CLASSIFICATION OF STROKE SYMPTOMS IN PATIENTS USING SELF ORGANIZING MAPS

ANUREKHA R[1*], KAVITHA M S[2], KARTHIK S[3]

[1*]Assistant Professor, Department of Information Technology,
Government College of Engineering, Erode-638316, Tamil Nadu, India
E-Mail: drranurekha@gmail.com

[2]Associate Professor, Department of Computer Science & Engineering,
SNS College of Technology, Coimbatore-641035, Tamil Nadu, India
E-Mail: drmskavitha@yahoo.com

[3]Professor and Dean, Department of Computer Science & Engineering,
SNS College of Technology, Coimbatore-641035, Tamil Nadu, India
E-Mail: profskarthik@gmail.com

Abstract

In this paper we use self-organizing maps (SOM) to classify the stroke symptoms from EMG signals for hand movement classification. The process involves pre-processing, feature extraction and classification of EMG signals from the input signals. The model is split into train and testing datasets with 80:20 ratio of 10-fold cross validation approach. The simulation is conducted in python to test the efficacy of the proposed model. The results show that the proposed method achieves higher grade of classification accuracy than the existing methods.

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1. Introduction

When a neurologic impairment is brought on by an instantaneous and targeted attack to the central nervous system, this type of injury is referred to as a stroke. This lesion can be brought on by vascular reasons such as cerebral infarction, cerebral haemorrhage, and other similar causes of damage to the blood vessels in the brain. It is one of the key reasons why people are unable to work or why they pass away at a young age [1]. The increasing world population and the growth of risk factors are both contributing to an increase in the risk of stroke [2], which is expected to continue to go up. Stroke survivors usually struggle with a wide variety of impairments, such as sensory dysfunction, motor dysfunction, cognitive and linguistic issues, and a variety of other difficulties [3].
Those who survive a stroke but are left with motor and wrist dysfunctions, as well as the inability to continue working, see a considerable decline in both their quality of life and their capacity to carry on with their careers. Rehabilitation and the process of restoring motor function in the upper limbs through therapy are crucial components of stroke rehabilitation. These features of

rehabilitation have the potential to dramatically improve rehabilitation results and minimise impairment [4].

The wrist motor function of the upper limb has received little attention, despite the fact that multiple research and trials have established the efficiency of current rehabilitation training and evaluation methodologies for upper limb functions following a stroke [5]. This is because the implementation of these methods takes significantly more time and effort than other approaches. After a patient has suffered a stroke, extensive study into treatments and rehabilitation methods that put an emphasis on the patient wrist motor function is essential in order to improve the quality of patient life and facilitate a recovery of the patient upper limb function.

However, there are certain drawbacks to the evaluation that is currently utilised by rehabilitation experts to measure the upper limb function in clinical practise [6]. There is a need for additional development in the evaluation and rehabilitation techniques of motor capabilities in the upper limb and wrist in individuals who have had a stroke [7]. This is something that should be kept in mind with increasing frequency in light of the expanding number of rehabilitation robots that are being developed and used in genuine clinical rehabilitation [8].

The motor function evaluation in stroke patients has been studied using various researches [9]-[12]; nevertheless, the results that have been found have been inconsistent. This is due to the fact that the evaluation procedure makes use of a diverse range of motor factors, which makes it more challenging to carry out research on the motor function evaluation [13].

In some research, intelligent rehabilitation robot technology is used. This technology is more complex and expensive to develop, which makes it more difficult to move around, as well as to expand its use to clinical applications, remote rehabilitation, and evaluation [14]. Because the wrist is the extremity endpoint and a major locus of movement, more research has to be done on cognitive rehabilitation training and quantitative measurement of the wrist. Patients who have suffered from strokes may gain a significant amount from this type of research [15].

In this investigation, we classified stroke symptoms based on electromyographic (EMG) signals for hand motions using a technique called self-organizing maps (SOM). This information comes from interviews with patients who have been diagnosed with the illness. Preprocessing is the first step in the process, which is followed by the extraction of features from the incoming data and, finally, the classification of the signals.

2. Related works

Patients who have suffered a stroke can recover from their injuries more quickly when they utilise robots that assist in rehabilitation, as has been proved in studies [16-18]. This particular kind of feedback is also referred to as haptic feedback or force feedback in some circles. However, the amplitude and direction of the forces that are emitted by the device need to be regulated in order to facilitate direct rehabilitation and make certain that training will not result in collateral damage to the limbs [19]. The development of therapeutic interventions that are centred on establishing synchronisation between the location, graphical environment and the sensory system, networks[22][23], computation improvements [24][25] makes extensive use of force feedback, which plays an important part in this development.

Xu et al. [20] carried out a study in which they recruited 40 stroke patients in order to study the rehabilitation effects on training the robot specifically on the motor function and stroke survivor activities. They discovered that subacute stroke patients who participated in rehabilitation robot training saw significant improvements in their upper limb motor function and their ability to perform everyday activities.

Andaluz et al. [21] utilised a haptic robot with Novint Falcon that offers feedback in addition with Leap motion sensors that provides

Oculus Rift to verify the upper limb rehabilitation with motor function. The goal is to improve patient ability to perform fine motor tasks. This setup makes use of the Oculus Rift as well as Leap motion sensors. Cappa et al. [22] found that individual movements were altered in terms of their smoothness, precision, and duration when force feedback was applied.

3. Proposed Method

In this section, we provide a detailed discussion of the series of events for classifying the stroke signals and its illustration is given in Figure 1.

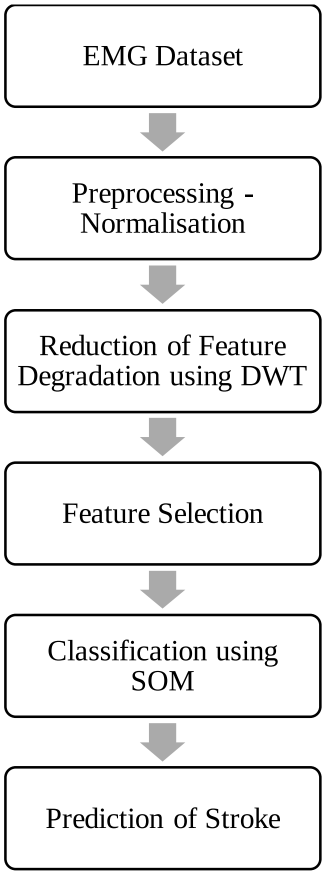

Figure 1: Proposed Model

Pre-Processing

Signals are obtained by downloading them from the UCI repository, and an explanation of the dataset is included in the part of the paper that is devoted to the findings and the discussion of those findings.

In the field of medical data analysis, preprocessing is vital since the quality of the diagnosis is dependent on the integrity of the raw input signal data. Without preprocessing, accurate diagnoses cannot be made. The EMG signal was normalised for the sake of this inquiry in order to cut down on the amount of background noise that was present.

Normalization is utilised so that any features that may be present in the input EMG signals can be removed through the use of filtering. In order to accomplish this, the maximum amplitude must be adjusted to either +1 or -1, with 0 serving as the baseline. In order to relocate a number of samples in close vicinity to the principal (*R*) peak, the windowing method is utilised.

Discrete Wavelet Transform

Preprocessing is performed on the EMG signals in order to prepare them for the discrete wavelet transform (DWT), which is then performed on the signals. The enhanced frequency and time precision in the input signals that DWT offers as a direct result of its localization capabilities are one of the primary reasons for its widespread application. In addition to this, DWT reveals the local characteristics of the input signals while simultaneously reducing the amount of deterioration in the features of the signals.

We make use of the discrete wavelet transform (DWT) because of its ability to keep the edges of the signal intact. Additionally, we make use of short time frames so that we may emphasise both low- and high-frequency information. Because of this finding, the DWT was utilised by the researchers quite frequently in their analysis of non-stationary signals. This was a direct consequence of the finding. If you solve the equation that follows (1), you should be able to obtain the formula for the generic DWT.

$$DWT(j,k)=\frac{1}{\sqrt{|2^j|}}\int_{-\infty}^{\infty}x(N)\,\mu\left(\frac{N-2^jK}{2^j}\right)dN$$

where denotes a representation of a wavelet function μ, $x(N)$ stands for the actual value of the wavelet, and 2^j and 2^jK stand for the scaling and shifting parameters, respectively.

Feature Selection

By using the Relief-F features selection technique, it is feasible to get rid of any features that aren't required by doing the following: first, computing the feature score of each attribute; then, ranking them according to that score; this will remove any features that aren't required. Utilizing the feature weights, which are also referred to as scores, that are generated by the FS technique that was described allows for the construction of the downstream model to be completed. In order to choose which characteristics to employ, the model of the system makes use of a number of distinct initial weights. The following are the methods that are utilised in order to restore the weight to its initial condition: Weight=0.

At the beginning of each epoch, Relief-F assigns vector for each feature, which is denoted by x, to a single sample. The algorithm then calculates the Euclidean distance between x and the other samples in order to determine which samples belong to which classes and which classes contain which samples.

The samples that are considered to be a near-hit are those that are positioned closer together within the same category, whereas the samples that are considered to be a near-miss are the ones that are located closer together within a different category. The feature vector includes information regarding the locations of the features (x). The cutoff value is established by calculating the mean of the values for the regions nearHit_i and nearMiss_i . Under arbitrary conditions, Relief-F is utilised to determine the total number of hits and misses produced by each class.

$$C_i = (x_i-\text{nearMiss}_i)^2 + C_i-(x_i-\text{nearHit}_i)^2$$

The selection of features by Relief-F are sent as to the SOM classifier, which is ultimately responsible for producing a disease prognosis.

Classification

The distance that exists between a prototype vector, which is the SOM node projection onto the input space, and the vector that is physically located closest to it in the input space is the sole criterion that is used in a conventional Kohonen SOM to decide where a SOM node should be located in the SOM latent space. This distance is used to decide where a SOM node should be located in the SOM latent space.

In our method, we take it one step further by reorganising all of the SOM nodes in the input space and latent space according to their distances from the node that is currently in first place. This is done in both spaces (best matching unit). When it comes to making modifications, keep the following rule of thumb in mind as a general guide:

$$\mathbf{r}_k(t+1)=\mathbf{r}_k(t)+\alpha(t)\cdot\left(1-\frac{\delta_{vk}}{d_{vk}}\right)\cdot\left(\mathbf{r}_v(t)-\mathbf{r}_k(t)\right),\qquad \forall\, k\neq v.$$

$\mathbf{r}_k(t)$ - SOM node position prior adjustment;
$\mathbf{r}_k(t+1)$ - SOM node position post adjustment;
$\mathbf{r}_v(t)$ - current winning node position;
δ_{vk} - distance between a current winning and SOM node and
d_{vk} - latent space.
$\alpha(t)$ - learning rate.

The som3d technique takes as input a number of volumetric attributes, and the mathematical dimensionality of these attributes is specified by the number of attributes that are provided. In other words, the more volumetric attributes that are provided, the more precise the results will be. Because the visualisation programme that we use can only handle 256 unique colour combinations, we were compelled to limit the size of the vectors to *J* = 256.

This decision was made in order to comply with the application limitations. A piece of software known as Z-score is responsible for standardising the data vectors that are put to use in this application. As a result, each of the coordinates that our volumetric input data consists of *x*, *y*, *z* is represented as a vector.

The study considers a volume, more precisely the normalised feature attributes, and they make use of principle component analysis (PCA) in order to map it onto a latent space that consists of two dimensions. As was said earlier, this definition is applicable to the latent space in a two-dimensional format. If there are six attribute volumes being input, then each potential variable (PV) in the two-dimensional latent space will have a dimension of 6. It takes 256 PVs to sample this 2D latent space in a manner that is consistent, hence the minimum number is 256. The positions of the PVs are modified after each training cycle, which ultimately leads to the development of a new prediction.

When the rate of updates drops below a specific level, the learning process is halted until it reaches that threshold again. There is a relationship between the number of iterations that are performed and the degree to which the PVs approach one another, in addition to the data points that are located in the latent space. There is a positive association here. Their radial distance from the sun and their azimuthal angle in relation to it are taken into consideration when calculating their hue, saturation, and value (HSV). After training is complete, a calculation is performed to determine the distance between each PV (denoted by $\boldsymbol{\xi}_p'$) and the multi-attribute data vector (denoted by $\mathbf{a}_m$) in each voxel (denoted by *m*).

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$$\left|\left|\mathbf{a}_m - \boldsymbol{\xi}_\mathbf{b}'\right|\right| = \min\left\{\left|\left|\mathbf{x} - \boldsymbol{\xi}_\mathbf{p}'\right|\right|\right\}$$

where
$\boldsymbol{\xi}_\mathbf{b}'$ - near PV
$\mathbf{a}_m$ - sample vector

Using this technique, two samples that are quite distinct from one another will appear to be of different colours of $\boldsymbol{\xi}_\mathrm{b}'$. This is due to the fact that they will be physically separated by a significant distance in the latent space. In contrast, if you take two samples from the same seismic volume and compare them, you will find that the colours of the samples are almost exactly the same. This is because the colours of the samples come from the same place in the seismic volume.

4. Results and Discussions

One of the many phases involved in processing medical data is disease prediction utilising electromyography (EMG), which is also one of these steps. In the current investigation, we suggest making use of a hybrid method that combines FE and SOM in order to provide a prediction regarding the development of muscular stroke. The DWT technique is used so that the intricacies of the regions are reflected more correctly, and so that the loss of fine information in the features is reduced as much as possible.

This configuration takes use of an Intel i7 CPU and 8 gigabytes of random access memory in order to carry out the proposed feature selection using the SOM technique in MATLAB 2020a (RAM). The performance of the participant is evaluated within the framework of the simulation based on a variety of factors, including accuracy, precision, recall, and error rate. At this time, the SOM epoch is set as 100, momentum as 0.9, weight decay as 0.0005, and the learning rate as 0.1.

Performance Metrics:

Equation (3) indicates how to calculate accuracy, and equation (4) demonstrates how to determine how many samples in the positive class were correctly categorised. Together, these two equations provide a comprehensive framework for analysing the data. The proportion of correctly positive-labeled samples may be calculated by the fraction of the total number of samples by the recall value acquired from the positive class. This will give the percentage of correctly positive-labeled samples. It is possible to determine the percentage of samples that have been appropriately positive-labeled.

$$\text{Accuracy}=(TP+TN)/(TP+FP+FN+TN)\times 100$$

$$\text{Precision}=(TN)/(FP+TN)\times 100$$

$$\text{Recall}=(TP)/(TP+FN)\times 100$$

$$\text{Error} = 100-\text{Accuracy}$$

where
TP - true positive,
TN - true negative,
FP - false positive and
FN - false negative.

Dataset

With the use of the UCI EMG-Lower Limb Dataset, an evaluation of the SOM efficiency. Access to the dataset can be obtained by navigating to the following URL: https://archive.ics.uci.edu/ml/datasets/EMG+dataset+in+Lower+Limb#. The final sample has a total of 22 persons, 11 of whom are considered to be normal patients, and 11 of whom are considered to be abnormal people (those with knee pathology). Each participant will be presented with three options: walking, standing, and sitting; however, they will only be allowed to select one of these possibilities.

Results and Discussion

The current methods for predicting muscle stroke are validated by a dataset that comprises of signals from recorded electromyography (EMG) or signals from electromyography done on the surface of the skin. This study validates 132 separate EMG signals that originate from the lower limbs, and it lists five different characteristics of each signal. In order to do an analysis of the input EMG signals of the datasets, the proposed approaches is compared with BPNN and CNN. The results of a comparison between the performance of the proposed SOM and that of the BPNN and CNN that already exist are presented in Figure 2-6 (both with and without FS).

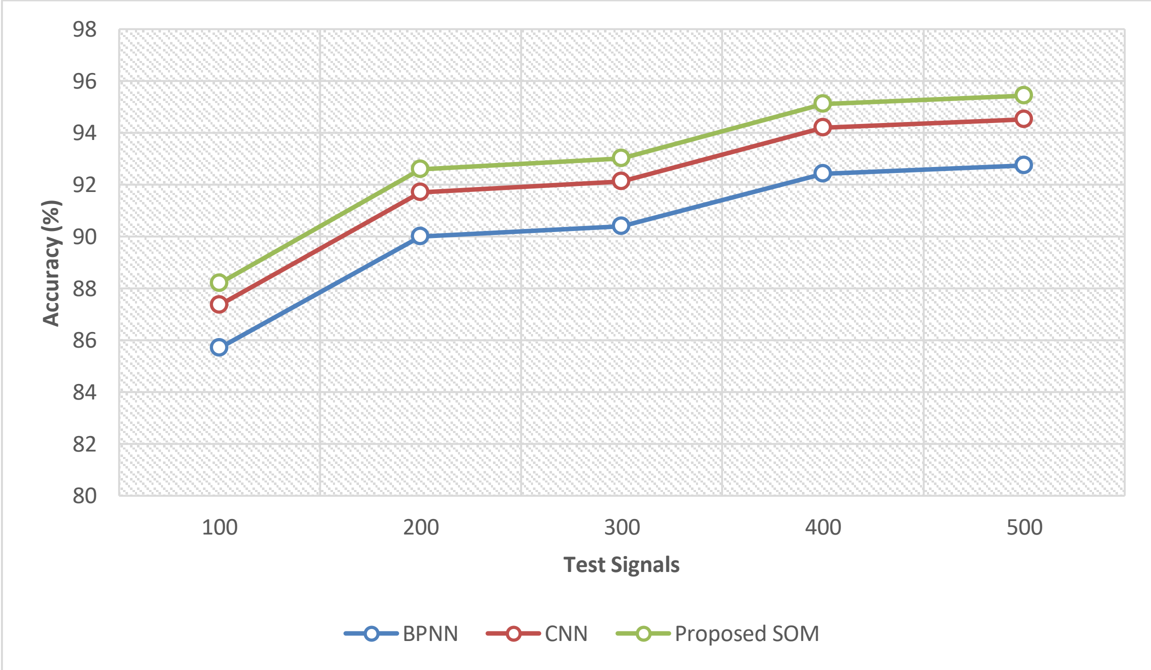

Figure 2: Accuracy

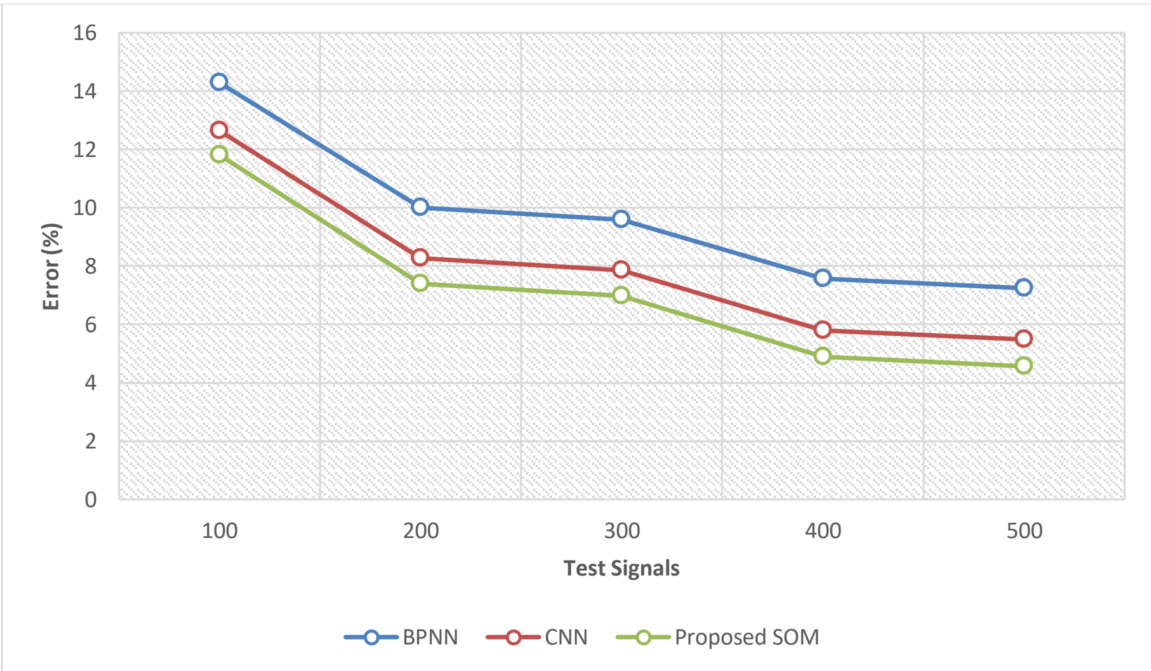

Figure 3: Error Rate

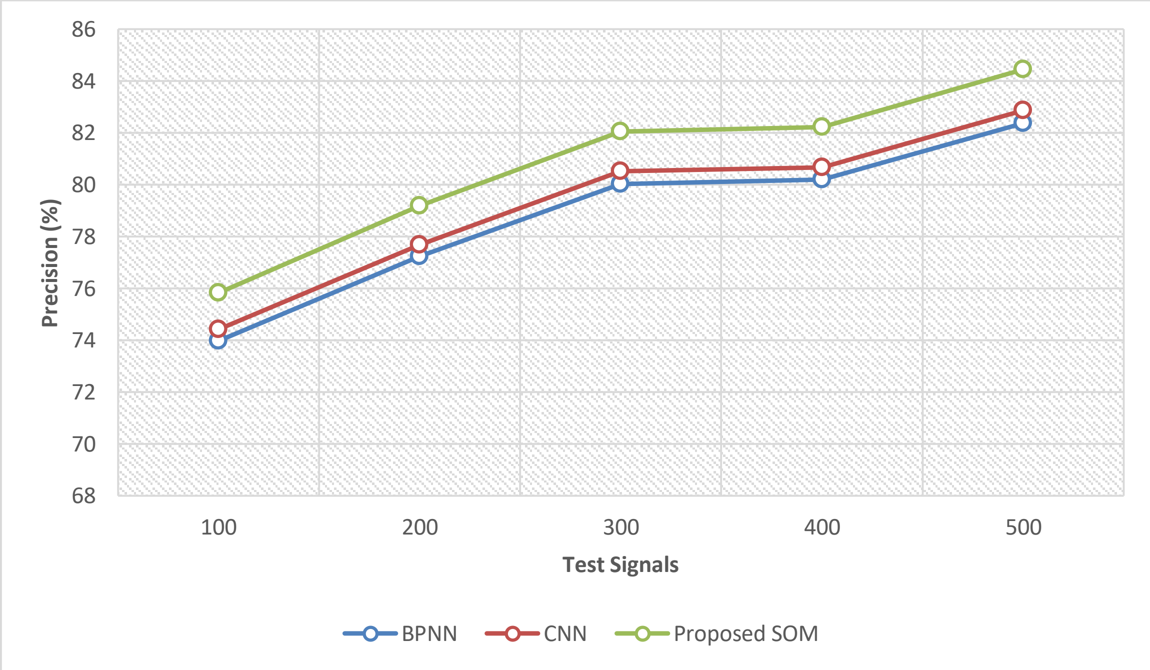

Figure 4: Sensitivity

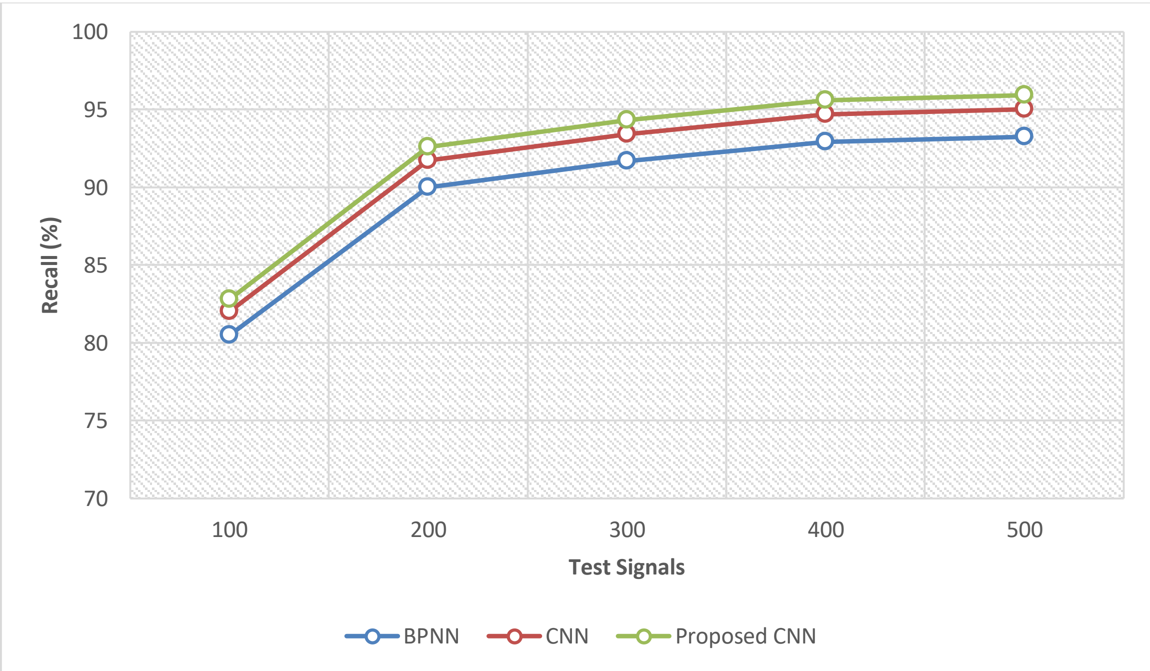

Figure 5: Specificity

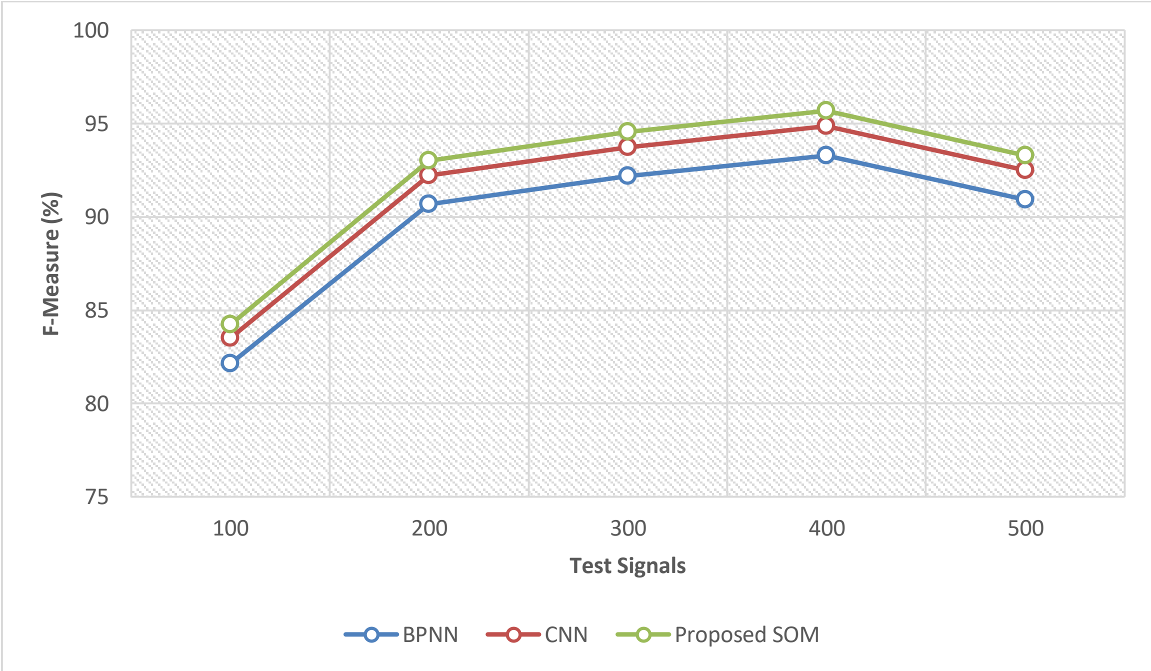

Figure 6: F-Measure

According to the results, the SOM achieves a higher classification accuracy than other methods by a factor of 99%. This finding was reached by comparing the proposed method to other methods that are currently considered to be state-of-the-art models. The f-measure rate, sensitivity, and specificity of the recommended approach are all enhanced when compared to the existing approaches. The rate at which f-measures are performed is not affected.

When compared, the accuracy of BPNN was only 70%, whereas the accuracy of SVM was 78% and the accuracy of SOM was 80%. When it comes to disease prediction, BPNN and CNN place a strong emphasis on training samples and make use of an extremely large number of features. On the other hand, SOM justifies its decision by comparing them to those of its immediate neighbours.

Relief-F is utilised in order to select the features that offer the greatest number of benefits to the user. The best accuracy that CNN could accomplish was 80% accuracy, while the best that BPNN could manage, even when using the Relief-F, was just 72% accuracy.

According to the results of the research, the hybrid FE with SOM strategy that was developed is more accurate than other methods that have been used in the past. In this particular experiment, the use of the DWT strategy improved the feature degradation, whereas the use of the methods that came before it did not enhance the feature degradation.

5. Conclusions

In this study, we apply SOM to tackle the problem of recognising stroke symptoms based on EMG signals of hand motions. The results of this study will be published in the journal Scientific Observational Methods. This is demonstrated by providing an example of the hand. Preprocessing is the first step in the process, which is followed by the extraction of features from the incoming data and, finally, the categorization of the signals. Using a 10-fold cross-validation strategy, the data for the model are split into two parts: a training dataset and a testing dataset, with the ratio being 80:20. Python is used to run a simulation so that an evaluation can be made regarding how well the proposed model will function. According to the findings, the proposed technique is capable of achieving a greater level of accuracy than the alternatives that are thought of as being state-of-the-art. When the findings were analysed with the classifiers that had been developed in the past, it was found that the hybrid method that was recommended performed better than any of them. The performance of every classifier, including the proposed SOM, deteriorated when the Relief-F strategy was not utilised as part of the classification process. In addition, the SOM technique learns the data for classification in an adaptive manner, and the proposed hybrid FS strategy is successful in selecting the appropriate feature to utilise in the classification. Both of these benefits are due to the fact that the SOM method learns the data.

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