sEMG-based deep learning framework for the automatic detection of knee abnormality

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Abstract

Knee abnormality is a vital issue that can be diagnosed utilizing a sEMG signal to detect muscle abnormalities. Manually analyzing EMG data is time-consuming and requires skilled doctors. Hence, this paper aims to provide an automated system for the diagnosis of knee abnormality. Here, sEMG signal acquired from four different lower limbs muscles of 22 volunteers with three activities: walking, sitting, and standing, of which 11 seem healthy, and the rest were diagnosed clinically with knee abnormality. Noises are present during the sEMG signal recording, so a multi-step classification approach is proposed here. At first, wavelet denoising was implemented to denoise the sEMG signals. Further,

the overlapping windowing method with a window size of 256 ms along with an overlapping of 25% was utilized to minimize the computational complexity. Afterward, a hybrid convolutional neural network with long short-term memory (Conv-LSTM) model is used for screening abnormal subjects. In this hybrid approach, a convolutional neural network (CNN) is used for temporal learning, while long short-term memory (LSTM) is for sequence learning. The results exhibit that the proposed wavelet-based denoising followed by Conv-LSTM model is the most precise and convenient model used for the detection of knee abnormality using sEMG signals so far.

1 Introduction

Knee pain is an ordinary illness that influences individuals of all age groups. The main cause of knee pain is aging, injuries like torn cartilage, ruptured ligaments, and knee osteoarthritis. Technology, such as tracking recovery progress, has a substantial potential for boosting the quality of lifestyle of such physically challenged people. As claimed by a study in [1], out of four individuals, one is a patient of joint symptoms or arthritis because of injury like knee osteoarthritis. The knee joint is the only joint that imparts motion of the leg within the body of a human being. In addition to acting as a shock absorber, it also stabilizes and provides balance to an individual's body. It constitutes distinct parts such as ligaments, cartilage, muscles, fluids, bones, and tendons. Formation of the knee joint that takes place via articulation among the femur, patella, and tibia. Thus, any abnormality or external harm to any parts of the knee joint can produce knee pain or abnormality in the knee [2].

Further, various medical imaging modalities such as magnetic resonance imaging (MRI), X-Ray, medical radiation, angiography, and computed tomography (CT) scanners can be used to detect abnormalities in the knee. MRI is an imaging approach that is utilized in radioscopy to configure images of the anatomy together with the physiological procedures of the body. They utilize intense magnetic fields, radio waves, magnetic field gradients along with a computer to create pictures of the body's organs. It is implemented to analyze pain in the knee; however, it is quite expensive. X-ray radiation generates images of body parts. Various problems that affect soft tissue, including internal organs, breaks, and fractures in the bone can be diagnosed with the help of an X-ray [3]. It is also utilized in the examination of knee pain. Computer tomography involves a computerized imaging process inside which confined X-ray radiation is directed toward the patient, that tends to generate signals which are treated with the help of a computer to create partial pictures of the body. Abnormalities of the knee can be traced by using wearable sensors such as gyrometer, EMG, accelerometer, etc. along with the visual sensors [4]. Electromyography is a demonstrative process that estimates the condition of nerve cells and muscles. EMG can also be utilized to recognize the activity of an individual by forecasting the actions in advance, and it quickly recognizes variations in the signal. There are two approaches to accumulate electromyography signals that is intramuscular EMG (iEMG) and surface EMG (sEMG) [5]. sEMG has several benefits compared to iEMG, as the probability of inflammation becomes nil; also electrodes could be implemented without any medical observation. The sEMG signal collected with the help of sEMG sensors for everyday human activities can be used in distinct applications like health monitoring, detection of neuromuscular disorders, automated command of upper and lower limb exoskeletons, etc [6, 7].

Recently, machine learning approaches have been widely used in the medical field to detect the various types of disease with the help of biomedical data [7]. Research over spinal cord injury by utilizing the sEMG signal that was collected while the activities of the upper limb were being executed is done by Silva et al. [9]. Chen et al. examined the human lower limb extension angle utilizing a deep neural network in [10]. For motorized lower prosthetic limbs, Varol et al. [11] established a multi-class real-time intended classification technique relying upon sEMG signals. Choi et.al [12] determined the pattern of sEMG signals based on neural networks. A comparative analysis of machine learning models for the detection of knee abnormality is discussed in [13]. Diagnosis of knee abnormality with imbalanced sEMG data for gait activity was examined by Vijayvargiya et al. [14]. They have shown the effect of an imbalanced signal during the diagnosis of a knee abnormality and have used various oversampling techniques to improve the performance of machine learning models. Ertuğrul et al. have developed an adaptive local binary pattern (ALBP) technique to extract features and classify the healthy and knee abnormal subjects with an accuracy of 85% [15].

Machine learning models are required to handcrafted features from the signals where features have to be selected by some machine learning or statistical methods. It is a very tedious task to choose the appropriate feature set manually. As per the study, deep learning models such as CNN, LSTM, GRU, etc. are used to overcome this problem. In the deep learning approaches, the features are first extracted by the algorithm, and then the classification process is performed. These deep learning models have been implemented to different applications and showed very high performance as per the previous studies [16]. CNN model is utilized for the processing of images, it also exhibits promising outcomes in acquiring features through stationary datasets. The architecture of CNN constitutes an input layer, an output layer, it also consists of several pooling layers, dense layers, convolutional layers, rectified linear unit layers in addition to dropout layers. It recognizes the main features without the need for supervision. The inability to evaluate the earlier or temporal data within time-series signals is one of the main problems with CNN. Though, to process and acquire temporal information, LSTM can be used.

According to an analysis of relevant literature, there are relatively few studies on knee abnormality identification using sEMG signals. The majority of research employs a handcrafted method, and there is currently no study that uses a deep learning strategy to identify knee problems using sEMG data. As a result, in this research, a combination of CNN and LSTM is presented to identify the knee abnormalities using the sEMG signal. The CNN-LSTM model comprises layers of CNN along with the LSTM network. A convolutional neural network is used for temporal learning whereas LSTM is used for sequence learning in the proposed CNN-LSTM model. Therefore, the CNN-LSTM [17] hybrid is an absolute model which permits learning on features for EMG signals together with long-term dependencies.

The major contribution of this research is:

1. This study comprises use of the sEMG signals that are acquired through leg muscles of an individual to recognize the knee abnormality by utilizing a hybrid Conv-LSTM-based deep learning framework.

2. In order to eliminate the artifacts of raw sEMG signals obtained via muscles of lower limb, wavelet denoising is employed as a section of preprocessing.

3. Performance parameters of individual models are also evaluated and compared with the proposed hybrid Conv-LSTM model. The proposed model is a high-performance model for automatic recognition of knee abnormality.

This paper includes the following section: In Sect. 2, an overview of the dataset is given. Section 3 comprises the proposed methodology. Section 4 consists of results along with discussions. Section 5 involves the conclusion and future scope.

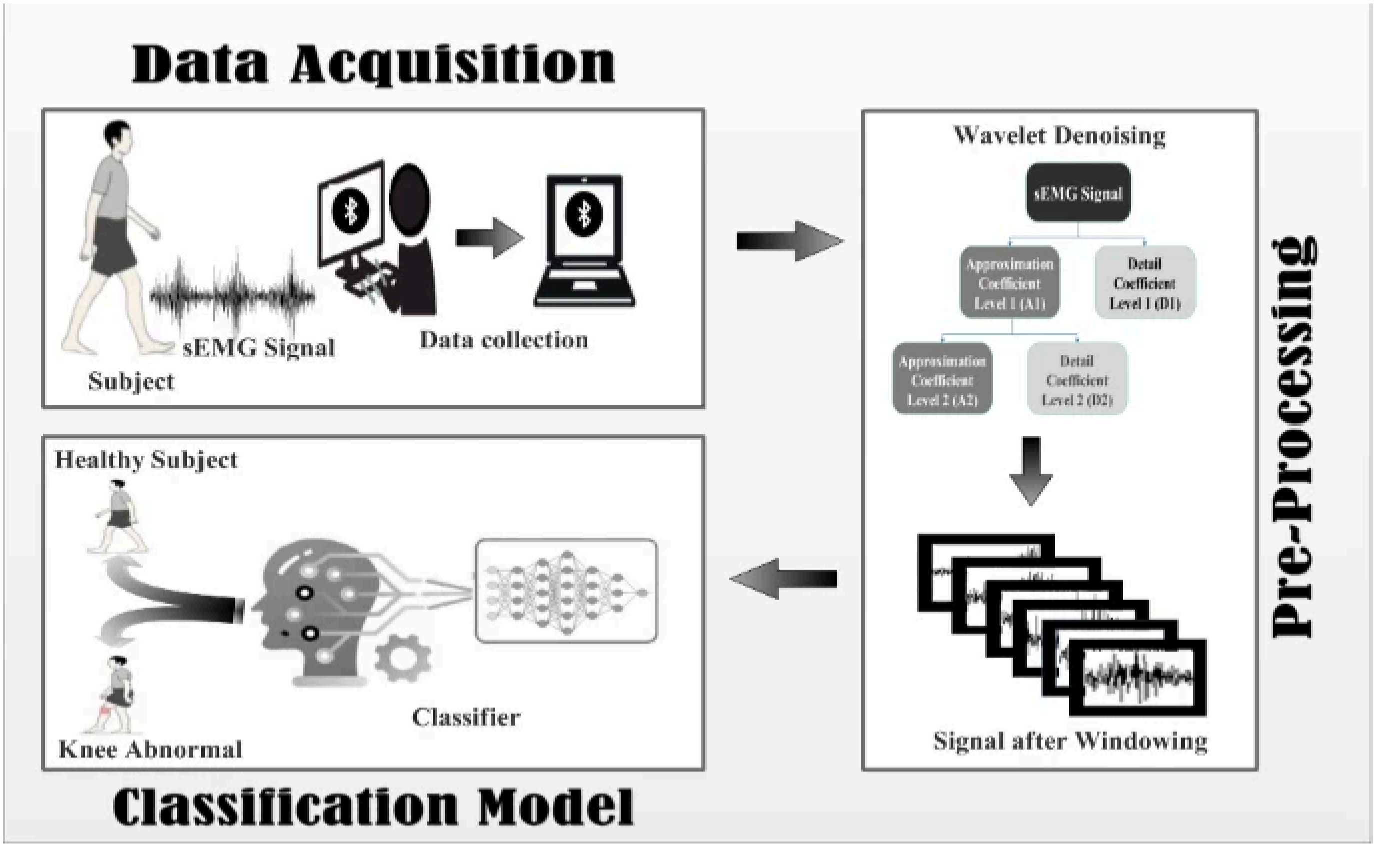
2 Dataset

In this paper, authors have used the publically available sEMG signal dataset at UCI machine learning repository via Lichman et al. [18]. The dataset involves twenty-two candidates whose age was above 18 years. Amid those candidates, eleven looks fit and knee abnormality was exhibited by rest. The dataset constitutes the sEMG signal of the lower limb of the participants. No preceding medical record was discovered with reference to injury or pain in the knee of candidates who were fit. Out of knee abnormal candidates, six were affected with anterior cruciate ligament (ACL), one was encountered with sciatic nerve injury and four suffered from a meniscus injury. While the participants were engaged in different tasks such as flexure of leg up, leg extension from sitting position, and walking, data were assembled by utilizing the DataLOG (MWX8) via biometrics Ltd along with a goniometer. By using a goniometer that is connected to the joint of the knee on the external side, the dataset of four muscles including vastus medialis(VM), semitendinosus(ST), biceps femoris (BF) along with rectus femoris (RF) was collected. In this research work, only the sEMG signal collected from the three different tasks: walking, sitting, and standing were used. The sEMG signal was obtained from the infected limb of the knee abnormal participants and the left limb of the healthy participant. Dataset was collected at a sampling rate of about 1000Hz along with 14-bit resolution. Filtration of signals was done with the help of a bandpass filter accompanied by passband frequency from 20 Hz to 460Hz.

3 Proposed methodology

This section illustrates the proposed methodology as shown in Fig. 1, for the detection of abnormalities in the knee through the sEMG signal. The dataset utilized in the following research is used via the UCI machine learning repository which includes sEMG signals from lower limbs of about 22 volunteers among which 11 are fit and the rest 11 are diagnosed with abnormalities in the knee. Initially, the sEMG signal is pre-processed, which involves the elimination of noises by using a discrete wavelet denoising approach. Further, the segmentation of signal is done by the overlapping windowing technique. Afterward, the deep learning models including CNN, LSTM, and proposed convolutional LSTM were used to analyze the data for knee abnormality detection.

Fig. 1



Flow diagram of proposed methodology

The following subsection includes the major part of the proposed methodology:

3.1 Wavelet denoising

Generally, four kinds of noises are commonly present while collecting the sEMG signal [19] such as (1) inherent noise generated via electronic appliances, (2) ambient noise resulting through electromagnetic devices, (3) inherent noise uncertainty because of the firing rate of motor units, and (4) motion artifacts generated through the sEMG electrodes movement. On that account, denoising of a signal is necessary, it also carried out before the signal is utilized for purpose of classification. To reduce the noise that is out of range for the sEMG signal spectrum band, a conventional approach of filtering including low pass, high pass together with bandpass may be utilized. sEMG signal proceeds through the bandpass filter (20 to 460 Hz). In recent research, a lot of different approach such as empirical mode decomposition (EMD), wavelet denoising, independent component analysis (ICA) have been utilized to minimize the noises in the sEMG signal [20]. Implementation of wavelet denoising on the sEMG signal that is obtained through lower and upper limbs has proven to be effective. The scheme to denoise the sEMG signal with the help of a wavelet denoising algorithm is demonstrated by Phinyomark et al. [21]. Among sEMG signals, several irregular noises such as white Gaussian noise are inconvenient to reduce via signal filtering. Hence, wavelet denoising is used to eliminate it. The expression for noisy signal $X(n)$ is stated as Eq. (1):

$$\begin{aligned} X(n) = Y(n) + K(n) \end{aligned}$$

(1)

wherein $Y(n)$ demonstrates original signal, $K(n)$ is white Gaussian noise, and $X(n)$ presents noisy signal.

The wavelet denoising based upon DWT comprises the following steps:

- Signal decomposition is done by the DWT;
- Select the threshold for each wavelet transform;
- To regenerate the denoised signal, the inverse wavelet transforms along with the threshold function is used.

As a result of the implementation of wavelet denoising over signals, discrete coefficients of wavelets are generated when the signal is passed via low-pass as well as high pass filters. With the help of the wavelet denoising approach, detail and approximation coefficients are acquired after signal decomposition and thresholding is accomplished. The total number of coefficients is decided by the level of decomposition. Two conventional approaches are present for thresholding wavelet coefficients: soft and hard thresholding [22]. In soft thresholding, there is a continuous deviation respective to the original signal whereas hard thresholding consists of incomplete information about the original signal. This study constitutes universal thresholding [23] that is implemented over detailed coefficients. The form of universal thresholding selection is represented as Eq. (2):

$$\begin{aligned} \lambda =\sigma \sqrt{2ln(M)} \end{aligned}$$

(2)

Herein, $\sigma = \text{(}MAD)/0.6745$ MAD is designated as median absolute deviation, M is the length of the signal.

This research consists of a wavelet denoising approach which is utilized along with sym4 originating from the family of symlet to the first level of decomposition [14]. In this previous study, calculated the value of mean squared error, mean absolute error, signal-to-noise ratio, and peak signal-to-noise ratio of the sEMG signal with different mother wavelets and level of decomposition on same dataset. They have proposed that sym4 originating from the family of symlet to the first level of decomposition is giving the best results compared to other mother wavelets and level of decomposition.

3.2 Segmentation

The segmentation is used as a part of pre-processing as it is a smart way to process time-series data used in a deep learning-based model to reduce the computational complexity. To implement the segmentation process, the windowing method is utilized. Two discrete methods of windowing are present to accomplish the process of segmentation: adjacent windowing and overlapping windowing [24]. The classification accuracy and classification response time will depend upon the window size of a signal. The accuracy of model increases with larger window size, but the response time is also increased. As per the previous studies , a delay of 150–250 ms interval is considered. So, we considered the overlapping windowing technique along with a window size of 256ms and an overlapping of 25% [25].

3.3 Deep learning frameworks

The model of CNN proceeds across the dataset through discrete hidden layers; however, the outcome is not supplemented back toward the network over here. Hence, models of CNN slightly lack in pursuing sequential information, though it is fine in acquiring temporal features. To eliminate this issue, a hybrid of the CNN and LSTM model (CNN-LSTM) is introduced in this paper. LSTM can be utilized for sequential data learning due to its capability of learning through training and it can also recollect whatever it has grasped to predict the adjacent element. It retains long-term dependencies and along with these features is also processed sequentially by LSTM.

3.3.1 Convolutional neural network

CNN is majorly used to acquire necessary features through sEMG signals to train the model. It generally comprises a composition of convolution operation and neural network. The convolution operation is practiced via streaming the particular kernel on the inserted data to obtain the feature map. A CNN model is majorly constructed using multi-layers, where high-level layers posses a significant quantity of kernels whereas lower-level layers constitute less quantity of kernels. In comparison with various computational classifiers, CNN possess lessened pre-processed data and feature extracted from the dataset. In contrast, CNN is basically utilized to employ 2D data including images and videos. Because of this, CNN is usually referred as 2D CNN. In recent times, 1D CNN are discovered as a moderation of 2D CNNs for time series data [26].

In this research work, feature extraction using CNN block considered three convolutional layers with 1 max-pooling layer. After that one fully connected layer is connected with the output layer. Here, signals are collected from the four channels and the window size used is 256, so the input sequence of 1D CNN is 1024, and batch size is considered 32. The ReLU activation function is used in a fully connected layer while the softmax activation function has been used in the output layer. The softmax function is employed as a classifier that predicts the input signal's class.

The input given to \(k\text {th}\) neuron of \(i\text {th}\) layer is determined by Eq. (3):

$$\begin{aligned} x_{k}^{l} = \sum _{i=1}^{N_{l-1}}\text {Conv}1D(W_{ik}^{l-1},o_{i}^{l-1}) + b_{k}^{l} \end{aligned}$$

(3)

Here x_{k}^{l} denotes the input provided to $k\text {th}$ neuron of $i\text {th}$ layer; b_{k}^{l} represents bias of $k\text {th}$ neuron of $i\text {th}$ layer; N_{l-1} designates the quantity of neurons within $(l-1)\text {th}$ layer and W_{ik}^{l} indicates the kernel through $i\text {th}$ neuron of layer $l-1$ to the $k\text {th}$ neuron of layer *l*. The output after implementating activation function to x_{k}^{l} is stated as Eq. (4):

$$\begin{aligned} y_{k}^{l} = f(x_{k}^{l}) \end{aligned}$$

(4)

Here *f*(.) symbolizes activation function and we have used ReLU function which is demonstrated as Eq. (5):

$$\begin{aligned} y_{k}^{l} = \max (0,x_{k}^{l}) \end{aligned}$$

(5)

Basically, its purpose is to restore the entire negative values with zero. After implementing the operation of max pooling to y output is given as Eq. (6):

$$\begin{aligned} o_{k}^{l}&= \text {for} \;\text {each} \;\text {pooling} \;\text {window} \;\max (y_{k}^{l}[0],y_{k}^{l}[1],...,y_{k}^{l}\\&[\text {pool size}]) \end{aligned}$$

(6)

Loss function which is utilized for back-propagation is given as Eq. (7):

$$\begin{aligned} \begin{aligned} L = -\sum _{i=1}^{C} t_{i}\text {log}(f(s)_{i}) \end{aligned} \end{aligned}$$

(7)

where the total number of classes in the dataset is denoted by C, t_{i} indicates the target output for input instance, and $f(s)_{i}$ is the probability determined by softmax function, which measures the likelihood of an input instance belonging to the $i\text {th}$ class.

Parameter updation in back-propagation is given as Eqs. (8) and (9):

$$\begin{aligned}&w_{ik}^{l-1}(t+1) = w_{ik}^{l-1}(t) - \alpha * \frac{\delta L}{\delta w_{ik}^{l-1}} \end{aligned}$$

(8)

$$\begin{aligned}&b_{k}^{l}(t+1) = b_{k}^{l}(t) - \alpha * \frac{\delta L}{\delta b_{k}^{l}} \end{aligned}$$

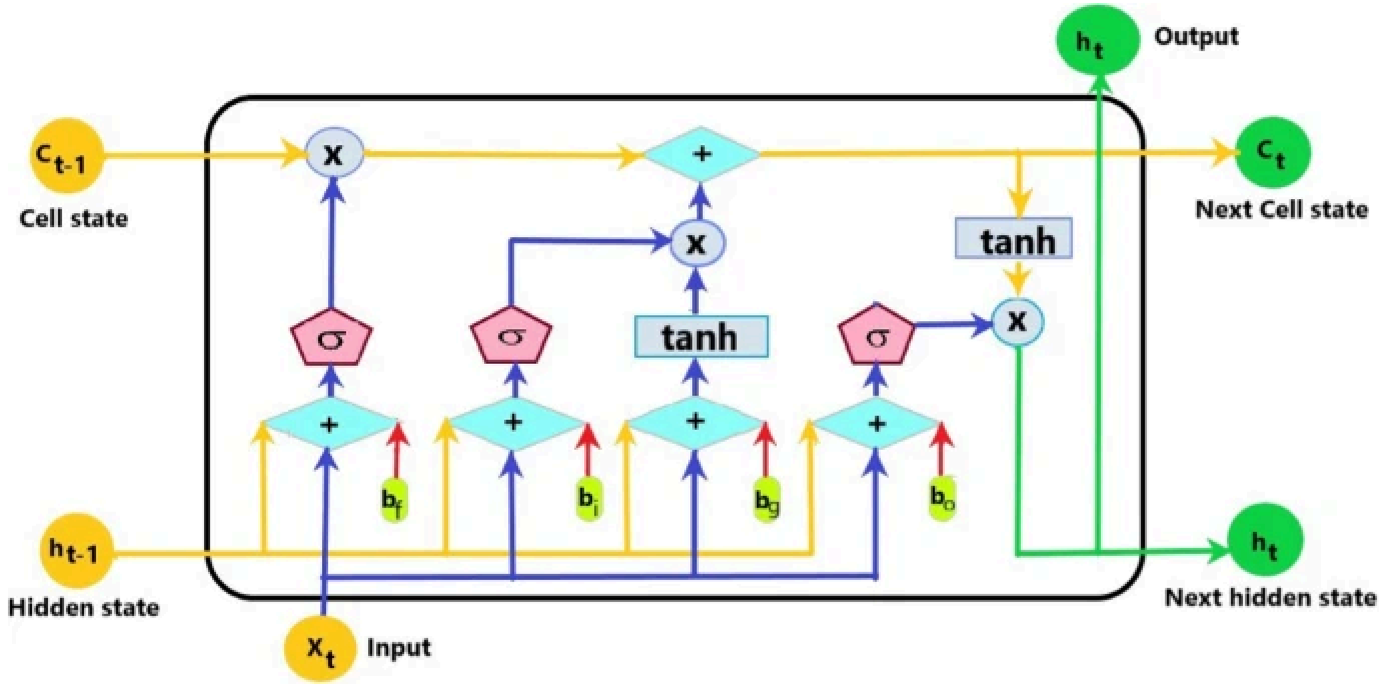
(9)

where α is a learning rate hyperparameter.

3.3.2 Long short-term memory

In 1997, Schmid Huber together with Hochreiter proposed the architecture of LSTM for sequence learning [27]. To represent the long-term as well as short-term memory, sequence learning is mandatory. These are designed to attenuate the issue of vanishing and exploding gradient. The ordinary LSTM network constitutes significant hidden units termed as memory cells that reminisce the preceding input for a long duration.

Fig. 2



Architecture of LSTM

Figure 2 illustrates the architecture of the LSTM cell which comprises forget gate, input gate, and output gate. A forget gate(f_t) eliminates the information from the cell state. This is essential to optimize the LSTM network's performance. Two inputs that is h_{t-1} together with x_t is fed into this gate. h_{t-1} denotes the hidden state of the preceding cell whereas x_t is the input at a specific time step. The specified inputs are then multiplied by their respective weights and a bias is added. Further, the sigmoid activation function is implemented over this value. The sigmoid function decides which value to be kept and which to be discarded. The equation of forget gate is demonstrated as Eq. (10):

$$\begin{aligned} f_t = \sigma [(W_{fh}*h_{t-1}) + (W_{fx}*x_t) + b_f] \end{aligned}$$

(10)

where: W_{fh} and W_{fx} are the weights assigned to activation state and input state, respectively, b_f denotes the bias.

Similarly, the equation for input gate can be calculated as Eq. (11):

$$\begin{aligned} i_t = \sigma [(W_{ih}*h_{t-1}) + (W_{ix}*x_t) + b_i] \end{aligned}$$

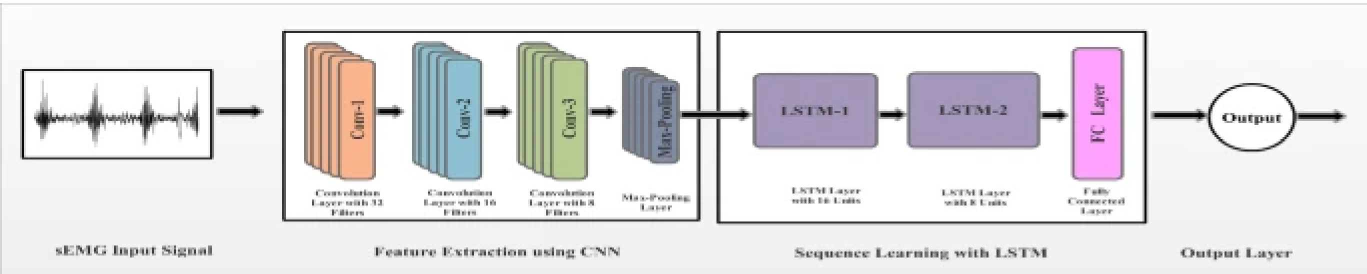
(11)

An input gate ((i_t)) adds information to the cell state. It consists of an input gate along with an input node. The input node is represented as Eq. (12):

$$\begin{aligned} g_t = \text {tanh} [(W_{gh}*h_{t-1}) + (W_{gx}*x_t) + b_g] \end{aligned}$$

(12)

Fig. 3



Proposed hybrid Conv-LSTM network

An output gate ((o_t)) ensures whether information regarding the current cell state is visible or not. The equation for the output gate is given as Eq. (13):

$$\begin{aligned} o_t = [(W_{oh}*h_{t-1}) + (W_{ox}*x_t) + b_o] \end{aligned}$$

(13)

A correlation is determined by the LSTM model for hidden activation h_t through the LSTM cell, which intakes x_t as the input at the current time step, in addition to this, it also obtains the information h_{t-1} from the preceding step.

Each cell of LSTM consists of a cell state c_t which acts as a memory that allows hidden units to retain information from the past. It is represented as Eq. (14):

$$\begin{aligned} c_t = c_{t-1}*f_t + i_t*g_t \end{aligned}$$

(14)

The model of LSTM generates hidden activation h_t which is utilized further in order to make predictions. It is depicted as Eq. (15):

$$\begin{aligned} h_t = \text {tanh}(c_t)*o_t \end{aligned}$$

(15)

3.3.3 Proposed hybrid Conv-LSTM model

The framework of the 8-layer hybrid CNN-LSTM model is demonstrated in Fig. 3. The initial three layers are the convolutional layer with the Relu activation function for extracting the features from the sEMG signals. Further, a max-pooling layer is used to reduce the number of parameters, so the complexity of the model is reduced. For sequence learning, LSTM layer 5 along with layer 6 is used. Fully-connected 7 layer is associated with 16 fully-connected neurons. The final layer that is layer 8 comprises 2 outputs neurons that distinguish among healthy and diagnosed (with knee abnormality) volunteers. Table 1 constitutes each layer used in the CNN-LSTM model and the parameter corresponding to each layer.

Table 1 Parameters of studied deep learning models

4 Results and discussion

4.1 Model parameters and performance indices

The proposed model needs to be trained on a training dataset that requires the weight parameters to be learned from the data. This research comprises the use of Adam optimizer [28] which involves the conventional back-propagation approach with cross-entropy loss function and stochastic gradient descent approach. The default values of entire six hyper-parameters including: learning rate (0.001), epsilon (0.00000001), beta1 (0.9), beta2 (0.999), and used locking (false) of adam's algorithms is utilized. Python using Keras libraries has been used to implement the model which is a freely available deep learning library from google. We trained our model with 50 iterations.

As the sEMG signal is a time-series signal, so here training and testing data is divided sequentially with starting 70% signal of each subject as a training dataset and the remaining 30% of the signal from each subject as a testing dataset. This problem is having two-class problems in which two different classes are: healthy and knee abnormal. The confusion matrix will be formed as Eq. (16):

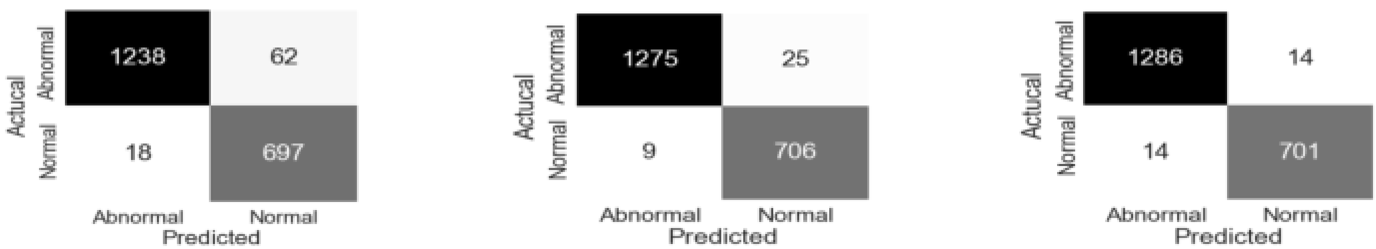
$$\begin{aligned} C = \begin{bmatrix} C_{AA} &{} C_{AN} \\ C_{NA} &{} C_{NN} \\ \end{bmatrix} \end{aligned}$$

(16)

where C_{AA} is the number of cases in knee abnormal class as predicted knee abnormal, C_{NN} is the number of cases in healthy (normal) class as predicted healthy, C_{AN} is the number of cases in knee abnormal class as predicted healthy, C_{AN} is the number of cases in healthy class as predicted knee abnormal. Here, four performance matrices: accuracy, sensitivity, specificity, and F-score are considered for the evaluation of models is shown in Table 2.

Table 2 Mathematical expression of performance indices

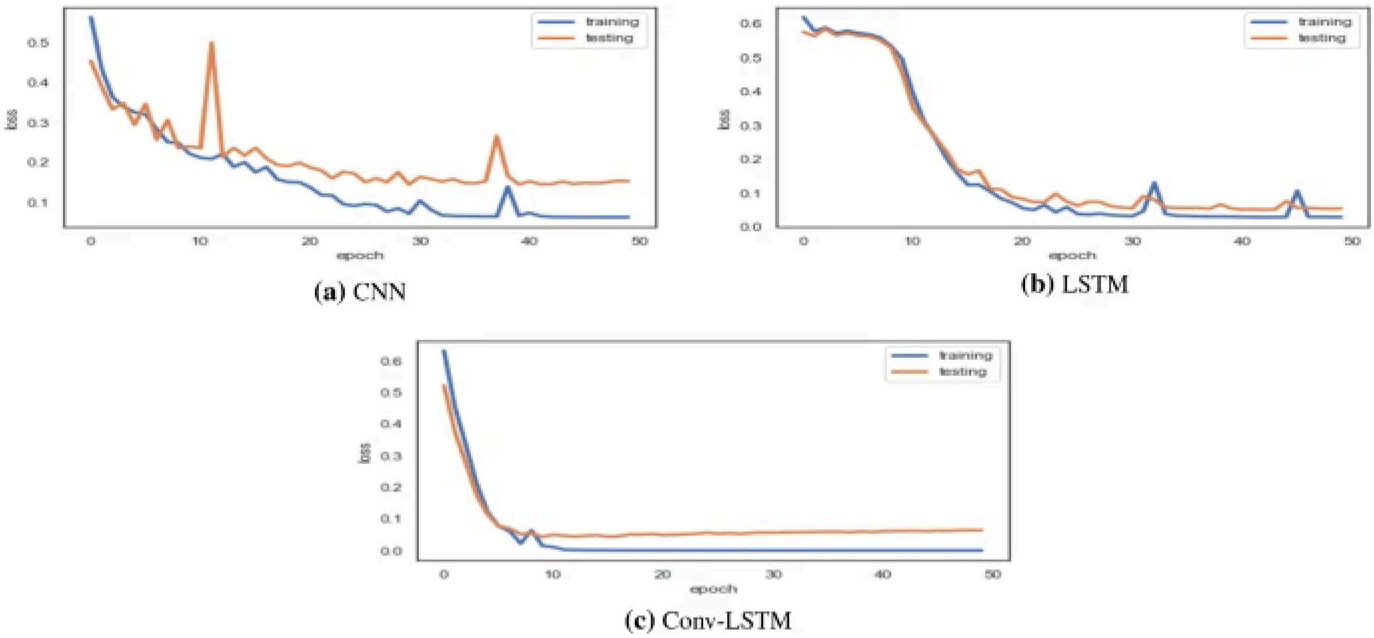
Fig. 4



(a) CNN (b) LSTM (c) Conv-LSTM

Confusion matrix

Fig. 5



Loss versus epoch plot

4.2 Performance evaluation

Table 3 comprises the performance of studied deep learning methods. These results indicate that the proposed hybrid Conv-LSTM method classifies the healthy and knee abnormal subjects more reasonably than other studied deep learning models. The accuracy of the proposed Conv-LSTM was 98.61% while for the CNN and LSTM deep learning models, it was 96.03% and 98.31%, respectively. Similarly, the F-score value of Conv-LSTM was 98.92% while for the CNN and LSTM deep learning models, it was 96.87% and 98.68%, respectively. Therefore, the accuracy of the proposed hybrid Conv-LSTM model is higher than the CNN and LSTM model.

Table 3 Performance parameters obtained from studied deep learning models in %

Figure 4 depicts the confusion matrix attained from the studied deep learning models: CNN, LSTM, and hybrid Conv-LSTM. The confusion matrix is utilized to illustrate the performance of models which comprises information regarding the predicted and true labels estimated by a model. Figure 4c shows the confusion matrix of the Conv-LSTM model in which a total of 1286 (98.92%) samples are correctly predicted as a knee abnormal and 701 (98.04%) samples are correctly predicted as healthy while 14 (1.96%) and 14 (1.07%) samples are incorrectly predicted as knee abnormal and healthy, respectively. Similarly, Fig. 4a and b are the confusion matrix for the CNN and LSTM models.

4.3 Computational evaluation

The studied deep learning models are tested on a 30% testing dataset after training. Figure 5a, b and c shows the plot between loss vs epoch for CNN, LSTM and hybrid Conv-LSTM models with test and train dataset. The following plots emphasize that with the increase in the number of the epoch, the value of the loss function decreases and after some epochs, it reaches a steady state, which indicates that the issue of over-fitting has reduced. Figure 5 shows that the proposed hybrid Conv-LSTM model reaches a steady state at near to the 10*th* epoch and accuracy also reaches its maximum value that is far better than the other studied models.

Table 4 Time taken per epoch

Table 4 shows the time taken for completion of an epoch of studied deep learning models. It shows that if the CNN layer is used to extract the feature, then the time taken to complete an epoch is required less. Here, 16 sec is required in the proposed hybrid Conv-LSTM while for the CNN and LSTM deep learning models, it was of 9 sec and 240 sec. Therefore, if the models are compared based on their computational time then the significant difference was found between the Conv-LSTM and LSTM, while a very less significant difference between Conv-LSTM and CNN.

The proposed work is compared with previous similar work on automated detection of lower limb knee abnormality detection. Ertuğrul et al. have developed an adaptive local binary pattern (ALBP) technique to extract features and classify the healthy and knee abnormal subjects with an accuracy of 84.85% [15]. Vijayvargiya et al. have conducted a comparative analysis of five machine learning models for classification between abnormal and healthy subjects of the knee [13]. This study extracted eleven time-domain features after denoising the signal by wavelet denoising technique. The extra tree classifier has been shown the best performance (91.3% accuracy and 88.8% f-score) in comparison with other classifiers, which are the support vector machine, decision tree, K-nearest neighbor, and random forest classifier. For an appropriate comparison, the dataset considered in our study is the same as the other contributors whose results have been discussed earlier.

5 Conclusion and future scope

This study proposed wavelet-based denoising followed by Conv-LSTM model for the automated knee abnormality detection using sEMG signal of lower limb muscles with three distinct activities. Initially, wavelet denoising is implemented to denoise the raw sEMG signals and then segmentation of sEMG signals is carried out by utilizing overlapping windowing technique. For screening of abnormal subjects, a hybrid Conv-LSTM model is proposed in which CNN is used for temporal learning and LSTM is used for sequence learning. Thus, the hybrid of Conv-LSTM shows the attributes of the best performer with an accuracy of 98.61% and computational time for an epoch of 16 sec. It appeared to be the most precise and convenient model that can be utilized for knee abnormality detection using sEMG signals.

To examine the proposed approach, the sEMG dataset utilized in this work consists of data collected from 22 subjects only. Thus, in the future, the approach could be justified by using a huge dataset obtained in real time. With the availability of more data, instead of just classifying it as abnormal or normal, the deep learning algorithm can be prepared to predict the level of knee abnormality in abnormal subjects. It could be incorporated in the network of the Internet of Medical Things (IoMT) for regular observation by a healthcare professional.

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