A Spiking Neural Network Approach for Classifying Hand Movement and Relaxation from EEG Signal using Time Domain Features

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Abstract: - High-performance prosthetic and exoskeleton systems based on EEG signals can improve the quality of life of hand-impaired people. Effective controlling of these assistive devices requires accurate EEG signal classification. Although there have been advancements in the assistive Brain-Computer Interface (BCI) systems, still classifying the EEG signals with high accuracy is a great challenge. The objective of this research is to investigate the accuracy of the EEG signal classification of the Spiking Neural Network (SNN) classifier for factual and exact control of prosthetic and exoskeleton systems for individuals with hand impairment. The EEG dataset has been taken from the BNCI Horizon 2020 website, which is for hand movement-relax events of a patient with high spinal cord injury (SCI) to operate a neuro-prosthetic device attached to the paralyzed right upper limb. The fusion of Dispersion Entropy (DE), Fuzzy Entropy (FE), and Fluctuation based Dispersion Entropy (FDE) with mean and skewness features are extracted from the Motor Imagery (MI) EEG signals and applied to the Spiking Neural Network (SNN) classifier. To compare the performance of this algorithm, these same features have been used in Convolutional Neural Network (CNN), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR) classifiers. It has been found that SNN has given the highest classification accuracy of 80% with a precision of 80.95%, recall of 77.28%, and F1-score of 79.07%. This indicates that SNN with these five features has greater potential in BCI system-based applications.

Key-Words: - Spinal Cord Injury, Electroencephalogram, Brain Computer Interface, Neuro-Prosthetic Device, Spiking Neural Network, Time Domain Features; Hand Movement – Relaxation.

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1 Introduction

This research has been aimed to assess the performance of Spiking Neural Network (SNN) classifier with the fusion of five time-domain features - Dispersion Entropy (DE), Fuzzy Entropy (FE), and Fluctuation-based Dispersion Entropy (FDE), mean and skewness for accurately differentiating hand movement and relaxation events from the EEG signal of a patient with hand disabilities due to Spinal cord injury (SCI), [1]. Spinal cord injuries (SCI), [2], [3], brain stem strokes, amyotrophic lateral sclerosis (ALS), [4], and other disorders can cause paralysis and impair voluntary motor function in the arms along with in the trunk, legs, and pelvic organs that range from minor and manageable to severe and permanent, [5]. Advances in prosthetic technology have allowed patients to walk again using lower-limb prosthetics, [6], [7]. As our hands perform various activities, the reproducing function has been more complex and complicated for upper-limb prostheses than lower-limb prosthetic devices, [8], [9], [10]. Tendon transfer and Tenodesis can restore arm and hand functionality in SCI but they depend on the availability and quality of compatible tendons and muscles and also there are operational risks, [11]. Tenodesis allows paralyzed persons to indirectly grasp objects by extending the wrist but the grasping force is often poor for performing basic daily activities like lifting a water bottle, holding cutlery for eating, etc., [12]. Recent progress in neuro-technology and robotics can help to restore hand and arm function after SCI or stroke without surgery, [13], [14], [15]. Scalp electroencephalogram (EEG) based Brain-Computer Interfaces (BCIs) can decode EEG signals to provide information about motor tasks that an individual performs (ME - motor execution), or attempts to perform (MI - motor imagery), into device control commands, [16], [17], [18]. As EEG signals contain a large volume of information, it is hard to analyze EEG data visually. When designing a BCI system, it is essential to classify EEG signals correctly to gain insight into the desired cognitive processes and translate them to seamlessly operate neuro-prosthetic devices and exoskeleton systems that assist movement or augment the abilities of the human body, [19], [20], [21]. The wrong command will make the patient feel discomfort. Assume that a patient wants to move his hand but the device maintains hand relaxation. This will happen frequently if the classification accuracy is poor. So, the classification accuracy must be high to achieve high performance for the BCI systems, [22], [23], [24]. The key way to achieve this goal is by preprocessing EEG signals followed by feature extraction, and classification using classifiers that relate bioelectrical brain signals with physical actions, [25], [26], [27].

There are several feature extraction techniques, such as time domain, frequency domain, and time-frequency-based feature extraction techniques, [28], [29]. Entropy-based time domain features have been successful in classifying EEG signals in numerous studies, [30], [31], [32]. Among different variants of entropy, such as sample entropy (SE), approximate entropy (AE), permutation entropy (PE), and dispersion entropy (DE), the latter has shown better performance for time series data analysis, [33], [34], [35]. Dispersion Entropy (DE) is better for capturing the temporal changes in the signal because it considers both the amplitude differences and the resemblance between adjacent signal points in addition to their similarity, [36]. The study reported in [37], applied a support vector machine (SVM) to DE and also to different variants of entropy such as SE, and PE, and found that DE has shown better performance compared to other entropies. Fuzzy Entropy (FE) is robust to noise but sensitive to signal complexity that computes the relative degree of uncertainty of the signal, [38]. Fluctuation Based Dispersion Entropy (FDE) is used to determine the dynamic changes of the fluctuations of the signal, [39]. Also, the mean and skewness features which provide statistical information about the distribution and asymmetry of the EEG signal, allow the classifier to make more refined distinctions between hand movement and relaxation events from the EEG signal.

To classify EEG signals Machine learning (ML) algorithms such as K-nearest neighbor (KNN), random forest (RF), support vector machine (SVM), Logistic Regression (LR) fuzzy nearest neighbor (FNN), etc. have been extensively used in research due to their ability to extract meaningful features and classify EEG signals with high accuracy, [40], [41], [42]. Artificial Neural Networks (ANN) are a class of Machine Learning (ML) algorithms inspired by the structure and function of biological neurons in the brain. Due to their capacity to recognize complex nonlinear relationships between the input features and the output classes, ANNs are more efficient than conventional statistical methods for classifying EEG signals, [43]. Spiking Neural Networks (SNN), Convolutional Neural Networks (CNN), etc. are subclasses of ANN. Unlike traditional ANN which uses continuous valued activation, SNN uses discrete time spikes to process and transmit information, [44], [45]. Thus it is more energy efficient, consumes less power, and is robust to noise, [46]. Due to its more biologically interpretable network structure and training principles, SNN is faster and more applicable to spatiotemporal data, [47], [48], [49].

1.1 Related Works

Many research studies have already been done where researchers applied different methods for decoding different hand movement attempts from EEG signals of persons with upper limb disabilities due to SCI or any other reasons. Researchers in [50], demonstrated the detection of different hand movement classes from low-frequency EEG signals of 10 individuals with SCI. They filtered the preprocessed EEG signal to 0.3-3Hz which was used as input to shrinkage linear discriminant analysis (sLDA) classifier. Besides, causal and non-causal time points of the EEG were given to the classifier. The obtained classification accuracy for five different hand movement classes (hand open, palmar grasp, lateral grasp, pronation, and supination) was 45%. They also tested their method online on a person with cervical SCI for palmar grasp and open class with 68.4% accuracy. Utilizing the same dataset used by [50], the authors in [51], employed movement-related cortical potentials (MRCPs), and time-frequency domain representation (Scalogram) of the dataset for classifying the EEG signal into five different hand movement classes (hand open, palmar grasp, lateral grasp, pronation, and supination). They used ConvNet AlexNet classifier for classification. They were able to obtain 76% average classification accuracy for classifying these five different classes by their proposed method. Authors in [52], reported a study where four chronic tetraplegics performed a complex sequence of EEG-controlled bilateral grasping of two exoskeletons. The researchers used a hierarchical classifier for the classification of different hand movements (left vs right, left vs rest, right vs rest). The EEG signals were Laplace filtered to detect the event-related desynchronization (ERD) at the C3 (left hemisphere) and C4 (right hemisphere) electrodes. If the classifier found ERD at C3 (left hemisphere) then it would identify the left exoskeleton, if ERD was at C4 (right hemisphere) then it would identify the right exoskeleton, and if the detected ERD was below a threshold, then the classifier would detect relax mode. Using this method, the average accuracy was found 58.68%. Researchers in [53], developed and estimated the accuracies of a P300-based BMI to operate a robotic arm orthosis. For this study, the authors used regularized linear discriminant analysis (RLDA) to classify target vs non-target from the EEG signal of 8 amyotrophic lateral sclerosis (ALS) patients. Here, target means the specified option to which the participants had to give focus, and non-target means the other options to any of those the participants should not give focus. In this study, linear combinations or projections of the EEG signal were extracted through spatial filtering by using canonical correlation analysis (CCA). The resulting projected signal was the extracted feature which was a set of signals with improved separability between the target and non-target classes. Using this feature and RLDA classifier, the average accuracy was found 58.68% for target vs non-target classification from the EEG data of 8 ALS patients.

In [50], and [53], researchers used sLDA and RLDA classifiers respectively and both of these classifiers are linear classifier which finds a linear combination of features that are mostly suitable for differentiating different classes, [54]. EEG signal is a non-linear signal with high temporal dynamics, so the classifiers used in those studies might face difficulties in effectively capturing the temporal dynamics existing in the EEG signal. In [51], researchers used ConvNet AlexNet which consumes high energy for processing due to the convolutional layer, [55]. Besides, the recorded accuracy in those studies is not so high, so the BCI systems may not do the best control.

Although there have been significant advancements in BCI technology, achieving high classification accuracy from the signal to obtain the best control over the neuro-prosthetic devices is still a great challenge. Besides, faster response with high accuracy for real-time operation of these assistive devices and energy-efficient methods are very important. By exploring new methods addressing all these issues, the quality of life of persons with hand impairments can be improved.

Reviewing the literature, it is anticipated that a Spiking Neural Network (SNN) classifier with time domain features that carry temporal information of EEG signal can be more suitable for EEG signal classification. That's why, in this research, we have proposed a method using a Spiking Neural Network (SNN) classifier with five time-domain features - Dispersion Entropy (DE), Fluctuation-based Dispersion Entropy (FDE), Fuzzy Entropy (FE), mean and skewness features to classify Motor Imagery (MI) EEG signal of a patient with spinal cord injury to operate a neuro-prosthetic device joined to the paralyzed right upper limb. To compare the performance of this method, the same features have been applied to Convolutional Neural Network (CNN), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR). The contributions of this research are as follows:

1. In this study, we shall apply SNN on time domain features (DE, FDE, FE, mean, and skewness) to classify EEG signals to detect hand movement and relaxation events. To our knowledge, the proposed method has not been applied to any dataset before to classify EEG signals.
2. To compare the performance of SNN, we shall apply five different classifiers (CNN, RF, SVM, KNN, LR) on these same features extracted from the same dataset.
3. The proposed method is expected to show better performance for classifying MI EEG signals for BCI system-based applications and critical diagnosis compared to other state-of-the-art MI EEG signal-based classifiers.

2 Methodology

Figure 1 shows the framework of the proposed method for classifying hand movement-relax EEG signals. At first, the recorded data is pre-processed using EEGLAB software. Then feature extraction is done from the selected channel using MATLAB. Dispersion entropy (DE), fluctuation-based dispersion entropy (FDE), fuzzy entropy (FE), mean and skewness features have been calculated from the EEG data. Finally, in Google Colab, the spiking neural network (SNN) has been applied to the extracted features to observe the performance of SNN in classifying the EEG dataset in terms of accuracy, precision, recall, and F1-score. To compare the performance of SNN, different classifiers such as CNN, Random Forest, KNN, SVM, and Logistic Regression were applied to the extracted features.

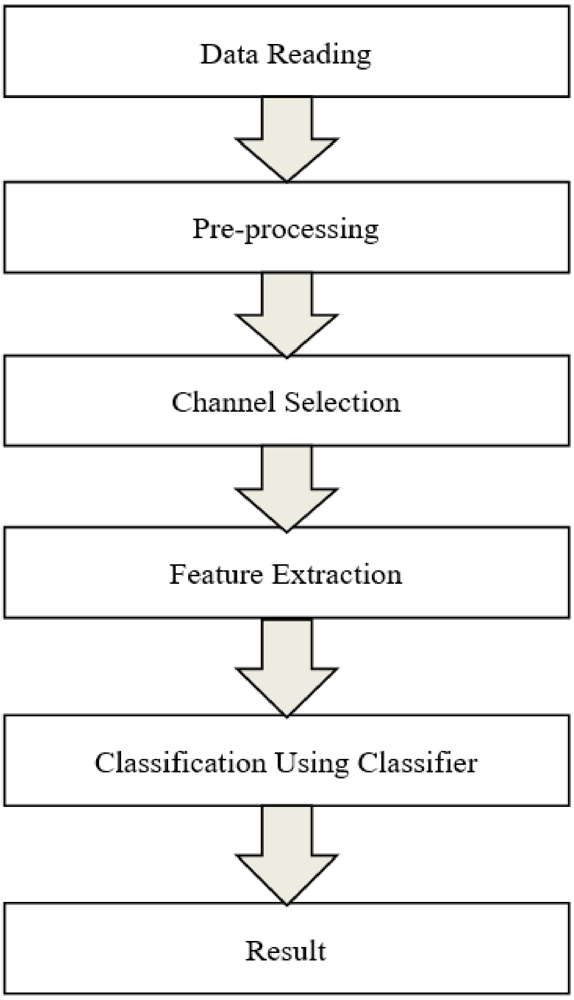

Fig. 1: Flowchart for Methodology

2.1 EEG Dataset Description

The EEG dataset has been collected from the BNCI (Brain-Neural Computer Interaction) Horizon 2020 database with the dataset accession number 002-2015 under the terms of the Creative Commons Attribution Non-commercial No Derivatives License (CC BY-NC-ND 4.0) granted by the Applied Neurotechnology Lab, Institute of Medical Psychology and Behavioral Neurobiology and Department of Psychiatry and Psychotherapy, University Hospital of Tübingen, Germany, [56].

The dataset contained EEG data of a subject (gender: male, age: 48) with high spinal cord injury. The paradigm was created to control an EEG/EOG hybrid BNCI to operate a neuro-prosthetic device attached to the paralyzed right upper limb of the patient through two different visual signal-based tasks that randomly appeared to the subject as shown in Figure 2. Thoughts of movement of the right hand (class 1) or close the exoskeleton upon seeing a “green square” and rest or no movement (class 2) when the subject sees a “red square”. The data was recorded in three different runs and in each run the two tasks appeared 24 times each in total separated by 4-6 seconds of inter-trial intervals (ITIs). Each indication (hand close or relax) was displayed for 5 seconds after which the exoskeleton was reset into the open position which required 1 second. The participant was allowed to freely make the exoskeleton motion to stop and go to the neutral position by using full left or right eye movements. While the EEG/EOG signals were recorded, the subject was seated comfortably at the desk. The dataset was saved in the Matlab format (.mat) containing the following information for each of the three different runs: Raw data in the format Samples x Channels, information about each trial start and end in samples (24 per run), the corresponding class for each trial (either 1 or 2), the sampling rate, information about each class, gender, and age of the subject.

The EEG signal was recorded from 5 channels (F4, T8, C4, Cz, P4) by maintaining an international 10/20 standard electrode placement system at a sampling frequency of 200 Hz, band-pass filtered at 0.4-70 Hz using an active electrode EEG system with a reference electrode placed at FCz and a ground electrode at AFz.

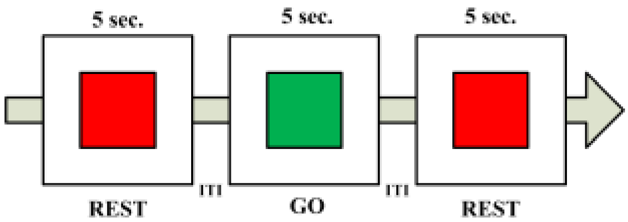

Fig. 2: Timing arrangement of the BNCI pattern

2.2 Preprocessing

The recorded EEG signal contains various types of noise, including environmental noise, muscle artifacts (electromyographic interference), eye movements (electrooculographic artifacts) electrode-related noise, etc. To remove this undesired noise and artifacts, preprocessing is done which enhances the signal quality.

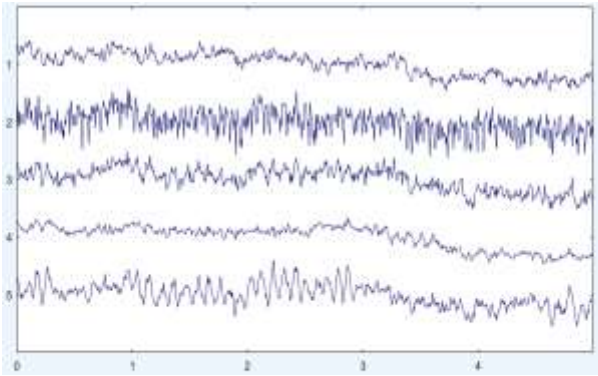
Fig. 3: Raw EEG Signal

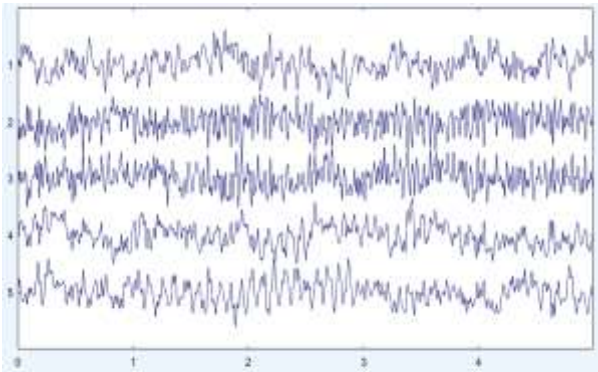
Fig. 4: Pre-processed EEG Signal

In this study, the hand movement-relax EEG dataset has been loaded to EEGLAB for preprocessing. Figure 3 shows the raw EEG signal. In this dataset, there are 6 channels, among them 5 are used for EEG recording and 1 is used for EOG signal recording. As we are intended to classify only the EEG signal, five EEG channels are kept and one EOG channel is removed. After loading the EEG signal, common average referencing is done. Then this data is filtered at 0.5-50 Hz using a basic FIR Filter to remove the undesired noise, and the clean line is done at 50Hz. Finally, to eliminate the artifacts caused by the muscle activity and eye blinking effect, independent component analysis (ICA) is done. The preprocessed EEG signal is shown in Figure 4.

2.3 Feature Extraction

In this study, we have made a feature matrix containing Dispersion Entropy, Fluctuation-based Dispersion Entropy, Fuzzy Entropy, Mean and Skewness features and the last column of the matrix shows the output class. The dataset we are working with has 2 classes- one is the movement class in the feature matrix denoted by 0 and another is the relax class in the feature matrix denoted by 1. All the features we have used are time domain features.

This dataset of the paralyzed patient had three runs and each run had 24 events. The events were of two types, namely, 'thoughts of movement' of a neuro-prosthetic device attached to the paralyzed right hand and 'rest or no movement'. Each event lasted for 5 seconds. The EEG dataset was recorded from 5 channels at a sampling rate of 200 Hz. So, for 3 runs from each channel, we get $(200 \times 5 \times 24 \times 3) = 72000$ data points and for all the 5 channels we get $(72000 \times 5) = 360000$ data points.

To calculate features for 1 second, we have made a sliding window of 200 data points to slide over all the EEG data points. Thus, the dimension of the feature matrix for each channel with all the 3 runs will be 360×6 where the first 5 columns contain features and the last 1 column represents the corresponding output class. Also, for all the 5 channels and 3 runs, the dimension of the feature matrix will be 1800×6. To maintain balance, we have taken an equal number of rows for each class and finally have got a 1350×6 dimension feature matrix.

For calculating mean and skewness, we have used the mean () and skewness () functions of MATLAB 2023a. To extract DE, FDE, and FE, we have developed code using the basic theory of these variants of entropies using MATLAB 2023a software.

2.3.1 Dispersion Entropy (DE)

Dispersion Entropy (DE) is a non-linear metric to determine the complexity or irregularity in time series data, [35]. If a time series data does not contain any irregularity or complexity, there will be no dispersion (zero dispersion) between consecutive data points. In that case, the DE value will be zero (0) which indicates uniformity of the data series. Conversely, if a time series data contains high irregularity where values of data points vary significantly concerning time, the DE value of the data series will be high indicating greater complexity and unpredictability in the data. To compute DE from time series data, it is transformed into a new signal with a few different patterns to detect the variations effectively existing in the signal, [36]. Unlike other variants of entropy such as Sample entropy, which primarily considers the frequency of patterns, DE measurement is sensitive to both the amplitude and frequency, [36]. As EEG data has high temporal dynamics which indicates high irregularity, so DE measurement from EEG signal might be advantageous. That is why in this study DE feature has been used from the MI EEG signal for hand movement vs relax event distinction.

To calculate DE from the preprocessed EEG data the following steps have been carried out.

i. Obtain a time series of data points.
ii. Select the embedding dimension (m) and a time delay (d).
iii. Create vectors of length m by embedding a time series with a delay of d. This entails using sequential data from the time series as vector coordinates.
iv. Calculate the Euclidean distance between each pair of points in each vector.
v. Count the number of distinct distances achieved in step four.
vi. Divide the count of each distance by the total number of vectors to compute the probability distribution of these unique distances.
vii. The dispersion entropy is then calculated using the following formula:

$$DE(x,m,c,d) = -\sum_{\pi=1}^{c^m} p(\pi_{v_0 v_1 \dots v_{m-1}}).\ln\left(p(\pi_{v_0 v_1 \dots v_{m-1}})\right)$$

For this study, the value of $m = 2$, the length of the vector is 200 for the paralyzed patient's dataset as the sampling frequency was 200 Hz. The value of c is 100, as the EEG signal amplitude is discretized into 100 levels and d is 1.

2.3.2 Fluctuation-Based Dispersion Entropy

Fluctuation-based dispersion Entropy (FDE) considers the differences between adjacent elements of dispersion patterns. This forms vectors with length $(m-1)$, where each element changes from $-c+1$ to $c-1$. Consequently, $(2c-1)^{m-1}$ potential fluctuation-based dispersion patterns are formed. The only difference between DE and FDE is the potential patterns used in the two approaches. For this study, we set $m = 3$ and $c = 100$.

2.3.3 Fuzzy Entropy (FE)

Fuzzy Entropy (FE) is a measure of the relative degree of uncertainty that is applied to estimate the fuzziness in a fuzzy set of EEG signals, [38]. It is robust to noise but sensitive to signal complexity, [38]. For a time-series data x_i with sample N, where, $i = \{1,\ 2,\ 3, \dots, N\}$, and embedding dimension m, form a vector sequence as follows:

$$X_m(i) = \{x_i, x_{i+1}, x_{i+2}, \dots, x_{i+m-1}\} - x_0(i)$$

where, $i = 1, 2, \dots, N-m+1$. Here, $X_m(i)$ denotes m succeeding m values beginning with ith point and generalized by eliminating a baseline:

$$x_0(i) = (\tfrac{1}{m})\sum_{j=0}^{m-1} x_{i+j}$$

To calculate Fuzzy Entropy from the vector $X_m(i)$, the following steps have been followed.

i. For each $X_m(i)$ the distance between vectors $X_m(i)$ and $X_m(j)$ has been calculated by using the following equation.

$$d_{ij}^m = [X_m(i), X_m(j)]$$
$$= max_{k=0,\dots,m-1}\left|X_{i+k} - X_0(i) - X_{j+k} - X_0(j)\right|$$
with $i, j = 1, \dots, N-m, j \neq i$.

ii. The degree of similarity $D_{m,ij}$ between $X_m(i)$ and $X_m(j)$ has been determined from:

$$D_{m,ij} = \exp(-\frac{d_{ij}^m}{r})^n$$

where, $r =$ the width of the boundary, $n =$boundary gradient of the exponential function, $d_{ij}^m =$ maximum absolute difference between $X_m(i)$ and $X_m(j)$

iii. Then the co-efficient $\emptyset_m(n,r)$ has been calculated based on the similarity degree $D_{m,ij}$ as follows:

$$\emptyset_m(n,r) = \frac{1}{N-m}\sum_{i=1}^{N-m}\left(\frac{1}{N-m-1}\sum_{j=1}^{N-m}(D_{m,ij})\right);$$
where, j ≠ i.

iv. Finally, Fuzzy Entropy has been calculated using the following equation:

$$FE(m,n,r,N) = \ln\emptyset_m(n,r) - \ln\emptyset_{m+1}(n,r)$$

In this study, x_i refers to the EEG signal's data. We set $N = 200, m = 10, n = 3, r = 4$.

3 Classifiers

This section presents a brief description of the classifiers used. In each classifier, 80% of the data have been used for training and the remaining 20% of data have been used for testing purposes.

3.1 Classification by Spiking Neural Network

A Spiking Neural Network (SNN) is a type of neural network inspired by the way biological neurons communicate in the brain. Unlike traditional neural networks that use continuous values, SNN processes information through spikes which makes it suitable for handling temporal data. So, SNN can handle high temporal dynamics existing in the data. Also, as the spike firing is not continuous, so it consumes lower power which makes it energy efficient.

After extracting features from the dataset, the spiking neural network (SNN) was trained and tested on those features and corresponding event values. Among several techniques of spike encoding such as rate coding, latency coding, and delta modulation, in this study rate coding was used to convert the feature values into spikes.

Leaky Integrate and Fire (LIF) neurons are used in SNN as the Hodgkin-Huxley Neuron Model increases complexity and the Artificial Neuron Model increases power consumption. LIF neurons are modeled after biological neurons. Each LIF neuron can be modeled by an RC circuit where C symbolizes the capacitance between conductive extracellular and intracellular medium and R denotes the biological neuron's current through ion channels.

According to the model, the membrane potential rises in response to an input current until it reaches a constant threshold voltage V_{th}, at which point a delta function spike occurs as output, and the membrane potential gets reset.

In biological neurons, the membrane potential is:

$$U_{mem}(t) = I_{in}(t)R + (U_0 - I_{in}(t)R)e^{-\frac{t}{RC}}$$

In analogical SNN neurons the membrane potential:

$$U[t+1] = \beta U[t] + (1-\beta)I_{in}[t+1]$$

Here, β is the decay rate.

$$\beta = 1 - \frac{1}{\tau} = 1 - \frac{1}{RC}$$

For deep learning purposes, the weighting factor of input, which is $(1-\beta)$, is considered the learnable parameter, W and $I_{in}[t]$ is replaced by $X[t]$, which is an input voltage or spike. So, in SNN neuron membrane potential is:

$$U[t+1] = \beta U[t] + WX[t+1]$$

LIF neuron takes the sum of weighted inputs and integrates the input over time with a leakage. If the integrated value exceeds a threshold, a voltage spike will be emitted from the LIF neuron. Output spike,

$$S[t] = 1, when\ U[t] > U_{thr}$$
$$S[t] = 0, when\ U[t] \le U_{thr}$$

After a spike is triggered, the membrane potential is reset by subtraction. So, after considering resetting, the membrane potential,

$$U[t+1] = \beta U[t] + WX[t+1] - S[t]U_{thr}$$

In this study, we have done two types of simulation. One uses summative data from five channels and another uses data from individual channels. For both cases, we have used similar values of hyperparameters except for the batch size. The list of hyperparameters that are used in SNN is shown in Table 1.

Table 1. List of Hyperparameters used in SNN

Hyperparameters	Value
No. of neurons in the input layer	5
No. of neurons in the hidden layer	200
No. of neurons in the output layer	2
Number of time steps	25
Decay Rate (Beta) for LIF Neurons	0.95
Optimizer type	ADAM optimizer
Learning rate	5×10^{-4}
Beta1 (β1)	0.9
Beta2 (β2)	0.999
Loss function type	Cross Entropy Loss

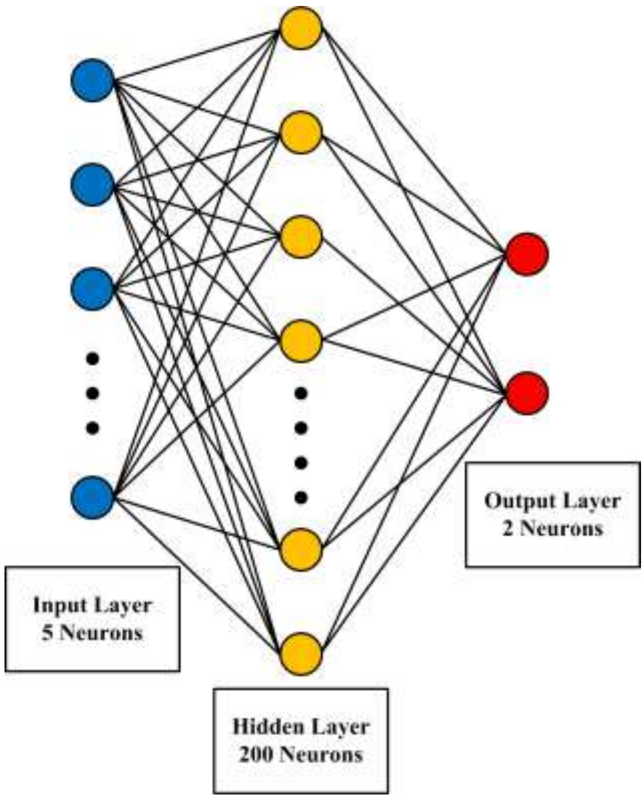

Fig. 5: Structure of SNN used in this study

The modeled SNN had three layers of neurons. The input layer has 5 LIF neurons, the hidden layer has 200 neurons and the output layer has 2 neurons. The structure of the SNN used in this study is shown in Figure 5. For both five-channel data classification and single-channel data classification this same structure of SNN has been used.

3.2 Classification by Convolution Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning (DL) model that can automatically capture spatial patterns from data, which makes it highly effective for image classification and spatial data analysis. It consists of several layers. The convolution layer is used to detect specific features such as, for image classification the features can be edges, textures, or simple shapes. The max-pooling layer is used to reduce the dimensionality of the extracted features by decreasing the number of features and retaining the most important features. The flatten layer makes 2D feature maps into 1D vectors and the dense layer is used for decision-making.

CNN is a Deep Learning algorithm that is used for classification purposes. The structure of CNN we have used in this study is shown in Figure 6. It consists of the input layer, 1 convolutional layer with ReLu activation function, 1 max-pooling layer, 2 fully connected dense layers, and a softmax layer which performs the classification tasks.

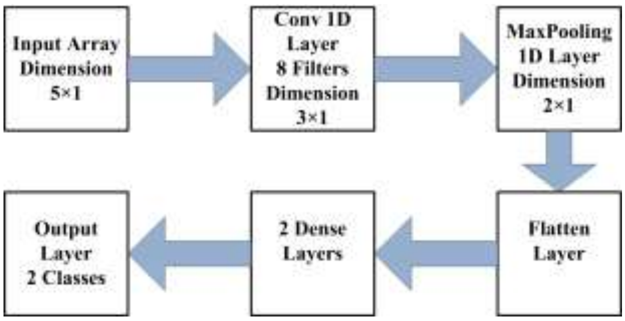

Fig. 6: Structure of CNN used in this study

The first layer is the input layer that defines the input shape and the shape of the input is 5 × 1. The second layer is the convolutional layer (Conv1) which has 8 learnable filters with a kernel size of 3 × 1 and convolves with the input. The third layer is the max-pooling layer with a kernel size of 2 × 1 which extracts the main features and speeds up the calculation. The extracted main features of the third layer are flattened by the Flatten Layer and used as input of Dense1 which has 100 hidden neurons and then another dense layer (Dense2) with 10 neurons and finally ends with a softmax layer having 2 neurons which predicts the classes. The proposed CNN has been implemented in Python with Keras and Tensorflow as the backend. It has been trained using the default parameters of the adaptive moment estimation (ADAM) optimizer for 50 epochs and a batch size of 32 until the cross-entropy function converges. For both five-channel data classification and single-channel data classification this same structure of CNN has been used. The hyperparameters used for this simulation are given in Table 2.

Table 2. List of Hyperparameters used in CNN

Hyperparameters	Value
Input Shape	(5, 1)
Number of Convolutional Layers	1
Number of Filters (Conv Layer)	8
Kernel Size (Conv Layer)	3×1
Padding (Conv Layer)	same
Activation Function (Conv Layer)	ReLU
Batch Normalization	Yes
Pool Size (MaxPooling)	2
Strides (MaxPooling)	2
Flatten Layer	Yes
Number of Dense Layers	2
Number of Neurons (Dense Layer 1)	100
Activation Function (Dense Layer 1)	ReLU
Number of Neurons (Dense Layer 2)	2
Activation Function (Output Layer)	Softmax
Optimizer Type	ADAM optimizer
Learning Rate	Default
Loss Function Type	Sparse Categorical

3.3 Classification by Random Forest (RF)

Random Forest (RF) is an ensemble learning method that is used for both classification and regression tasks. It combines the results of multiple decision trees to produce an output to improve accuracy and reduce overfitting issues.

It is based on the concept of bagging where subsets are generated from the training data and then they are used to train multiple decision trees independently. Each decision tree makes its own prediction and the final output is determined by averaging the results in case of regression or taking a majority vote in case of classification. This approach helps RF to capture diverse patterns that are presented in the data and provides robustness and helps to make reliable predictions.

In this study, we used 100 decision trees where the Gini Index was used as a quality measure in each tree node (n_estimators=100, criterion='gini'). These same hyperparameters were used for both individual channel-wise EEG signal classification and multiple channels' EEG signal classification.

3.4 Classification by Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm that is used for both classification and regression tasks. This algorithm focuses on finding the optimal hyperplane (boundary) to maximize the distance between this hyperplane (boundary) and the closest data points of different classes. By maximizing this distance, SVM ensures the best possible separation of data points to enhance its generalization ability. SVM can handle both linear and non-linear data. For non-linear data, SVM uses kernel functions to transform data into higher dimensions that allow for linear separation.

In this study, we used kernel='poly', C=15 for individual channel-wise EEG signal classification and kernel='sigmoid', C=5 for multiple channels' EEG signal classification.

3.5 Classification by K-Nearest Neighbors

K-Nearest Neighbors (KNN) is an instance-based machine learning (ML) algorithm that is used for both classification and regression purposes. It stores all the training data, so when a new data point (test data) needs to be predicted, it computes the distance between the new point and all existing training data points. The computed distance can be Euclidean distance, Manhattan distance, or Minkowski distance. The smallest distance indicates the nearest neighbor. The most crucial step is to choose the number of nearest neighbors (k) which has a direct influence on the performance of this ML algorithm. In the case of classification, prediction is based on the majority class among the number of nearest neighbors (k) but in the case of regression, prediction is based on the average value of the number of nearest neighbors (k).

In this study, we used 10 numbers of nearest neighbors (k) for both individual channel-wise EEG signal classification and multiple channels' EEG signal classification.

3.6 Classification by Logistic Regression (LR)

Logistic Regression (LR) is a machine learning (ML) algorithm that is used for binary classification. It models the probability of a given input data belonging to a particular class by fitting a logistic function to the data. This function is:

$$y = (w, x) = \frac{1}{1 + e^{w_0 + x_1 w_1 + \cdots + x_n w_n}}$$

where, x = input features
w = corresponding weights of input features

For binary classification by using this algorithm, the output of the function y must be 0 and 1, and weights (w) of corresponding features are computed using a solver which has to meet the condition.

In this study, we used penalty='l2', C=1.0, solver='newton-cg', class_weight='balanced', and max_iter=1000. These similar hyperparameters were used for both individual channel-wise EEG signal classification and multiple channels' EEG signal classification.

4 Results and Analysis

This section presents the simulation results and analyzes the performance of the proposed SNN classifier with five different classifiers (CNN, RF, SVM, KNN, LR) using the same feature matrix. Also, a comparative analysis with some similar research works related to different upper limb movement classifications using EEG signals has been illustrated. First, we made a feature matrix by extracting DE, FDE, FE, mean, and skewness features from the EEG signal using MATLAB 2023a software and stored it in a text file. Then the text file was loaded to Google Colab to run the classification algorithm using different classifiers (SNN, CNN, RF, SVM, KNN, LR). For determining the performance metrics, the elements of the confusion matrix were assigned as (2,2): true positive (TP), (1,1): true negative (TN), (1,2): false positive (FN), and (2,1): false negative (FP). We have used the same feature matrix for all the classifiers so that we can investigate the performance of SNN with other classifiers (CNN, RF, SVM, KNN, LR). For comparative analysis among the classifiers two types of simulation have been conducted: 1) using the combined EEG data from five channels (F4, T8, C4, Cz, P4), and 2) using EEG data from individual channels separately.

4.1 Performance comparison of Classifiers using Summative Data from Five Channels

Table 3 shows the performance of different classifiers based on the simulation results using the feature matrix derived from the combined EEG data of the five channels (F4, T8, C4, Cz, P4) in terms of accuracy, precision, recall, and F1 score. Here, we observe that Spiking Neural Network (SNN) has given the highest performance for all metrics, with an accuracy of 80%, precision of 80.95%, recall of 77.28%, and an F1-score of 79.07% among all the classifiers. This indicates that SNN is highly effective at leveraging the complexity of the features we have used. The high accuracy indicates that SNN can correctly predict both classes (either hand movement or relaxation) with high accuracy across all the predictions. The high precision of SNN reflects the accuracy of correctly identifying hand relax events concerning the total number of events that the SNN classifier predicted as hand relax events while the strong recall suggests its ability to identify hand relax events among the total number of hand relax events that actually occurred in the dataset.

Table 3. Classification Performance of Different Classifiers for Classifying EEG signal using 5 channels' (F4, T8, C4, Cz, P4) data

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SNN	80	80.95	77.28	79.07
CNN	64.07	69.41	58.33	63.4
RF	71.85	74.42	69.06	71.64
SVM	63.33	68.52	53.24	59.92
KNN	63.33	69.23	51.8	59.26
LR	64.81	70.75	53.96	61.22

The balanced F1-score means the effectiveness of SNN in maintaining a strong balance between precision and recall which ensures both accurate identification and comprehensive detection of relevant instances. Random Forest (RF) classifier shows competitive performance with an accuracy of 71.85%, precision of 74.42%, recall of 69.06%, and an F1-score of 71.64% but compared to SNN, RF's performance is slightly lower. Still, it has a good balance between precision and recall which implies RF can effectively handle the diverse patterns in EEG data. Logistic Regression (LR) exhibits moderate precision but has given lower recall which means it is less effective in identifying all relevant instances of hand relax event. Like LR, the performance of Convolution Neural Network (CNN), Support Vector Machine (SVM), and, K-Nearest Neighbors (KNN) classifiers is lower compared to RF and SNN which indicates these classifiers are less effective at leveraging the complexity of the features we have used.

Figure 7, Figure 8, Figure 9, Figure 10, Figure 11 and Figure 12, show the confusion matrix obtained from different classifiers for classifying the combined EEG data of five channels (F4, T8, C4, Cz, P4) that gives further insights into their performance. For the SNN classifier, the confusion matrix shown in Figure 7 reveals a balanced distribution of correctly and incorrectly predicted samples among different classes which indicates robust performance in identifying the true hand movement and relax events and minimizes wrong identification of these events. SNN's balanced performance compared to other classifiers suggests its suitability for applications requiring high accuracy and reliability in detecting actual commands from the EEG signal such as neuro-prosthetic device control or brain-computer interfaces, etc.

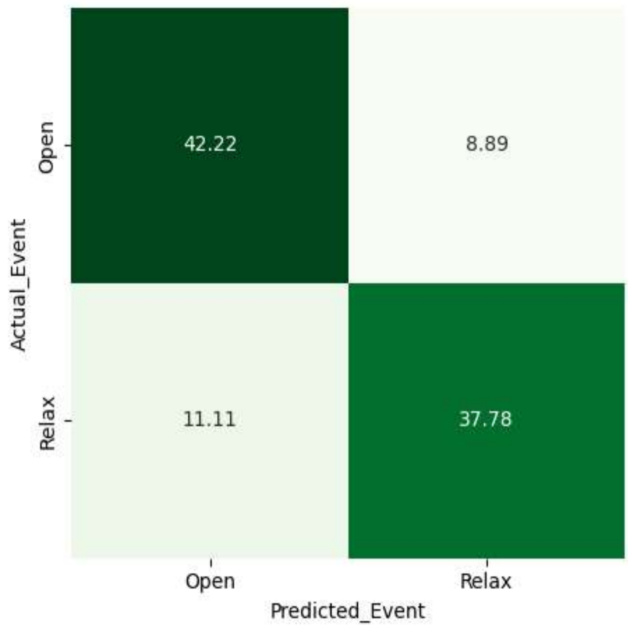

Fig. 7: Confusion Matrix obtained from SNN

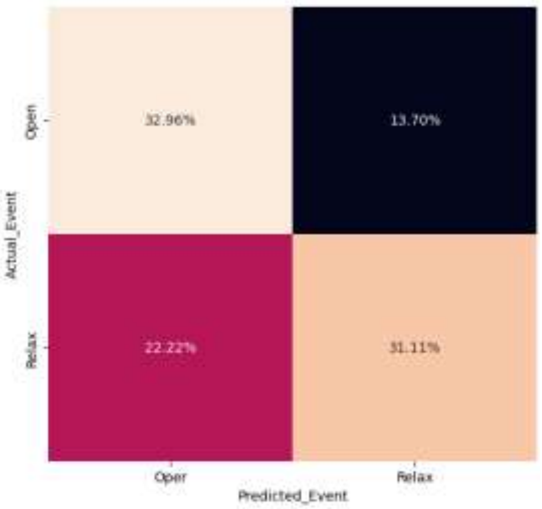

Fig. 8: Confusion Matrix obtained from CNN

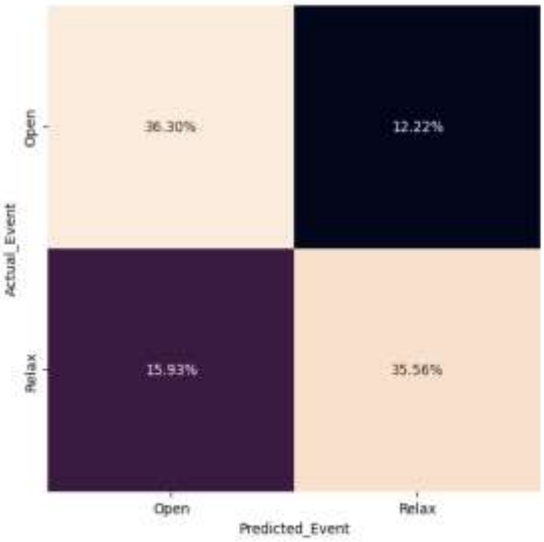

Fig. 9: Confusion Matrix obtained from RF

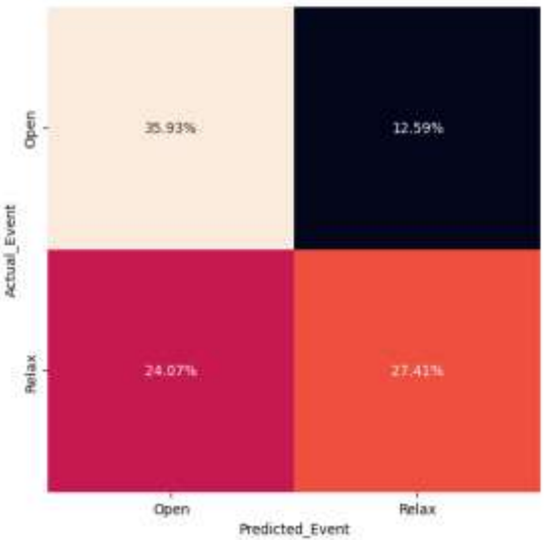

Fig. 10: Confusion Matrix obtained from SVM

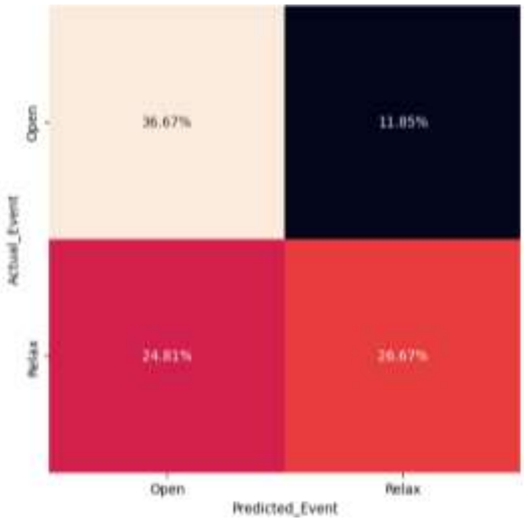

Fig. 11: Confusion Matrix obtained from KNN

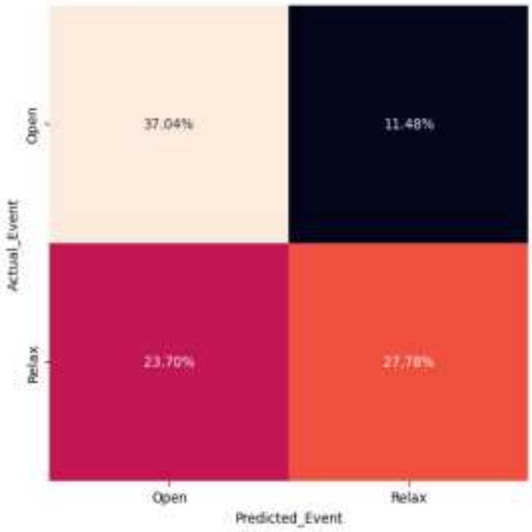

Fig. 12: Confusion Matrix obtained from LR

4.2 Performance Comparison of Classifiers using Data from Individual Channel

For classification using a feature matrix derived from EEG data of individual channels (F4, T8, C4, Cz, P4), the same features have been used for different classifiers (SNN, CNN, RF, SVM, KNN, and LR). Performance (accuracy, precision, recall, and F1-score) of different classifiers based on the simulation outcomes are illustrated in Table 4, Table 5, Table 6, Table 7, Table 8 and Table 9.

Table 4 represents the performance of the SNN classifier for 5 single channels' EEG data classification. Among the 5 channels, we have got the highest classification accuracy of 79.17% from the EEG data of channel F4 with a precision of 85.7%, recall of 87.3%, and the F1-score of 86.49%. Conversely, Channel Cz shows the lowest accuracy of 58.33%, with a precision of 56.14%, recall of 86.49%, and F1-score of 68.09%. For the remaining channels (T8, C4, and P4), the obtained accuracies are at a moderate level, with T8 at 68.06%, C4 at 73.61%, and P4 at 68.05%.

Table 4. Results for EEG signals classification by Spiking Neural Network (SNN)

Channel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
F4	79.17	85.7	87.3	86.49
T8	68.06	67.86	88.37	76.77
C4	73.61	73.02	95.83	82.88
Cz	58.33	56.14	86.49	68.09
P4	68.05	67.69	95.65	79.28

Table 5 represents the classification results of CNN for individual channel's EEG data classification. Here, channel C4 has the highest classification accuracy of 72.22% but precision, recall, and F1-score, all are 0. This indicates that CNN has been unable to correctly classify any positive instances (hand relax event) for this channel, resulting in no true positives (true relax prediction). In Contrast, channel P4 shows the lowest accuracy of 51.39%, with a precision of 54.17%, recall of 35.14%, and F1-score of 42.63%. For the remaining channels (T8, Cz, and F4), the obtained accuracies are at a moderate level.

Table 5. Results for EEG signals classification by Convolutional Neural Network (CNN)

Channel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
F4	56.94	17.86	38.46	24.39
T8	69.44	0	0	0
C4	72.22	0	0	0
Cz	59.72	56.67	51.52	53.97
P4	51.39	54.17	35.14	42.63

Table 6 presents the classification results for single channel's EEG signals using the Random Forest (RF) classifier. Here both channel F4 and P4 have achieved the highest classification accuracy of 77.78% but other performance metrics are not the same. For channel F4, precision is 81.4%, recall is 81.4%, and F1-score is 81.4% whereas for channel P4 precision is 76%, recall is 90.47%, and F1-score is 82.61%. On the other hand, C4 has given the lowest classification accuracy of 68.05% with a precision of 61.82%, recall of 94.44%, and F1-score of 74.73%.

Table 6. Results for EEG signals classification by Random Forest (RF) Classifier

Channel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
F4	77.78	81.4	81.4	81.4
T8	72.22	80	76.6	78.26
C4	68.05	61.82	94.44	74.73
Cz	76.38	85.71	76.6	80.9
P4	77.78	76	90.47	82.61

From Table 7, it is observed that the highest classification accuracy of 73.63% has been achieved from data of both channels F4 and Cz. For Channel F4, the precision is 71.43%, recall is 93.02%, and F1-score is 80.81%, indicating strong detection of true positives and a balanced performance. However, channel Cz shows high precision but a lower recall.

Table 7. Results for EEG signals classification by Support Vector Machine (SVM)

Channel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
F4	73.61	71.43	93.02	80.81
T8	61.11	69.39	72.34	70.83
C4	50	50	100	66.67
Cz	73.61	96.67	61.70	75.32
P4	59.72	61.02	85.71	71.29

According to Table 8, for single channels' EEG data classification by using KNN, channel F4 has given the highest classification accuracy of 72.22%, with a precision of 75.56%, recall of 79.07%, and F1-score is 77.27% indicating a well-balanced performance.

Table 8. Results for EEG signals classification by K-Nearest Neighbors (KNN)

Channel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
F4	72.22	75.56	79.07	77.27
T8	59.72	68.75	70.21	69.47
C4	54.17	52.83	77.78	62.92
Cz	55.56	66.67	63.83	65.22
P4	41.67	50	50	50

From Table 9, we can see that both the Cz and P4 channels' data have given the highest classification accuracy of 72.22%. For Channel Cz, the precision is 93.55%, the recall is 61.70%, and the F1-score is 74.36% which shows high precision but lower recall. For Channel P4, the precision is 82.35%, the recall is 66.67%, and F1-score is 73.68% which indicates a balanced performance.

In most of the cases of classifying EEG data taken from a single channel, it has been observed that SNN, RF, SVM, and KNN classifiers have achieved high classification accuracy by classifying EEG data of channel F4 and the accuracy values are 79.17%, 77.78%, 73.61%, 72.22% respectively. Also, for the remaining classifiers, obtained classification accuracy by using data from channel F4 is passable. Among all the classifiers, Spiking Neural Network (SNN) has shown the best performance which is consistent with our previous findings where classification was done using summative EEG data taken from five channels.

Table 9. Results for EEG signals classification by Logistic Regression (LR)

Channel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
F4	69.44	86.21	58.14	69.44
T8	68.06	78.57	70.21	74.16
C4	62.5	63.64	58.33	60.87
Cz	72.22	93.55	61.70	74.36
P4	72.22	82.35	66.67	73.68

From the simulation results of both cases we found that SNN has shown superior performance compared to other classifiers (CNN, RF, SVM, KNN, LR) we have used in this study. It might be because SNN is designed such that it can effectively capture temporal dynamics existing in data. SNN mimics the behavior of biological neurons, which process information based on spikes occurring over time. The DE, FDE, and FE feature that we have used in this study are focused on capturing irregularities existing in the EEG signal over time. So, the information captured by these features (DE, FDE, FE) in a time-dependent manner might be leveraged by SNN due to its inherent ability to process temporal information. Also, the mean and skewness features which provide statistical information about the distribution and asymmetry of the EEG signal, allow SNN to make more refined distinctions between hand movement and relaxation events from the EEG signal. CNN is primarily designed to capture spatial patterns from data, which makes it highly effective for image classification and spatial data analysis. However, the entropy features utilized in this study contain temporal information of the EEG signal, which may not be well-suited for CNN and could potentially diminish its performance. Random Forests is an effective ML algorithm for handling non-linear relationships among features but is not suited well for temporal sequences. This may lead to lower performance of RF. SVM is best suited for linearly separable data but it struggles with non-linear time-dependent data. The lower performance of SVM may be due to its inability to effectively handle the non-linear temporal information captured by the DE, FDE, and FE features from the EEG signal. KNN is a distance-based method and is not able to learn temporal patterns strongly which may lead KNN to perform badly for these entropy features (DE, FDE, FE). Logistic Regression (LR) is a linear classifier that is less suited for handling non-linear relationships in the data. The entropy-based features used for this classification study are non-linear. Consequently, LR performs lower with these entropy features. Therefore, while other classifiers (CNN, RF, SVM, KNN, LR) cannot effectively handle the non-linear temporal information captured by the entropy features extracted from EEG data, SNN outperforms them due to its capability to capture temporal dynamics and its biological plausibility.

4.3 Comparative Analysis with Existing Methods

In section 1.1, a review of some notable works related to our research has been discussed where researchers applied different methods for their models for decoding different hand movement attempts from EEG signals of persons with hand impairment. In this section, a comparative analysis of our proposed method with those existing methods related to our research has been presented.

Table 10 (Appendix) summarizes the results obtained from previous studies about different hand movement classifications of patients with disabilities using EEG signals with different methods. Researchers in [50], investigated the time-domain of low-frequency EEG signals of 10 persons with SCI by Shrinkage Linear Discriminant Analysis (sLDA) classifier and obtained 45% accuracy for 5 different hand movement classes (hand open, palmar grasp, lateral grasp, pronation, and supination) and tested online on a person with cervical SCI with 68.4% accuracy for palmar grasp vs hand open.

Authors in [53], used a regularized linear discriminant analysis (RLDA) classifier for target vs non-target classification with 8 amyotrophic lateral sclerosis (ALS) patients and achieved 80.53% classification accuracy. In [50] and [53], researchers used sLDA and RLDA classifiers respectively and both of these classifiers are linear classifier which finds a linear combination of features that are mostly suitable for differentiating different classes. EEG signal is a non-linear signal with high temporal dynamics, so the used classifiers in those studies might face difficulties in effectively capturing the temporal dynamics existing in the EEG signal.

In [51], the researchers employed movement-related cortical potentials (MRCPs), and time-frequency domain representation (scalogram) of the dataset of ten participants with subacute and chronic cervical spinal cord injuries for classifying the EEG signal into five different hand movement classes (hand open, palmar grasp, lateral grasp, pronation, and supination). They used the ConvNet AlexNet classifier for classification and obtained 76% average classification accuracy by their proposed method. Though the accuracy of this method was relatively high, due to the convolutional layer ConvNet AlexNet classifier may consume high energy for processing. Using a hierarchical classifier, the authors in [52], got 58.68% average classification accuracy for EEG-controlled bilateral grasping of two exoskeletons by four chronic tetraplegics.

In our research, a fusion of Dispersion Entropy (DE), Fuzzy Entropy (FE), and Fluctuation based Dispersion Entropy (FDE) with mean and skewness features are extracted from the motor imagery (MI) EEG signals of a patient with high spinal cord injury to operate a neuro-prosthetic device attached to his paralyzed right upper limb. The extracted features are applied to the Spiking Neural Network (SNN) classifier to investigate its classification accuracy for detecting hand movement–relax events to operate the exoskeleton. Using the proposed method, indeed a high classification accuracy of 80%, precision of 80.95%, recall of 77.28%, and F1-score of 79.07% are estimated. This performance has been found better compared to most of the other similar research works that specifically used the EEG signals of people with hand impairments. So, this proposed method can provide robustness for neuro-prosthetic control, which can help improve the quality of life of people with hand impairment.

5 Conclusion

This study represents a novel approach for classifying hand movement-relax EEG signals of an SCI patient using the Spiking Neural Network (SNN) which is applied to a time domain feature matrix containing Dispersion Entropy (DE), Fuzzy Entropy (FE), Fluctuation-based Dispersion Entropy (FDE), mean, and skewness to operate a neuro-prosthetic device attached to paralyzed right upper limb. To compare the performance of our proposed method, the same features have been applied to Convolutional Neural Network (CNN), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR) classifiers. Two types of simulation have been conducted for this study: one using the feature matrix derived from the EEG data of the five channels (F4, T8, C4, Cz, P4) collectively and another using the feature matrix derived from the EEG data from individual channels. For both cases, our proposed approach has shown superior performance compared to other classifiers we utilized. Our proposed method has also demonstrated better performance compared to other BCI system-based research works relying on EEG signals of hand-impaired individuals using different methods and datasets. The performance of our proposed method for classifying hand movement vs rest ensures better control of neuro-prosthetics which will increase the reliability of the BCI devices. Along with good performance in classification, SNN is an energy-efficient neural network. Due to its biological plausibility, SNN may consume low power. This may help to extend the battery life which will increase the reliability. Due to its energy-efficient property, it can be useful for portable BCI systems. Moreover, low-latency SNN can be useful for BCI systems that require real-time response. Therefore, our proposed method has great potential for applications in neuro-rehabilitation engineering and BCI systems, where real-time, low power consumption, and accurate movement detection are crucial. In this research, we have used a small dataset that contains EEG data of only one person with SCI. To justify the generalizability of our proposed method, this method should be tested on a large dataset that comprises the EEG signal of several persons with SCI and also on a diverse dataset for different types of classification tasks such as disease detection, emotion detection, etc. Also, in future research, exploring the synergistic integration of hybrid EEG-

EOG, EEG-fNIRs, and EEG-EMG modalities holds promise for further enhancing the overall performance and robustness of Brain-Computer Interface (BCI) systems, paving the way for more sophisticated and versatile applications in various domains. In the future, researchers may look into how combining hybrid EEG-EOG, EEG-fNIRs, and EEG-EMG modalities can improve the overall performance and reliability of Brain-Computer Interface (BCI) systems. This could lead to more advanced and flexible uses in many areas.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly for language editing. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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APPENDIX

Table 10. Related works for upper limb movement classification using EEG signal

Research work	Signals	Volunteers	Method	Classes	Accuracy
[50]	EEG	10 persons with SCI	sLDA	5 hand movement classes	45.00%
				Palmar grasp vs hand open	68.40%
[51]	EEG	10 persons with SCI	ConvNet	5 hand movement classes	76.00%
[52]	EEG	4 chronic tetraplegics	Hierarchical classifier	Hand Movement vs Rest	58.68%
[53]	EEG	8 ALS patients	Regularized LDA	Target Vs Non-Target	80.53%
Our method	EEG	1 person with SCI	SNN	Hand Movement vs Relax	80.00%