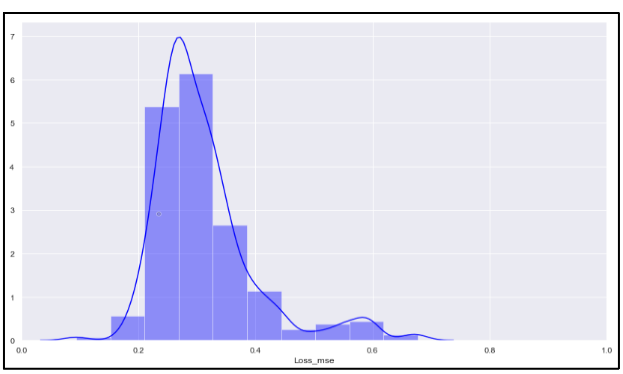

Figure 9. Distribution of the reconstruction loss for the multilayer autoencoder for kinematics data set

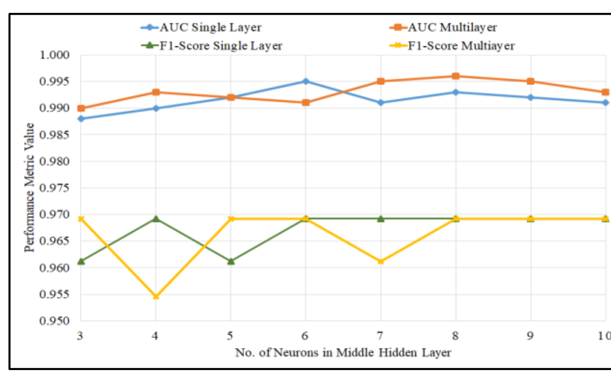

Figure 12. Effect of no. of neurons in the middle layer on the performance of multilayer autoencoder for multimodal data

The performance of both single and multilayer autoencoder networks was similar for this data set with a slightly higher value of AUC for the multilayer autoencoder (Table IV). Instead of just relying on the accuracy metric, the AUC with sensitivity and specificity were also considered to compare the models' performance due to single-class classification problem.

The multilayer model was trained using the normal gait data and it converged with a loss (MSE) of around 0.01 using 'relu' activation function for all layers (Fig. 8) which was lower than the multilayer kinematics model. Based on the distribution of loss function (Fig. 9), the threshold value of loss function for abnormal gait was determined as 0.8 (Fig. 10) and the model was evaluated using various performance metrics.

TABLE IV. EXPERIMENTAL RESULTS FOR THE PROPOSED MODELS

Data Set	Performance Metrics						
	Hidden Layers	*AUC*	*Accuracy*	*Sensitivity*	*Specificity*	*Precision*	*F1-Score*
Kinematics	Single	0.785	0.685	0.712	0.661	0.661	0.685
	Multilayer	0.807	0.731	0.923	0.554	0.658	0.768
Multimodal	Single	0.990	0.983	0.984	0.983	0.955	0.969
	Multilayer	0.992	0.983	0.984	0.983	0.955	0.969

TABLE V. PERFORMANCE COMPARISON WITH EXISTING MODELS

Study Reference	Parameters and Performance		
	Features	*Technique*	*Avg. Accuracy*
[7]	Joint positions	Sparse deep autoencoder	86.10%
[8]	Sptio-temporal, joint angles	KNN, SVM and Bayesian	96.67%
[12]	Kinematics	KNN	84.00%
[17]	Plantar pressure image	DBSACN, SVM	91.40%
[18]	Kinematics	Nonlinear ARX	93.55%
Proposed Model	Integrated kinematics and EMG	Deep autoencoder	98.30%

The single/multilayer model trained with 'Adam' optimization algorithm was found better than the models trained using other optimization algorithms based on the AUC and F1-score values (Fig. 11). Fig. 12 shows the impact of middle hidden layer neurons on the performance of both networks. There was not much improvement noticed in AUC and F1-score values after 6 hidden neurons for single layer model. While for multilayer model, the best performance was with 8 middle layer hidden neurons and 50 neurons for second layer of encoder and decoder.

The results presented in this study show that the autoencoder network is able to represent the original data set with a very small number of dimensions and it can provide an accurate prediction of gait abnormality patterns using these reduced features. The performance of proposed multimodal solution is superior to the kinematics model and the existing systems where only one type of data (e.g. joint positions) have been used for monitoring the gait patterns (Table V).

The identification of abnormal gait patterns is an important measure for evaluating the success of rehabilitation regimen for knee injured or post-operated patients. Long-term problems such as knee joint stability, osteoarthritis and cartilage degeneration may be present in subjects having impaired gait patterns. The application of autoencoder neural network with integrated kinematics and EMG features has been found quite accurate in detecting the abnormal gait. Moreover, the use of unsupervised learning technique has been found suitable for this domain where the abnormal gait data are either not readily available or can be collected only from few subjects. So, instead of using the under-/over-sampling techniques for developing a classification model, better results can be achieved with the help of autoencoder neural networks. However, the development of an automated system for gait abnormality detection depends not only on the nature of data used to train the model but also on few other factors which need to be determined experimentally including the size of code (latent space) and threshold value. The number of available samples for normal and abnormal gait and the demographics of the subjects are few other issues which must also be considered while designing such system.

5. CONCLUSIONS AND FUTURE WORK

This study proposed a method for identification of abnormal gait patterns based on an unsupervised machine learning technique, namely deep autoencoder. The extracted kinematics and neuromuscular features were integrated and used as input to train the model. The new gait patterns can be classified as normal or abnormal based on the threshold value determined from the training model. The proposed model has been tested on a group of healthy and knee injured/post-operated (having abnormal gait) subjects. The multimodal multilayer model with high values of different evaluation metrics (99.2% AUC, 98.3% accuracy and 96.9% F1-score) show the effectiveness of the system. This model can be used as a decision support system by the clinicians, physiatrists and physiotherapists to detect the abnormal gait patterns in subjects during screening or rehabilitation process. In future, more data will be collected to test the effects of age and gender on the classification of abnormal gait using the proposed model. Moreover, the use of generative adversarial networks will also be explored in future for identifying the gait abnormality and the results will be compared with the proposed model.

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