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Lower Limb Analysis Based on Surface Electromyography (sEMG) Using Different Time-frequency Representation Techniques

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Abstract**—Using time-frequency representation techniques, projecting 1D sEMG signals onto a 2D image space can help diagnose several muscle activities. The acquired sEMG signal can provide valuable representative information about the muscle activity firing rates during muscle contraction. Different phases of muscle activity can be discernible via the sEMG signals by extracting discriminating features. The behavior of muscle activity was acquired in measurements of five muscles, i.e., RF, BF, VM, ST, and FX. Previous attempts to visualize lower limb analysis to extract sEMG features adopted One-dimensional (1D) sEMG segments. This work proposes a comparative experiment between three time-frequency representation techniques. The three time-frequency representation techniques, scalogram, spectrogram, and persistence spectrum, were used to map muscles' (1D) sEMG signal straightening the knee. The two-dimensional (2D) projected images are then fed into a convolutional neural network (CNN) model for detecting knee abnormality. The experiments are performed via 10-fold cross-validation. The number of kernels is incremented along with model layers. The fully connected layers were adjusted according to the loss value. Besides, tuning the hyper-parameters of the dropout parameters and the ReLU activation function to verify optimal performance. This research shows that the scalogram image representation gives significantly better performance than the spectrogram and persistence spectrum in recognizing knee abnormality. In addition, this study may help in guiding the diagnosis of several human muscle activities via the sEMG signal. A more diverse of muscles can be further investigated and can be useful for future work to enhance the diagnosis accuracy.**

Keywords**— sEMG; CWT; STFT; Scalogram; Spectrogram; Persistence spectrum; Lower Limb Analysis; muscle abnormality; time-frequency representations.**

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I. INTRODUCTION

Surface Electromyography (sEMG) is a muscle activity recording that is detectable on the body surface upon the muscle [1]. It is considered that sEMG is produced by changes in active muscle fibers [2]. Recent detection techniques have explored the sEMG frequency responses during muscle actions [3]. The acquired sEMG signal can provide valuable information about various characteristics of muscle activity firing rates during voluntary isometric contraction [4]. Different muscle activity phases can be discernible via the sEMG signals by extracting discriminating features by deep learning classification schemes [5].

Few attempts have been made to improve lower limb analysis of the non-invasive surface electromyographic (sEMG) signals [6]. Previous methodologies have investigated sEMG features based on One-dimensional (1D) sEMG segments [7]. This work uses different time-frequency representation techniques to generate a two-dimensional (2D) spectrogram from (1D) sEMG segments. The two-dimensional (2D) spectrogram images are then fed into a convolutional neural network (CNN) model for detecting knee abnormality.

This paper judges the performance of lower limb classification by setting up comparative experiments for three time-frequency representation techniques. The three time-frequency representation techniques are scalogram, spectrogram, and persistence spectrum. The spectrogram generated by wavelet transform is known as a scalogram [8]. Continuous wavelets transform (CWT) preserves time shifts and time scale in terms of variable time-frequency resolution [9], as shown in Fig. 1. The spectrogram is generated by Short-Time Fourier Transform (STFT) is a linear representation in terms of frequency and time that is convenient in the analysis of nonstationary multicomponent signals [10] as shown in Fig. 2. The persistence spectrum is computed based on the time percentage that a given frequency persists within the signal [11]. It is a histogram-based spectrum represented by power frequency [12]. The longer frequency presents in a signal, the higher its percentage of time and, thus, the brighter its color in representation [13], as shown in Fig. 3.

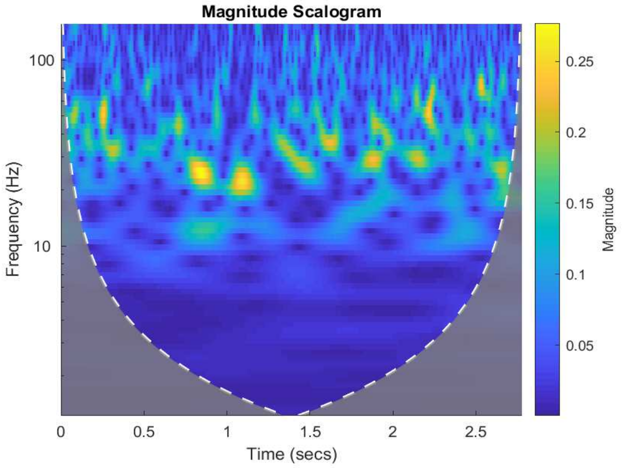

Fig. 1 Scalogram image representation in terms of time and frequency for a sample sEMG signal

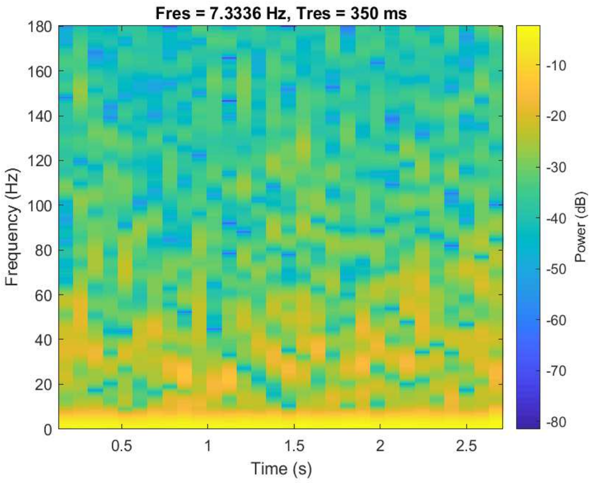

Fig. 2 Spectrogram image representation in terms of time and frequency for a sample sEMG signal

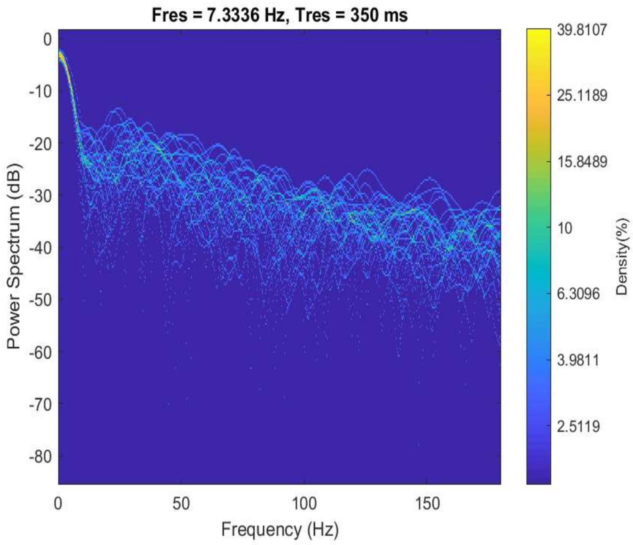

Fig. 3 Persistence spectrum image representation in terms of frequency and power spectrum for a sample sEMG signal

The main objective of this paper is to develop a diagnostic approach that could help in detecting knee abnormality. Three movements associated with the knee muscle are analyzed: leg extension, gait from flexion of the leg up, and the sitting position. The sEMG signal is picked up through surface electrodes from the stump of the subject [14]. Data acquisition was conducted with four electrodes and the goniometer in the knee [5]. The targeted muscles are Recto Femoral (RF), Femoral Biceps (BF), Vastus Medialis (VM), Semitendinosus (ST), and Flexion at the knee (FX). Data augmentation was also performed using a time series generator to segment the samples and their targets [13]. The augmentation step resulted in 1056 records of sEMG segment signal for the five corresponding muscles.

Due to the complexity and sensitivity to noise, different sEMG signals may not be discernible due to a lack of discriminative features [15]. Detecting muscle abnormality using deep learning by 1D CNN can extract features automatically from ECG 1-D signal [16]. This detects features in the time domain while ignoring characteristics in the frequency domain [17]. The deep model can extract deep architecture that generally forms a multilevel of features from the projected images [18]. Unlike previous studies for muscle classification, which focused on using an additional feature extraction process to extract features [5], [19-20].

The classification performance in processing 2-D images using the CNN model has been better than that in the 1-D time-domain signal. [21]. This research proposes using automatic deep feature extraction in learning the model without additional feature extraction. Projecting (1D) sEMG segments onto two-dimensional (2D) spectrogram images can help in developing a deep-learning model-based sEMG signal [12]. The mapped images can then be fed into a convolutional neural network (CNN) model for detecting knee abnormality. This approach improves lower limb analysis of sEMG signals through (2D) scalogram format rather than (1D) sEMG signal. Classification of knee abnormality through (2D) scalogram format can increase discrimination performance through the new automatic feature extracted via deep learning architecture [22].

A. Many researchers in the literature have demonstrated improving the classification of different activities based on different forms of acquired signal signals. Some of the literature methods classified different types of muscle movements based on sEMG signals. Jiang et al. [23] presented an sEMG signals analysis method using discrete Wavelet Transform (DWT) for detecting and characterizing signal patterns. They adopted traditional feature extraction techniques using an external feature extraction process. They applied wavelet function based on signal-to-noise (SNR) and the signals' mean square difference (RMSD) values. The raw signals were used to calculate Sym and Bior wavelets with four decomposition levels. The signal database was recorded from two triceps brachii, biceps, and upper arm muscles. Three levels were calculated with a maximum time of 3s of force contraction, i.e., low, medium, and high. They evaluated the performance of the algorithms of the SEMG signal. The result shows a suitable classification analysis of sEMG signals of different arm motions with an accuracy of 88.90%. However, their traditional framework still faces many problems.

Zhang et al. [7] employed the wavelet transform in based EMG signals in analyzing physical situations. The method uses traditional Fourier methods in signal processing and feature extraction. Their model was designed to characterize three movement patterns related to the forefoot: toes, tiptoe, and upwarp. To obtain the wavelet coefficients, they decomposed the original sEMG signal into five levels via the db4 wavelet. They trained the signals of each movement using the backpropagation network through gradient descent and a varying learning rate. They also tested the model with the rest of the samples and achieved an identification rate of 93.33%.

Ibraheem et al. [24] investigated the diagnosis of Patellofemoral (PF) osteoarthritis based on sEMG signal. Their predictive model adopts extracting discriminative features in the classification process. sEMG signals were recorded for five muscles from healthy adult patients while. The targeted muscles' offset, onset, and time duration features were used to construct the discriminatory training model. This training model of muscle features is used to train the classifiers of several large margins. Their results show that the fast large-margin classifier reached higher results than support vector machines (SVMs) and other classifiers. Their model reached an average accuracy of 98.8%.

These techniques adopted the traditional technique of extracting discriminating features of sEMG signals and constructing a classification model. Others adopted the novel technique, mapping the signal from one-dimensional space to a two-dimensional matrix. However, these employed other types of signals, i.e., EEG, ECG, and respiratory sound. Some of these publications are as follows:

Xu et al. [25] used wavelet frequency-time transform and convolutional network to diagnose motor imagery (MI) EEG hand movement signals. They evaluated their model on Dataset from a Brain-computer interface (BCI) competition. They first performed preprocessing to remove the noise from 1D ECG signals. Then, they used wavelet transform time-frequency image to map 1D to 2D image space. The projected images were fed into a 2-Layer convolutional neural network of different sizes. The obtained accuracy reached 90% by evaluating the performance of the proposed approach on the BCI dataset.

Byeon et al. [22] compared deep models and scalograms in characterizing electrocardiograms (ECG). They transformed signals of ECG into a frequency domain using a wavelet. They investigated using the ECG scalogram as input to deep convolutional networks to classify morphological imagery. They used pre-trained deep models in training data. They performed their experiments on Physikalisch-Technische Bundesanstalt (PTB)-ECG database for performance evaluation. They observed performance ranges from 0.73%—0.94% using ResNet and AlexNet pre-trained models.

Salles et al. [26] used a pre-trained Alexnet CNN to predict respiratory disorders. They investigated the conversion of respiratory sound segmented signal into scalogram format. These converted segments into scalograms are fed into the CNN pre-trained architecture for training and testing. They evaluated the model performance on a dataset of four different categories, i.e., lung sounds, normal, wheezes (monophonic & polyphonic), crackles (coarse and fine), and low-pitched wheezes (Rhonchi). Their proposed approach reached 79.04 % to 81.27 % validation accuracy, up to 83.78 % accuracy.

Kim et al. [27] proposed a user recognition method that utilizes deep ensemble networks in the recognition of three different signals, i.e., electromyogram (EMG), electroencephalogram (EEG), and electrocardiogram (ECG). They first performed preprocessing step for (1-D) ECG signals to remove noise or distortion by frequency filtering. Subsequently, they projected 1-D ECG signals onto a 2D image space format. The transformed 2-D ECG signals are fed into an ensemble-network-based user recognition system. They used the ECG database of MIT-BIH NSRDB. This data was acquired with 128 sampling points for 18 samples. Five were men aged 26 to 45 years, and thirteen were women aged from 20 to 50 years. They partitioned data into 4,500 samples for training data, 2700 for data validation, and 1800 for testing. The results show that the ensemble networks give higher results than a single network. Particularly, the o ensemble networks performance reached up to 13% higher compared to the single network.

Sannino et al. [19] investigated the recognition of shockable rhythms (ShR) based on the surface electrocardiogram (ECG). They used continuous wavelet transform (CWT) to recognize ShR from a signal. They employed converting (1D) ECG segments into 2D time-frequency by time-frequency representations technique. They used CWT to feed CG signal into the convolutional neural network (CNN) model. A 12-layer CNN model was used for the automatic detection of ShR. The proposed algorithm was evaluated with 115 ECG records and achieved a performance accuracy of 98.82%.

The techniques that adopted mapping the signal to the 2-D space employed other signal types, i.e., EEG, ECG, and respiratory sound. sEMG has a complex signal due to its sensitivity to several external artifacts that result from muscle motion or electrode location over the surface of the muscles. This research demonstrates mapping the time-frequency representations of the sEMG signal into the two-dimensional matrix.

The proposed architecture feeds the 2-D representations of sEMG signal into the convolutional neural network (CNN) model for detecting lower limb muscle abnormality. This would open the door for detecting other muscle abnormalities during different movement types, which may be a potential clinical tool. The rest of this work is organized as follows. Section 2 demonstrates the diagnostic approach for detecting knee abnormality. Section 3 gives a brief description of the dataset used and the results reached. Finally, Section 4 concludes the proposed approach.

II. Materials and Method

In this section, the steps of characterizing lower limb muscle abnormality using the time-frequency representations approach. The proposed characterization model consists of the subsequent steps, as shown in Fig. 4.

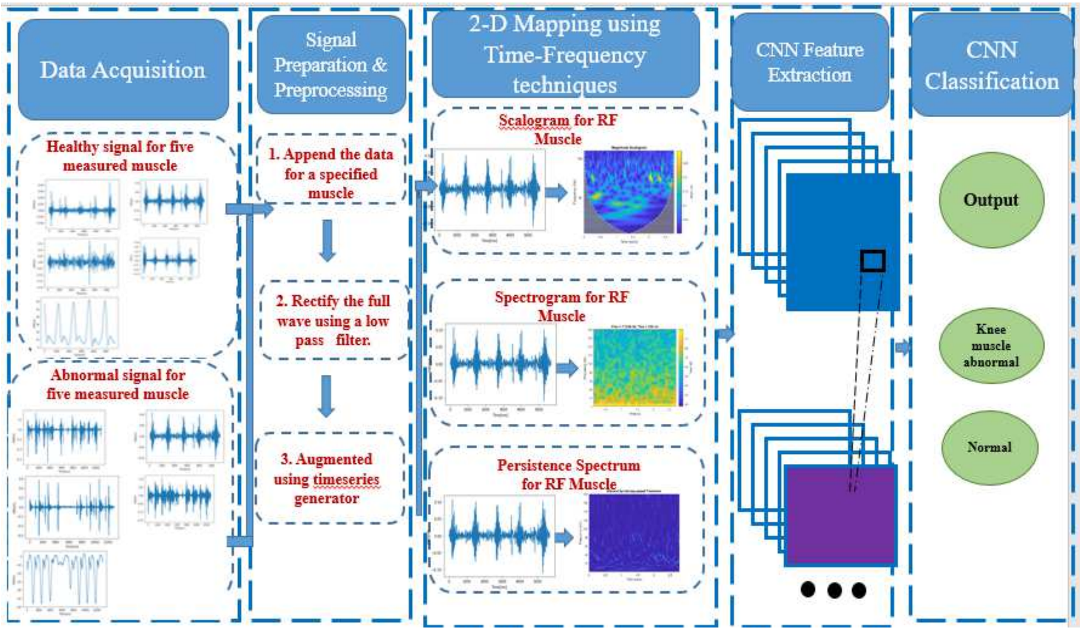

Fig. 4 The Lower Limb Muscle Abnormality Characterization Framework based sEMG

A. sEMG Signal Acquisition

Data was acquired via the placement of 4 electrodes (biceps femoris, rectus femoris, semitendinosus, and vastus medialis) on the muscle of interest and the goniometer in the knee. Thus, five-time series resulted corresponding to four electrodes on the targeted muscles besides the flexion at the knee. Each series contains five motion repetitions for each subject. Each data file contains five columns for the muscles being measured, i.e., Recto Femoral (RF), Femoral Biceps (BF), Vastus Medialis (VM), Semitendinosus (ST), and Flexion at the knee (FX). To visualize the behavior of the knee muscle, three movements were concerned: gait, flexion of the leg up, and leg extension from a sitting position. Typical sEMG signals of normal and abnormal knee acquired from five targeted muscles are shown in Fig. 5,6,7,8,9.

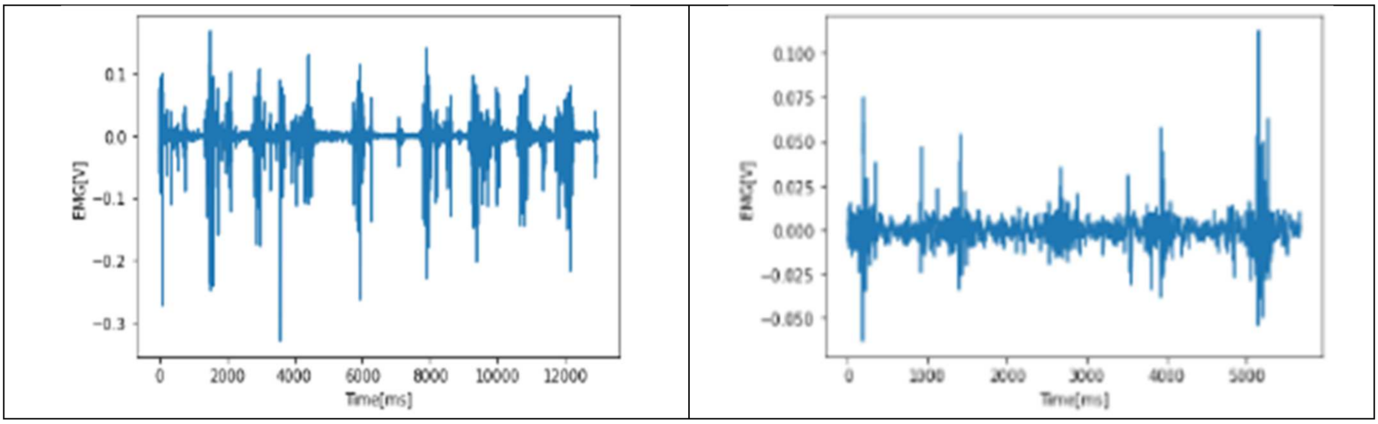

Fig. 5 The typical sEMG signals of the (A) abnormal knee and (B) normal acquired from Biceps Femoris muscle (BF).

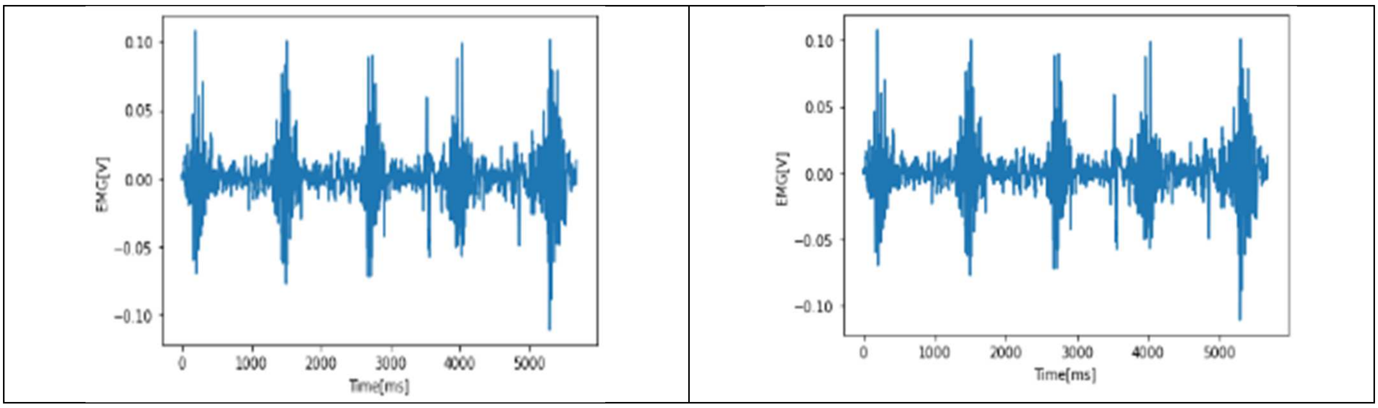

Fig. 6 The typical sEMG signals of the (A) abnormal knee and (B) normal acquired from Rectus Femoris muscle (RF).

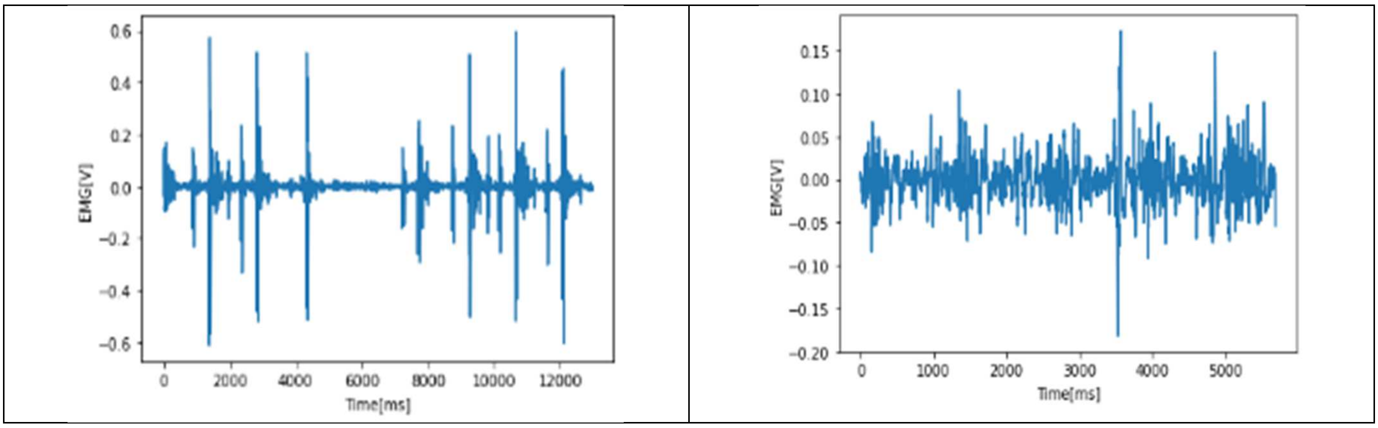

Fig. 7 The typical sEMG signals of the (A) abnormal knee and (B) normal acquired from Vastus Medialis muscle (VM)

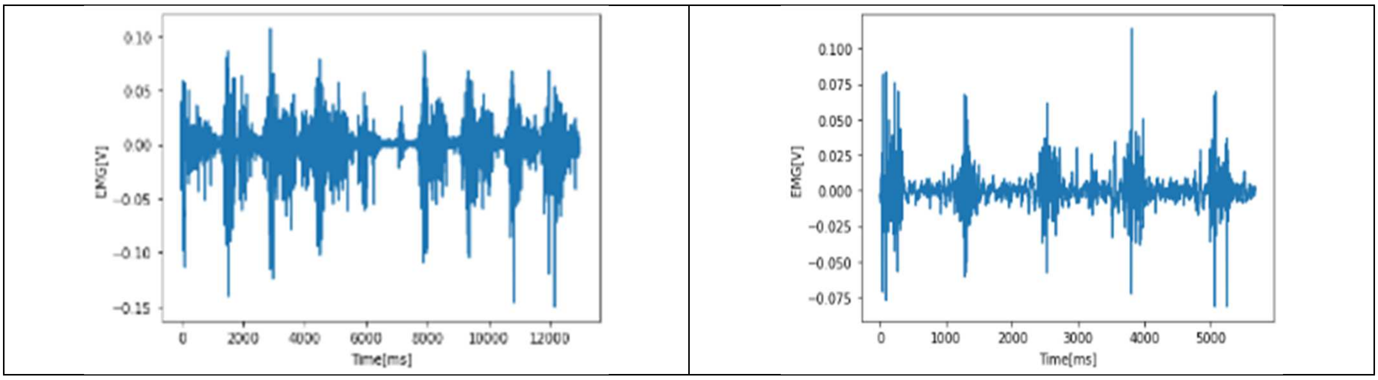

Fig. 8 The typical sEMG signals of the (A) abnormal knee and (B) normal acquired from Semitendinosis muscle (VM)

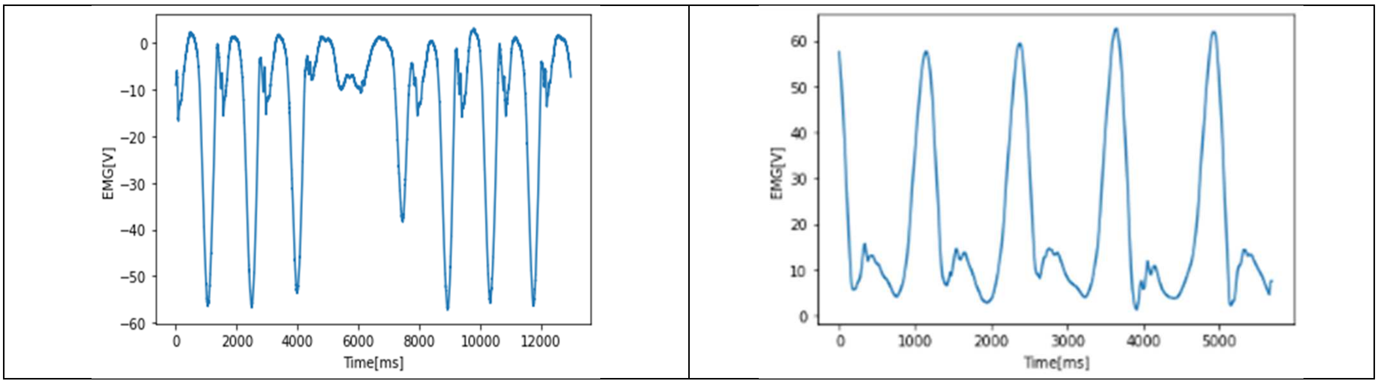

Fig. 9 The typical sEMG signals of the (A) abnormal knee and (B) normal acquired from flexion at the knee (FX)

B. Signal Preparation and Pre-processing

The raw data files contain 22 samples. Eleven of them are normal, and the other 11 with knee pathology. Each subject has three different shots. The resulting dataset contains 66 records for knee Abnormality along with normal ones in terms of five attributes describing the corresponding muscles measured. For each muscle attribute, the data are gathered in a specified muscle data file. Thus, the resulting data files are 10 muscle data file for muscle's normal and abnormal measurements. After data preparation, a preprocessing step is applied to remove any artifacts, so that minimum signal loss occurs [18]. The dataset was also augmented using a time-series generator to extend data samples and their targets [9]. The augmentation step resulted in 1056 records of sEMG sequence signal in terms of the five corresponding muscles.

Figure (10) shows the preparation and preprocessing of the proposed model

Algorithm 1: Preparation and preprocessing steps

Input: Data file contains five columns for muscles measurements.
Output: Obtaining concatenated measurements for each specified muscle.
Begin For j = 1: no. of data files
For i = 1: no. of muscles
  Append the data for a specified muscle.
  Rectify the full wave using a low pass filter.
  Augmented using timeseries generator.
  Copy the data of the specified muscle to a csv file.
END

Fig. 10 The algorithm for the preparation and preprocessing steps

C. 2-D Mapping Generation using Time-Frequency techniques

As reported in the literature review, extracting discriminative features from 1-D ECG signals ignores their frequency domain characteristics and lacks discriminatory features [6-7], [23]. Moreover, performing the classification via 2D images format has reached higher than using the 1D time-domain signal. Thus, mapping the 1D sEMG signal in time series into 2D space can help explore all discriminatory features in both frequency and time domains [11], [16], [22], [25], [27]. The knee muscle time-domain segments were mapped into 2D time-frequency space using three time-frequency representation techniques. The three time-frequency representation techniques are scalogram, spectrogram, and persistence spectrum.

1) The scalogram is generated by continuous wavelet transform (CWT). CWT preserves time shifts and time scales in terms of time-frequency resolution [11]. Wavelet transform can analyze the sEMG signals in the time and frequency domain and defined by the mother function given by (1) [26]:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-a}{b}\right) \quad (1)$$

The wavelet function can be shifted and scaled by a and b parameters. The continuous wavelet transform (CWT) can be obtained by mapping the wavelet function [25]. The scale parameters of the wavelet function can be used to dilate the time causing the opposite frequency domain effect as given by (2) [26]:

$$W(a,b) = \int_{-\infty}^{\infty} \psi_{a,b\,(t)}\, f(t)dt = \psi_{a,b}\, f \quad (2)$$

In CWT, the scale parameter is equivalently proportional to the time scale and inversely proportional to the frequency scale [15]. Thus, the scalogram is better at analyzing sEMG signals thanks to the adaptive characteristic of wavelet transform [22]. The following figure shows 2D time-frequency map examples that were generated from the sEMG segments for one of five muscles; RF in the two cases is normal and abnormal, as shown in Fig. 11.

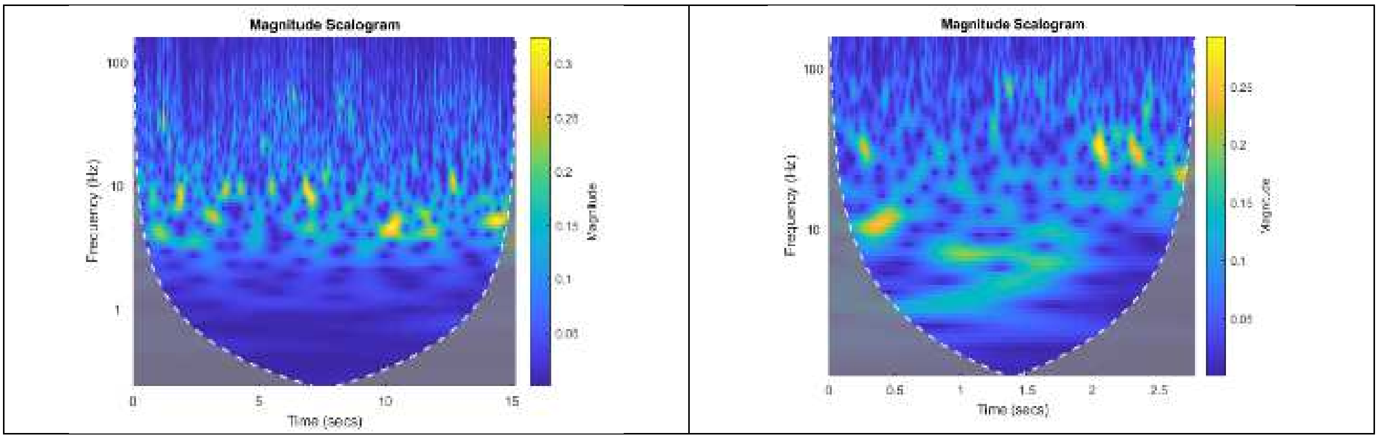

Fig. 11 The scalogram was generated from sEMG for (A) abnormal knee and (B) normal RF muscle.

The scalogram figure includes discriminative characteristics in both frequency and time domains [11]. Moreover, the obtained time-frequency map of each sEMG segment was fed into the subsequent CNN layers to extract the deep features automatically and accurately to classify normal and abnormal knees.

The scalogram is the absolute value of the wavelet coefficients of the sEMG signal [10]. It can transform the signal from the frequency to the time domain [17]. The 2-D matrix from the 1D signal can then be analyzed on multiresolution. The scalogram representation can be more comprehensive than the time domain, which is limited and cannot represent infinite time [8]. The frequency and time-space representation within the scalogram shows the signal distribution in terms of phase and frequency so that complex signals can be analyzed efficiently and easily [11].

In other words, the scalogram representation helps to visually determine the signals at various scales and frequencies and investigate various hidden features in the frequency–time-domain [22]. The mapped scalogram image format is then fed into subsequent CNN layers, which reveal better performance in multiresolution imagery classification [11].

2) The spectrogram is the squared magnitude generated by Short-Time Fourier Transform (STFT) [16]. STFT is a linear frequency-time representation of a signal that maps 1-D time signal into 2-D time and frequency representation [18]. Thus, it can also help in analyzing and synthesizing sEMG signals. STFT gives the spectral information at diverse time signal segments, providing an estimation of time and frequency and can be defined by (3) [2]:

$$STFT_x(t,w) = \int_{-\infty}^{\infty} x(\tau)\, w(\tau - t) e^{-2\eta f t} d\tau \quad (3)$$

where $x(\tau)$ denotes the sEMG signal, $w(\tau - t)$ denotes the observation window. The variable t slides the window over the signal $x(\tau)$. The spectrogram, the squared magnitude of the can be expressed as [18]:

$$S_x(t,f) = \left|\int_{-\infty}^{\infty} x(\tau)\, w(\tau - t) e^{-2\eta f t}\right|^2 d\tau \quad (4)$$

where $x(\tau)$ denotes the sEMG signal, $w(\tau - t)$ denotes the observation window. The variable t slides the window over the signal $x(\tau)$.

Spectrogram can be used to visualize the energy distribution and power of the signal along with the frequency and time domain [15]. In sEMG processing, energy distribution can isolate muscle activation from the baseline [28]. The mapped spectrogram image format is also used as input to CNN of deep learning to classify knee muscle abnormality. The following figure shows 2-D time-frequency map examples generated from the sEMG segments for one of five muscles; RF in the two cases is normal and abnormal, as shown in Fig. 12.

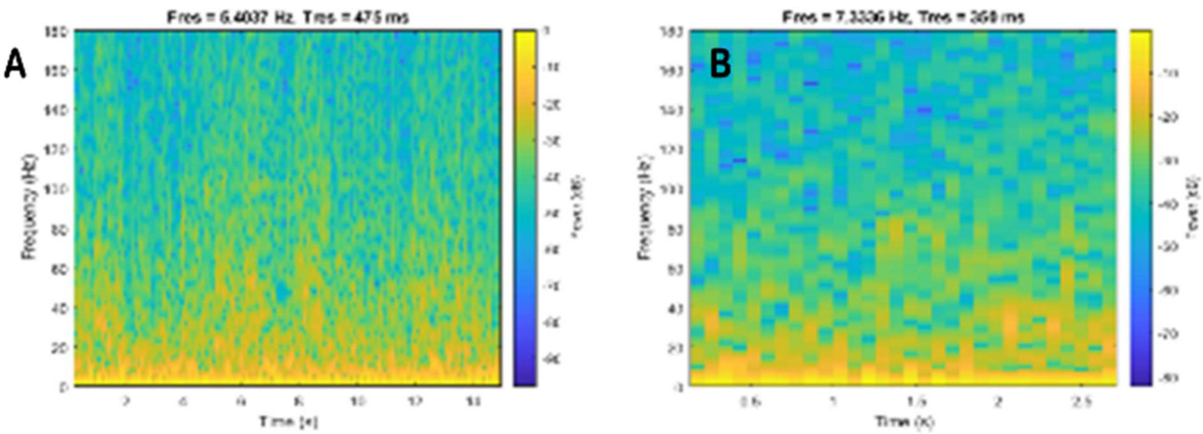

Fig. 12 The spectrogram was generated from sEMG for (A) abnormal knee and (B) normal of Rectus Femoris (RF) muscle.

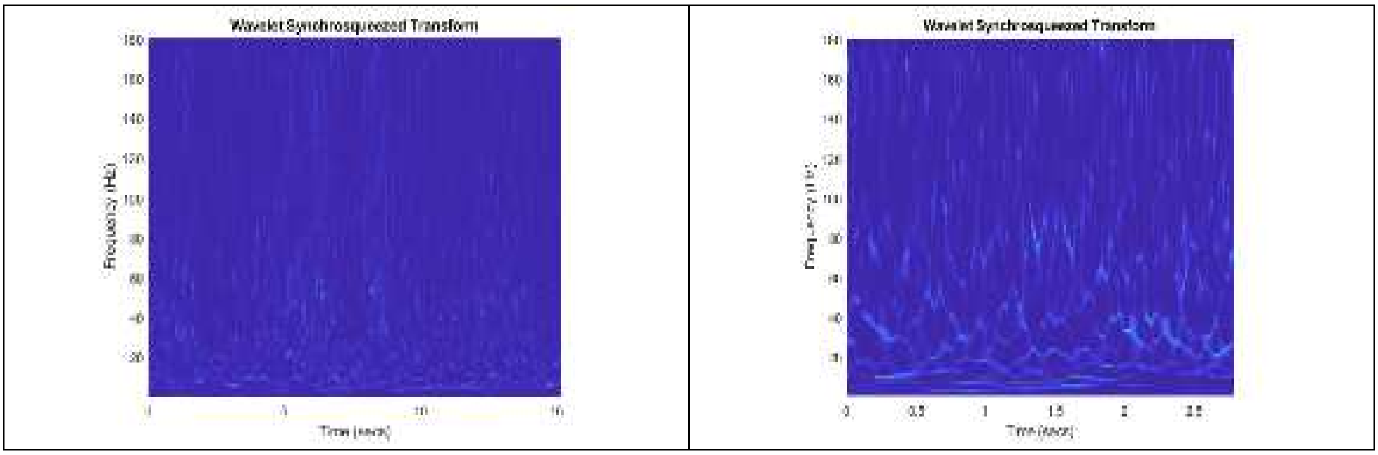

Fig. 13 The persistence spectrum generated from sEMG for (A) abnormal knee and (B) normal Rectus Femoris muscle.

3) The persistence spectrum is another method for the frequency analysis of signals. It is computed based on the time percentage that a given frequency persists within a signal [29]. The persistence spectrum sharpens the localization of spectral estimates and can also shrink the time-frequency maps around instantaneous frequency curves [30]. This method is especially appropriate for tracking and extracting the signal's ridges of time-frequency [13]. The following figure shows a 2D time-frequency map generated from the sEMG segments for one of five muscles; RF in the two cases is normal and abnormal, as shown in Fig. 13.

Converting signals into the frequency domain to overcome the sensitivity of sEMG signals to noise has been done using three frequency analysis techniques. Feeding the mapped image format to the convolution network provides meaningful sEMG signal classification.

D. Lower Limb Abnormality Characterization

This work explores the classification of lower limb abnormality via deep features of 2D sEMG frequency-time space with various diversity levels. The developed 2D deep CNN model can achieve more accurate classification than in classical learning approaches via manually extracted features. Novel deep learning techniques can provide a discriminative model by adjusting all information about the input data. Thus, defining the features manually for sEMG samples disturbed by various noise types is useless. The comprehensive features via the hidden conventional deep learning layers can efficiently generate implicit knowledge schemes for a more reliable classification basis [16].

Based on the CNN architecture, this work develops a CNN model of 12- layers to characterize sEMG segments into normal and abnormal ones automatically. The CNN model is developed to efficiently utilize the 2D structure of the mapped input images to perform binary classification. The proposed deep model is designed to input the mapped images format of sEMG frequency-time instead of time segments of sEMG. The scalogram, spectrogram, and persistent spectrum formats feed the CNN model in a 2D matrix.

Four convolutional layers are designed after the input layer; each has a correspondent pooling layer. The convolutional layers are then followed by three fully connected layers for accurate learning and deep feature extraction. The sizes of the convolution kernel, the strides, and the feature map are given in Fig. 14.

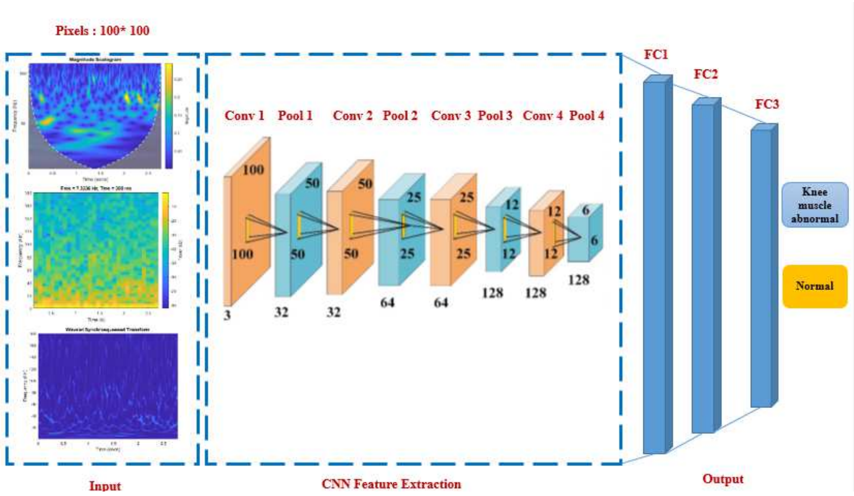

Fig. 14 The proposed 2D CNN model for detecting abnormal knee muscle

Moreover, the training of the deep model is mainly dependent on fine-tuning hyperparameters to overcome the problem of overfitting [6]. Parameter fine-tuning is adjusted to optimize the training and avoid the overfitting problem. The experiments are performed using 10-fold cross-validation for all eight models on the dataset. The number of kernels was designed increasingly along with model layers. Besides, the fully-connected layers were performed according to the loss value to verify optimal performance. Moreover, the dropout parameter was set to 0.5 for all CNN layers to avoid overfitting problems, and the activation function used was ReLU.

The proposed architecture and the hyper-parameters were adjusted using 10-fold cross-validation across experiments. Moreover, the mapped image format was randomly shuffled and divided into ten subsets. Ninety percent of the sEMG maps were used as training sets, and the remaining ten percent of the images were used as testing sets. Moreover, 80% of the training images were used to train the proposed deep model, and the remaining 20% was used for validating the model. Particularly, the performance of the proposed CNN models was evaluated using the sEMG database by calculating performance metrics such as accuracy (ACC), loss, validation loss (Val loss), and validation accuracy (Val acc). The performance metrics are calculated based on the true negative (TN), false negative (FN), true positive (TP), and false positive (FP).

III. Results and Discussion

A. Experimental Environment

In this study, different environments were experienced to reach the proposed lower limb muscle abnormality characterization framework:

Scalogram, spectrogram, and persistence spectrum creation were done using the MATLAB 2017 Time-Frequency Gallery. Besides, reading data and noise removal. Deep learning experiments were performed using google (Colab) Collaboratory. Colab is a GPU-centric application for accelerating deep learning. The runtime hardware configuration that was used to execute the model was 12 GB RAM, GPU Nvidia K80, and 2496 CUDA cores.

B. Experimental Results

For evaluating results, 22 samples of knee pathology each have three different shots. The dataset has 66 records for knee abnormalities and normal ones in terms of five attributes describing the corresponding muscles measured. For each muscle attribute, the data are gathered in a specified muscle data file. The augmentation step resulted in 1056 records of sEMG sequence signal for each of the five muscles measured. A sampling frequency of 1000Hz was used for acquiring Real-time Datalog to the internal computer storage.

Various performance metrics are adopted to evaluate the significance of the proposed lower limb characterization framework. The accuracy (Acc), loss, Validation Loss (Val Loss), and Validation Accuracy (Val Acc) is calculated based on the true negative (TN), true positive (TP), false negative (FN), and false positive (FP).

TABLE I
THE PERFORMANCE EVALUATION IN TERMS OF ACCURACY FOR THE THREE COMPARATIVE 2D- INPUT FORMATS TO CNN

2D- input format to CNN	Accuracy				
	RF	BF	VM	ST	FX
Scalogram	0.865	0.863	0.845	0.893	0.857
Spectrogram	0.839	0.834	0.865	0.814	0.835
Persistence Spectrum	0.776	0.771	0.886	0.764	0.847

TABLE II
THE PERFORMANCE EVALUATION IN TERMS OF VALIDATION ACCURACY FOR THE THREE COMPARATIVE 2D- INPUT FORMATS TO CNN

2D- input format to CNN	Validation Accuracy				
	RF	BF	VM	ST	FX
Scalogram	0.824	0.844	0.832	0.832	0.787
Spectrogram	0.803	0.886	0.829	0.803	0.787
Persistence Spectrum	0.718	0.741	0.867	0.731	0.775

To evaluate the model's performance, a comparative experiment is performed for three time–frequency representation techniques: scalogram, spectrogram, and persistence spectrum. Table I and II show the lower limb deep model classification accuracy and loss using different 2D input format for sEMG for each of the five knee muscles.

Tables III and IV show the lower limb deep model validation accuracy and loss using different 2D input formats for sEMG.

TABLE III
THE PERFORMANCE EVALUATION IN TERMS OF LOSS FOR THE THREE COMPARATIVE 2D- INPUT FORMATS TO CNN

2D- input format to CNN	**Loss**				
	RF	**BF**	**VM**	**ST**	**FX**
Scalogram	0.111	0.157	0.218	0.268	0.261
Spectrogram	0.214	0.318	0.221	0.101	0.156
Persistence Spectrum	0.147	0.226	0.264	0.171	0.258

TABLE IV
THE PERFORMANCE EVALUATION IN TERMS OF VALIDATION LOSS FOR THE THREE COMPARATIVE 2D- INPUT FORMATS TO CNN

2D- input format to CNN	**Validation Loss**				
	RF	**BF**	**VM**	**ST**	**FX**
Scalogram	0.212	0.216	0.279	0.135	0.287
Spectrogram	0.244	0.260	0.284	0.260	0.213
Persistence Spectrum	0.217	0.276	0.175	0.173	0.274

C. Discussion

The comparison measurements are listed in table V. The results of the proposed deep model using scalogram frequency representation are ACC 86.4%, Val Acc 86.4%, loss 0.203, and Val Loss 0.225. While the results of the proposed deep model using spectrogram frequency representation are ACC 83.7%, Val Acc 82.1%, loss 0.202, and Val Loss 0.248. On the other hand, the results of the proposed deep model using persistence spectrum frequency representation are ACC 80.8%, Val Acc 766%, loss 0.211, and Val Loss 0.223.

TABLE V
THE AVERAGE PERFORMANCE FOR THE THREE COMPARATIVE 2D- INPUT FORMAT TO THE CNN MODEL

2D- input format to CNN	ACC	Val Acc	Loss	Val Loss
Scalogram	86.4%	86.4%	0.203	0.225
Spectrogram	83.7%	82.1%	0.202	0.248
Persistence Spectrum	80.8%	76.6%	0.2113	0.223

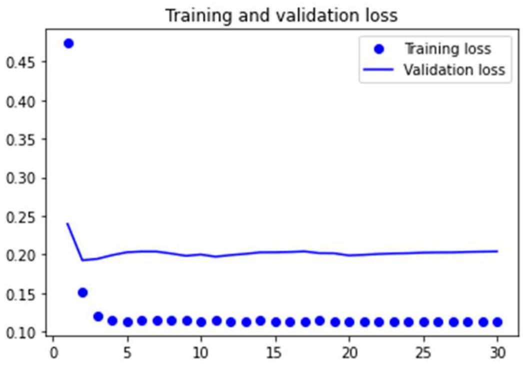

Fig. 15 The loss curves for training and validation over epochs

The results of the proposed model using scalogram representation outperform other frequency representation techniques. The scalogram frequency representation method shows higher results because of its ability to multi-scale analysis and avoids selecting the window size as in the STFT method. The loss curves for training and validation are constructed to visualize the performance for the proposed lower limb abnormality detection model. Fig. 15 displays the loss curves for training and validation over epochs, and the graph figures a stable evaluation score over the training epochs.

IV. CONCLUSION

This paper proposes a comprehensive sEMG-based model detecting lower limb muscle abnormality. The developed model mainly depends on mapping the sEMG signal into 2D space and then feeding it to the CNN deep model. Detecting knee muscle abnormality is done by extracting deep features during CNN training. The performance of lower limb classification was evaluated by setting up a comparative experiment using three time-frequency representation techniques. Scalogram, spectrogram, and persistence spectrum generate 2D image format from sEMG signal. The proposed model's results using scalogram representation outperform other frequency representation techniques. The scalogram frequency representation method shows higher results because of its ability to multi-scale analysis and avoids selecting the window size as in the STFT method. The 2D image representation can help explore all informative features in both frequency and time domains. This technique could be a potential clinical tool for detecting other muscle abnormalities during different types of movement for future work.

REFERENCES\

[1] I. R. Mendo, et al. "Machine Learning in Medical Emergencies: a Systematic Review and Analysis," Journal of medical systems, vol. 45., Aug. 2021, doi:10.1007/s10916-021-01762-3.

[2] G. Ramos, et al. "Fatigue evaluation through machine learning and a global fatigue descriptor," Journal of healthcare engineering, 2020.

[3] E. Maleki, et al. "On the efficiency of machine learning for fatigue assessment of post-processed additively manufactured AlSi10Mg, " International Journal of Fatigue, vol. 160. 2022.

[4] O.W. Samuel, et al. "Intelligent EMG pattern recognition control method for upper-limb multifunctional prostheses: advances, current challenges and future prospects," Ieee Access, pp. 10150-10165, July 2019.

[5] S. Bhagwat and P. Mukherji, "Electromyogram (EMG) based fingers movement recognition using sparse filtering of wavelet packet coefficients," Sādhanā 45.1, pp. 1-11, 2020.

[6] S. A. ElGhany, M. R. Ibraheem, M. Alruwaili and M. Elmogy, "Diagnosis of Various Skin Cancer Lesions Based on Fine-Tuned ResNet50 Deep Network," *Computers, Materials & Continua*, vol. 68, no. 1, pp. 117–135, 2021, doi:10.32604/cmc.2021.016102.

[7] X. Zhang, Y. Wang and R. P. S. Han, "Wavelet transform theory and its application in EMG signal processing," *Seventh International Conference on Fuzzy Systems and Knowledge Discovery*, Aug. 2010, DOI: 10.1109/FSKD.2010.5569532.

[8] N.Sairamya, L. Susmitha, S. George and M.Subathra, "Hybrid Approach for Classification of Electroencephalographic Signals Using Time–Frequency Images With Wavelets and Texture Features," Intelligent Data Analysis for Biomedical Applications, Academic Press, pp. 253-273, 2019.

[9] S. Salcedo-Sanz, et al. "Persistence in complex systems," Physics Reports, vol. 957, pp. 1-73, 2022.

[10] S. Jayalakshmy and G. F. Sudha, "Scalogram based prediction model for respiratory disorders using optimized convolutional neural networks," *Artificial Intelligence in Medicine*, vol. 103, pp. 101809, Mar. 2020, doi.org/10.1016/j.artmed.2020.101809.

[11] F. Jing, C. Zhang, W. Si, Y. Wang and S. Jiao, "QFM Signals Parameters Estimation Based on Double Scale Two Dimensional Frequency Distribution," in IEEE Access, vol. 7, pp. 4496-4505, 2019, doi: 10.1109/ACCESS.2018.2888540.

[12] C.Y. Lee and T. A. Le, "Identifying Faults of Rolling Element Based on Persistence Spectrum and Convolutional Neural Network With ResNet Structure," *IEEE Access*, vol. 9, pp. 78241–78252, 2021, DOI: 10.1109/ACCESS.2021.3083646.

[13] B. Liu, Z. Zhangand R. Cui, "Efficient Time Series Augmentation Methods," *13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, Oct. 2020, DOI:10.1109/CISP-MEI51763.2020.9263602.

[14] M. V. Balas and B. Agarwal, "Deep Learning Techniques for Biomedical and Health Informatics," 2020, doi.org/10.1016/C2018-0-04781-7.

[15] N. Arizumi and T. Aksenova, "Fast Continuous Wavelet Transform for Brain Computer Interface using piecewise polynomials," 2019 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), 2019, pp. 1-6, doi: 10.1109/ISSPIT47144.2019.9001739.

[16] M. S. Diab and S. A. Mahmoud, "Continuous Wavelet Transform OTA-C Band Pass Filter on Field Programmable Analog Arrays," 2020 Advances in Science and Engineering Technology International Conferences (ASET), 2020, pp. 1-5, doi: 10.1109/ASET48392.2020.9118234.

[17] S. Jayalakshmy, L. Priya and G.Sudha, "Synthesis of respiratory signals using conditional generative adversarial networks from scalogram representation," Generative Adversarial Networks for Image-to-Image Translation, Academic Press, 2021,

[18] F. Demir, et al. "Surface EMG signals and deep transfer learning-based physical action classification," Neural Computing and Applications 31.12, pp. 8455-8462, 2019.

[19] G. Sannino and G. D. Pietro, "A deep learning approach for ECG-based heartbeat classification for arrhythmia detection," *Future Generation Computer Systems*, vol. 86, pp. 446–455, Sep. 2018, doi.org/10.1016/j.future.2018.03.057.

[20] G. Ruffini, D. Ibañez and M. Castellano, et al., "Deep Learning With EEG Spectrograms in Rapid Eye Movement Behavior Disorder," *Frontiers in Neurology*, vol. 10, Jul. 2019, doi.org/10.3389/fneur.2019.00806.

[21] S. A. Singh and S. Majumder, " Short and noisy electrocardiogram classification based on deep learning," Deep Learning for Data Analytics, Academic Press, pp. 1-19, 2020.

[22] Y.H. Byeon, S.B. Pan and K.C. Kwak, "Intelligent Deep Models Based on Scalograms of Electrocardiogram Signals for Biometrics," *Sensors*, vol. 19, no. 4, pp. 935, Feb. 2019, doi.org/10.3390/s19040935.

[23] D. Jiang, et al. "Force estimation based on sEMG using wavelet analysis and neural network," 2019 9th International Conference on Information Science and Technology (ICIST). IEEE, 2019.

[24] M. R. Ibraheem, J. adel, A. E. Balbaa, S. El-Sappagh, T. Abuhmed and M. Elmogy, "Timing and Classification of Patellofemoral Osteoarthritis Patients Using Fast Large Margin Classifier," Computers, Materials & Continua, vol. 67, no. 1, pp. 393–409, 2021, doi:10.32604/cmc.2021.014446.

[25] B. Xu et al., "Wavelet Transform Time-Frequency Image and Convolutional Network-Based Motor Imagery EEG Classification," in IEEE Access, vol. 7, pp. 6084-6093, 2019, doi: 10.1109/ACCESS.2018.2889093.

[26] R. S.Salles et al., "Visualization of Quality PerformanceParameters Using Wavelet Scalograms Images for Power Systems," Congresso Brasileiro de Automática-CBA. Vol. 2. No. 1. 2020.

[27] M.G. Kim, H. Ko and S. B. Pan, "A study on user recognition using 2D ECG based on ensemble of deep convolutional neural networks," Journal of Ambient Intelligence and Humanized Computing, vol. 11, no. 5, pp. 1859–1867, Jan. 2019, doi.org/10.1007/s12652-019-01195-4.

[28] L. Nanni, A. Rigo, A. Lumini and S. Brahnam, "Spectrogram Classification Using Dissimilarity Space," Applied Sciences, vol. 10, no. 12, pp. 4176, Jun. 2020, doi.org/10.3390/app10124176.

[29] N. Yahya, H. Musa, Z. Y. Ong and I. Elamvazuthi, "Classification of Motor Functions from Electroencephalogram (EEG) Signals Based on an Integrated Method Comprised of Common Spatial Pattern and Wavelet Transform Framework," Sensors, vol. 19, no. 22, pp. 4878, Nov. 2019, doi: 10.3390/s19224878.

[30] C. N. Savithri and E. Priya. "Statistical analysis of EMG-based features for different hand movements," Smart Intelligent Computing and Applications. Springer, Singapore, pp.71-79, 2019.