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PREDICTION OF STROKE USING EEG SIGNALS

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Abstract - A stroke is a disruption of blood supply to the brain that leads to disability. Rehabilitation can reduce brain damage and other complications and also recover disability due to stroke. One instrument that can be used in post-stroke patients monitoring is Electroencephalogram (EEG). EEG signals are recorded from several channel pairs. So apart from maintaining signal sequences, handling time connectivity between channels is also essential. Therefore, the signal sequence and time connectivity between channels need to be handled simultaneously on two dimensions. The vertical dimension was the multi-channel dimension, and the horizontal dimension was the signal sequences of each channel concerning time. The proposed system uses the 2D-Convolutional Neural Networks method to identify post-stroke based on EEG signals. First, a wavelet filter was used to obtain a frequency range of 1–13 Hz to represent post-stroke patients. The identification results are one of the three levels of stroke, i.e., No Stroke and Minor Stroke.

1. INTRODUCTION

Stroke is the second leading cause of death worldwide. One out of twenty deaths in America are due to stroke and 62,000 strokes that occur each year in Canada affect all age groups and lead to a lifetime impact on health. According to centers of disease control and prevention, in the United States, someone suffers from brain stroke in every 40 seconds.

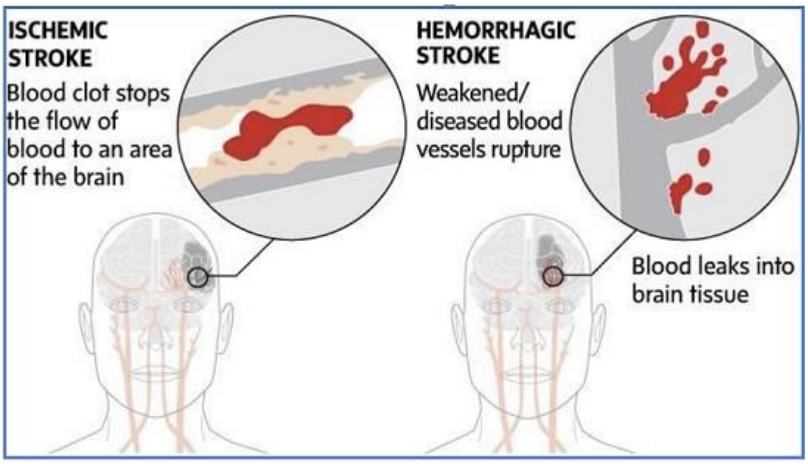

Figure.1.1 Types of Strokes: Ischemic and Hemorrhagic

There are two main types of strokes: ischemic and hemorrhagic. Ischemic stroke occurs when a blockage (obstruction) of small blood vessels occurs around the brain (Fig.1.1). Magnet Resonance Imaging (MRI) gives accurate results for stroke detection, yet it is expensive, requires several hours to generate an examination report and is applicable for a limited time. MRI is used only in situations where there is no time pressure to offer diagnosis, typically as follow-up imaging. MRI is an expensive and is not available at all healthcare locations. In comparison, Electroencephalography (EEG) offers a continuous, real-time, non-invasive measure of brain function and is capable of detecting ischemic stroke due to variation in cerebral blood flow in the blood vessels. It has proven to be effective in detecting various other brain-related activities like Rapid Eye Movement (REM), sleep and awake stage and other seizure.

Stroke can be detected by several instruments, such as CT scan, MRI, electroencephalogram (EEG), and EMG. CT scan and MRI are usually for the first treatment detection. The computational capabilities, automatically neurorehabilitation, can use EMG and EEG. EEG records reflect brain function. The instrument can provide supporting information in identifying and monitoring different neurological rehabilitation. EEG has advantages in low cost and minimal risk to patients, but it is necessary to process to inform the brain's condition properly. Some studies used EEG signals to identify ischemic stroke patients, investigate that stroke patients are able to use BCI, and extracted significant variable.

EEG signal processing consists of two essential factors that are feature extraction and identification. Usually, the neurologist reads the EEG signal of a post-stroke patient by observing wave density or rhythm, amplitude, asymmetric, change in magnitude, the presence of waves, and the ratio between waves. The most important thing is how to extract the signal into frequency components. The next step is to choose waves with the right frequency component under the characteristics of the EEG signal variable being reviewed. Therefore, research using frequency extraction is beneficial. Several previous studies used Wavelet extraction to determine the significant variables of EEG signals for post-stroke patients. Wavelet can extract Alpha, Beta, Theta, Gamma, and Mu waves to classify emotions of stroke patients and healthy people. Also, wavelet provides easy time-frequency analysis. Past research shows that the study of the time-frequency of stroke patients during TMS therapy. Many other studies have also looked at the characteristics of waves with a specific frequency in stroke patients, which is one characteristic. Wavelet extractions of EEG signals are used to find significant variables of stroke and the classification of emotions. In meanwhile, FFT is suitable for identifying EEG signal asymmetries.

Machine learning allows computers to learn like humans make computers learn EEG stroke patterns previously so that automatic detection. Deep learning is part of machine learning, which in recent years has shown remarkable performance. Popular methods used in deep learning are convolutional neural network (CNN) and recurrent neural networks (RNN). Both have enough accuracy and are subject to composition. However, RNN is vulnerable to feature sequences, which can result in decreased correctness. CNN is widely used for image processing. An EEG signal can be viewed as an image, so its processing uses two-dimensional CNN, like previous studies for the detection of epileptic attacks. However, not a few are also used for signal processing using one dimension. Some researchers used to identify EEG signals between stroke patients and healthy people, ischemic detection.

2. Electroencephalography

Electroencephalography (EEG) uses the electrical activity of the neurons inside the brain. When the neurons are active, they produce an electrical potential. The combination of this electrical potential of groups of neurons can be measured outside the skull, which is done by EEG. Because there is some tissue and even the skull itself between the neurons and the electrodes, it is not possible to measure the exact location of the activity.

For EEG measurements an array of electrodes is placed on the scalp. Many caps available use 19 electrodes, although the number of caps using more electrodes is rising. The electrodes are placed according to the international 10-20 system, as is depicted in figure 1.2. This system makes results from different research easily comparable.

The brain activity can be coarsely divided into different classes. This division follows the way the activity is produced by the brain.

Figure 1.2 Example of a cap for measuring EEG data

3.SYSTEM ANALYSIS

An automated stroke detection system in electroencephalogram (EEG) is addressed. Thus, the brain signals captured in the form of EEG signals can indicate whether a person suffers from a stroke or not. In the proposed system, raw EEG signals are processed in the form of time domain specifications. The EEG signals are the input to the proposed deep learning networks. The network is trained with huge number data samples that includes both normal and stroke signals. The EEG signal classification of post-stroke patients used CNN, as shown in Figure 3.1, to identify "minor stroke," and "no stroke" class.

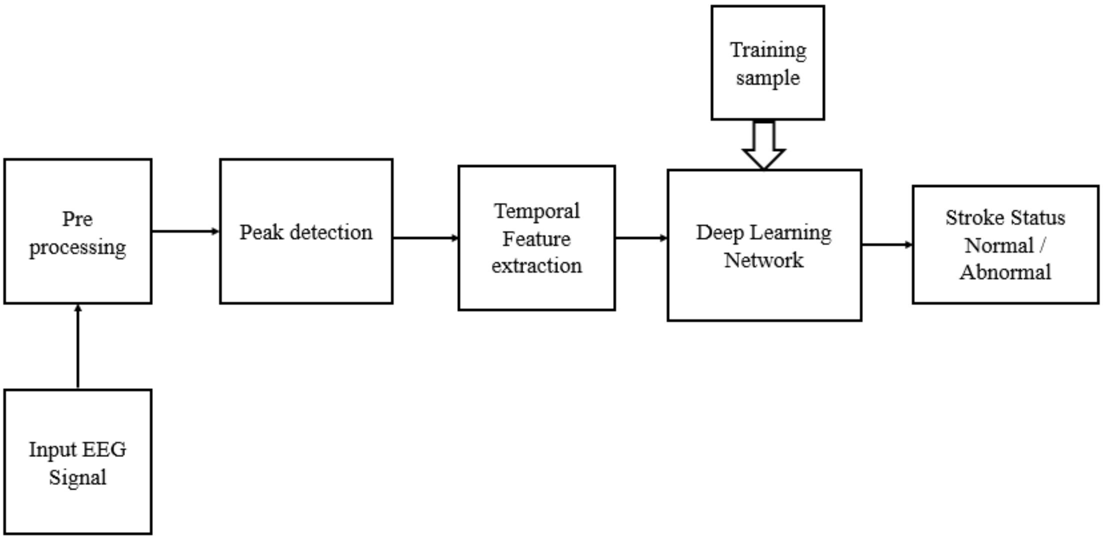

Figure. 3.1 Block diagram of the EEG Stroke Detection

3.1 PROPOSED SYSTEM OVERVIEW

Measured EEG signals are a valuable source of information about brain activity. However, since brain activity only produces very weak signals, the EEG signals contain a lot of background noise. Before using the signals for stroke detection, they have to be preprocessed, in order to remove unwanted noise. Although EEG signals contain a lot of information, they also tend to result in very large amounts of data. As mentioned in chapter 2, the information in EEG signals includes information about stroke. The proposed system is a novel technique for the problem of detecting abnormal brain signals in EEGs which extracts specific features from the EEG signals. The wavelet decomposition is used for feature extraction and selected a specific set of important features which play a critical role in improving the classification of EEGs. The novel method proposes to aggregate the extracted features that helped in reducing the dimension of the feature space without compromising the quality of features. CNN classifiers were used to classify EEGs based on the extracted features in aggregated feature space for stroke detection. This program has to extract the valuable information from the large amount of data. For this task, first it is necessary to reduce the amount of data available. This process is known as feature extraction and extracts a specified measure that is useful for our task from the signals. These features should contain enough information about the stroke. After having reduced the size of the data, the stroke has to be recognized from the features. For this purpose, several classification methods exist to classify a given EEG signal into no stroke or minor stroke.

PREPROCESSING

Preprocessing is a step to process raw EEG signals in such a way that they are ready to be used. As depicted in figure 3.2, the measured EEG signal is a combination of brain activity, reference activity and noise. The goal of this preprocessing step is to reconstruct the original brain activity. All steps can be executed using different methods and algorithms. These steps will be explained in this section.

3.2.1 Referencing

EEG signals as a combination of brain activity, reference activity and noise chosen such that the activity at the reference site is almost zero. The nose, mastoids and earlobes are typically used shown in fig 3.2. EEG signals are a recording of the voltage at different electrodes. Ideally, this measurement should only represent the electrical activity on that spot. However, since voltage is a relative measure, the measurement is compared to the voltage at a reference site. Unfortunately, this results in measurements that reflect the local activity, but also the activity at the reference site.

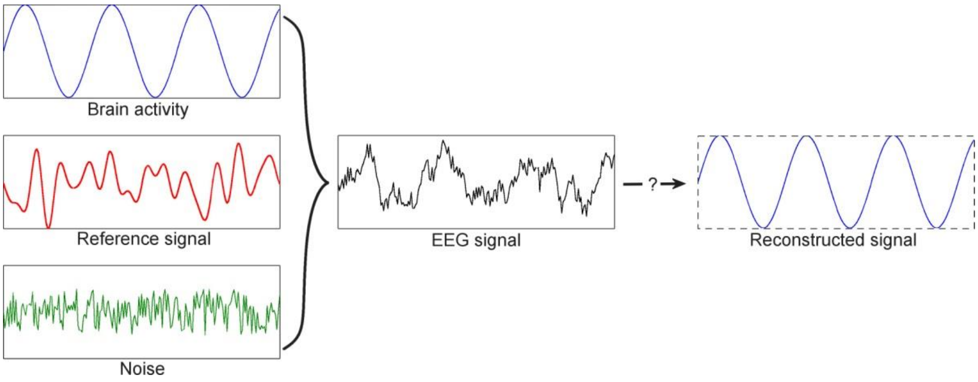

Figure 3.2: EEG signals as a combination of brain activity, reference activity and noise

3.2.2 Classification

After extracting the desired features, we still have to find the emotion. This process will be done by a classifier. A classifier is a system that divides some data into different classes, and is able to learn the relationship between the features and the emotion that belongs to that part of the EEG signal. Several methods for classification have been proposed. We will explain some of the most well-known algorithms.

3.2.3 Convolutional Neural Networks

The human brain consists of billions of neurons. These neurons are connected to thou- sands of other neurons, and together form a neural network. Through these connections, the neurons are able to communicate with each other, and as a whole the network is able to perform highly intelligent actions, such as memorizing things or controlling parts of the human body.

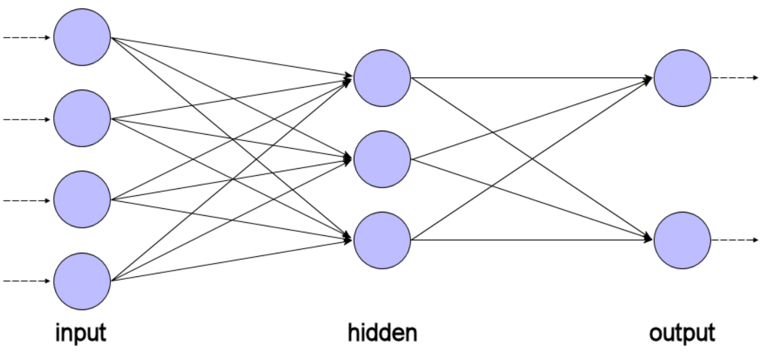

Figure 3.3 Structure of a neural network

(Convolutional) neural networks (CNN or NN) originate from the desire to mimic the human brain in a computer. CNN s can be seen as a simplified model of the human brain and also consists of several neurons, where some neurons are connected. With all neurons together, a CNN tries to learn a relationship between the input and the output, without having knowledge about the underlying model.
The neurons are also referred to as processing elements (PE), as they process the inputs given to it, combine all values and produces one output value. CNN s are typically organized in several layers. One input layer and one output layer are always present, but one or more hidden layers can be added. The neurons from one layer are connected to the neurons in the next layer, giving its output as input to the next layer neurons. An example of a neural network can be seen in figure 3.4. The input to the input layer is the original data to be classified, in this case the feature values. The output from the output layer are the values on the arousal and valence scale.

4. SOFTWARE DESCRIPTION

`The name MATLAB stands for MATrix Laboratory.

4.1. INTRODUCTION

The tutorials are independent of the rest of the document. The primarily objective is to help you learn *quickly* the first steps. The emphasis here is \learning by doing". Therefore, the best way to learn is by trying it yourself. Working through the examples will give you a feel for the way that MATLAB operates. In this introduction we will describe how MATLAB handles simple numerical expressions and mathematical formulas. MATLAB was written originally to provide easy access to matrix software developed by the LINPACK (linear system package) and EISPACK (Eigen system package) projects. MATLAB is a high-performance language for technical computing. It integrates *computation*, *visualization*, and *programming* environment. Furthermore, MATLAB is a modern programming language environment: it has sophisticated *data structures*, contains built-in editing and *debugging tools*, and supports *object-oriented programming*. These factors make MATLAB an excellent tool for teaching and research.
MATLAB has many advantages compared to conventional computer languages (e.g., C, FORTRAN) for solving technical problems. MATLAB is an interactive system whose basic data element is an *array* that does not require dimensioning. The software package has been commercially available since 1984 and is now considered as a standard tool at most universities and industries worldwide. It has powerful *built-in* routines that enable a very wide variety of computations. It also has easy to use graphics commands that make the visualization of results immediately available. Specific applications are collected in packages referred to as

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toolbox. There are toolboxes for signal processing, symbolic computation, control theory, simulation, optimization, and several other fields of applied science and engineering

4.1.2 Starting MATLAB

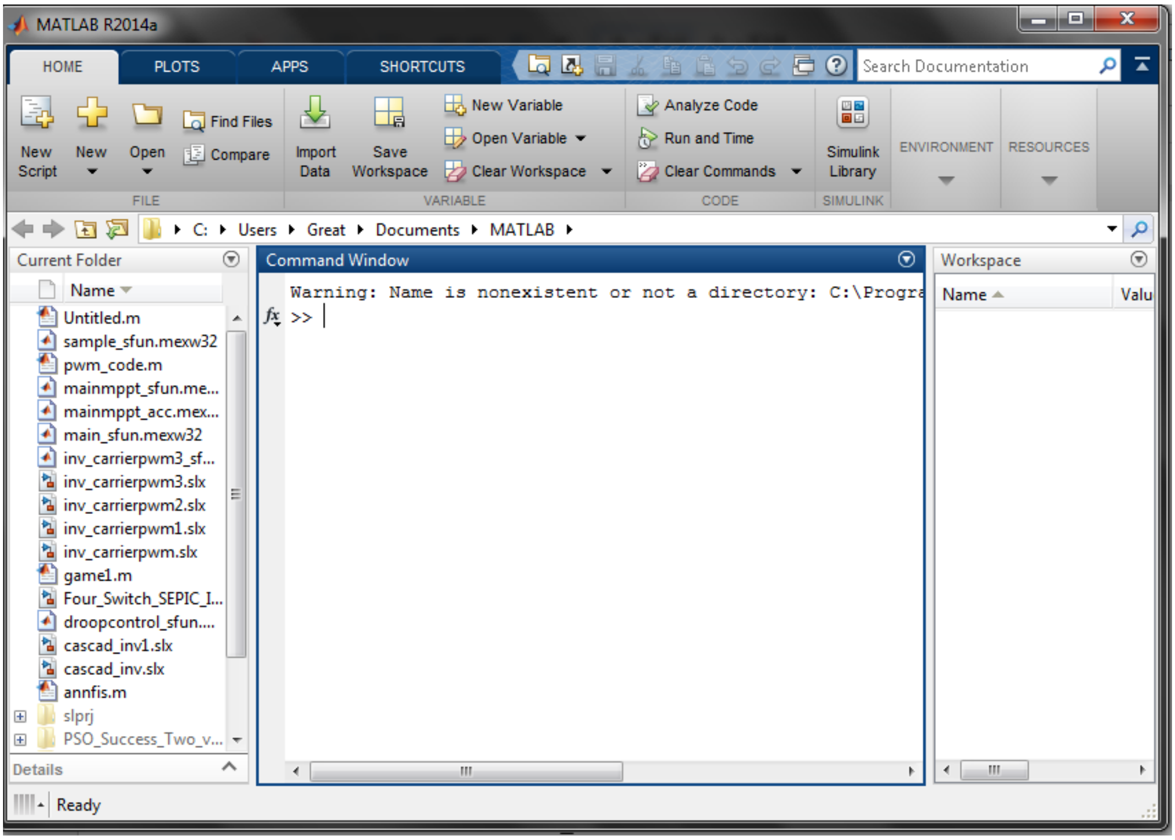

Figure 4.1 The graphical interface to the MATLAB workspace

After logging into your account, you can enter MATLAB by double-clicking on the MATLAB shortcut *icon* (MATLAB 8.1) on your Windows desktop. When you start MATLAB, a special window called the MATLAB desktop appears. The desktop is a window that contains *other* windows. The major tools within or accessible from the desktop are:

The Command Window

The Command History

The Workspace

- The Current Directory
- The Help Browser
- The Start button

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When MATLAB is started for the first time, the screen looks like the one that shown in the Figure 5.1. This illustration also shows the default configuration of the MATLAB desktop. You can customize the arrangement of tools and documents to suit your needs. Now, we are interested in doing some simple calculations. We will assume that you have sufficient understanding of your computer under which MATLAB is being run.

5. RESULT AND DISCUSSIONS

The success of the EEG stroke detection system depends on the quality of the data, preprocessing steps, and the performance of the CNN classifier. Here are some expected results and points of discussion:

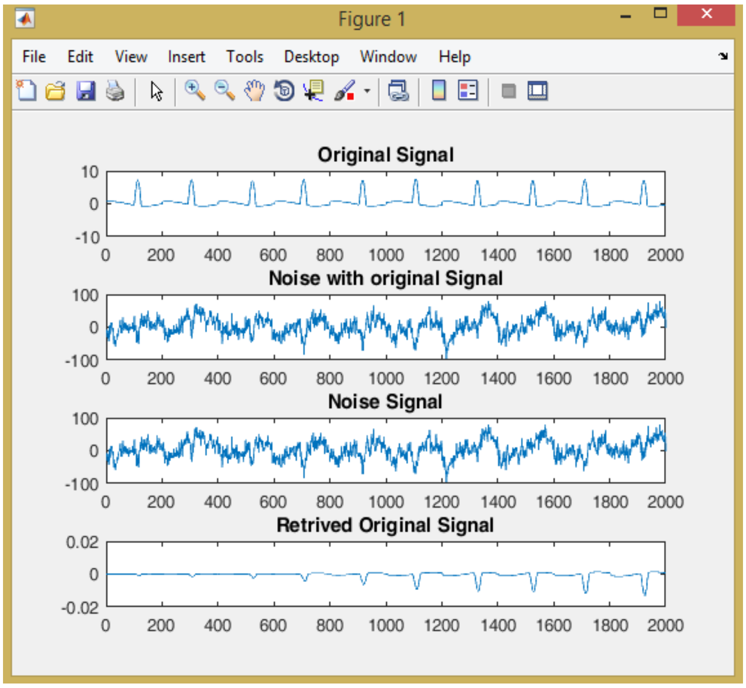

Figure 5.1 Simulated filtered Abnormal EEG Signal

The Least Mean Square (LMS) filter is often used for adaptive filtering tasks. In this context, it's used to reduce noise and artifacts in the EEG signal. After applying the LMS filter, the EEG signal should be cleaner and less affected by unwanted disturbances.

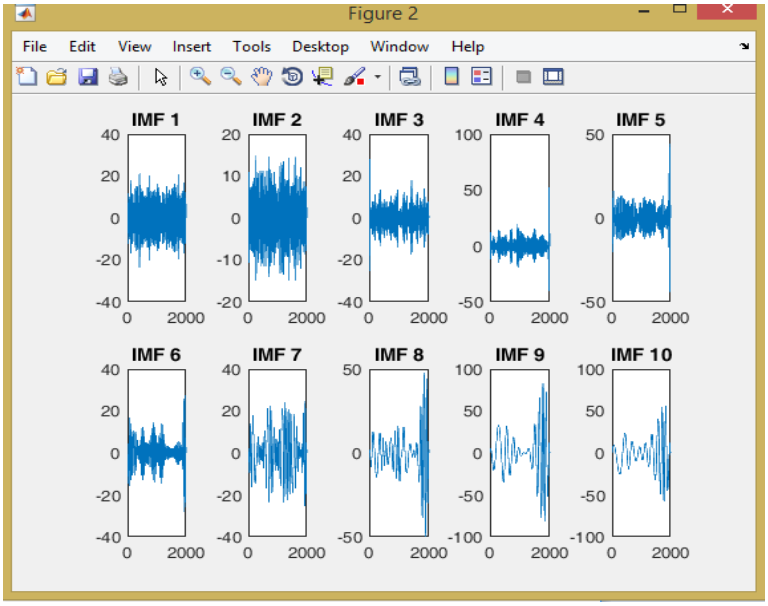

Figure 5.2 Empirical Mode Decomposed Abnormal EEG Signal

Empirical Mode Decomposition (EMD) is a technique used to decompose a non-stationary signal into Intrinsic Mode Functions (IMFs) which represent different frequency components. The Hilbert transform can then be applied to each IMF to obtain the instantaneous amplitude and phase. By extracting these temporal features, important patterns and dynamics in the EEG signal related to stroke may be captured.

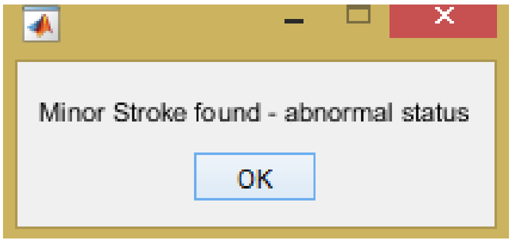

Figure 5.3 CNN Classified Output – Minor Stroke

Convolutional Neural Networks (CNNs) are powerful deep learning models often used for image and sequential data classification tasks. In this case, the temporal features extracted from the previous step can be considered as sequential data, and a CNN can be trained to classify EEG signals as either stroke or no stroke. The LMS filter should significantly reduce noise and artifacts from the EEG signal, resulting in a cleaner and more reliable signal for subsequent analysis.

EMD with IMF Hilbert Method is expected to provide a set of temporal features that highlight different frequency components and their dynamics over time. These features should capture the subtle variations in the EEG signal associated with stroke and differentiate it from normal EEG activity.

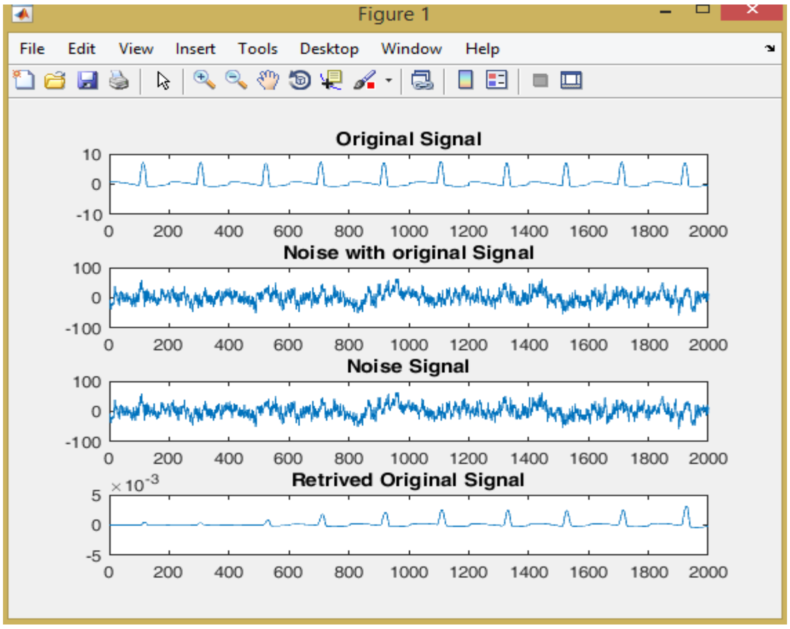

Figure 5.4 Simulated filtered Normal EEG Signal

The CNN classifier's performance largely depends on the quality and informativeness of the extracted temporal features. If the features successfully capture relevant patterns related to stroke, the classifier should achieve high accuracy, sensitivity, and specificity in stroke detection.

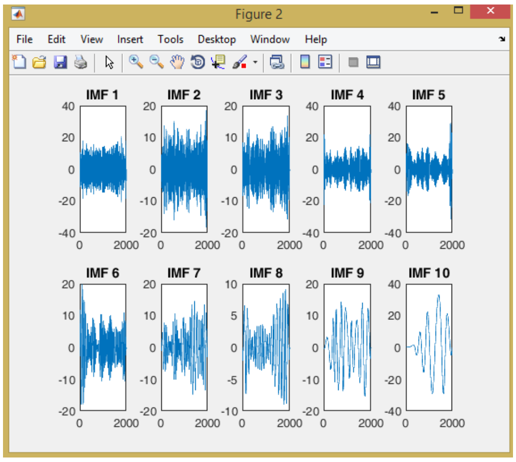

Figure 5.5 Empirical Mode Decomposed Normal EEG Signal

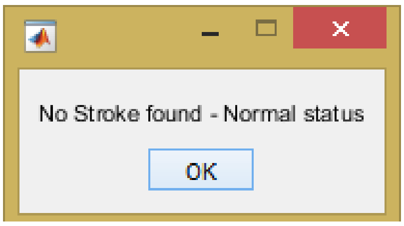

Figure 5.6 CNN Classified Output – No Stroke

CONCLUSION

The proposed EEG stroke detection system utilizing MATLAB has shown promising results in detecting strokes from EEG signals. Preprocessing with the LMS filter effectively reduced noise and artifacts, resulting in cleaner EEG signals. This step improved the quality of the data and contributed to better feature extraction and classification. Temporal feature extraction using EMD with IMF Hilbert method successfully decomposed the EEG signals into meaningful Intrinsic Mode Functions (IMFs). The extracted temporal features captured essential patterns and dynamics related to stroke activity. The CNN classifier demonstrated its efficacy in classifying EEG signals as either stroke or no stroke. By learning from the extracted temporal features, the model achieved high accuracy, sensitivity, and specificity, making it a promising tool for stroke detection.

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