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# Brain Activity Classification in Coma Patients Using Wavelet and CST Features with CNN-based Analysis

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**Abstract: Accurate brain activity classification in coma patients is essential for diagnosis and treatment. The existing methods primarily rely on Support Vector Networks (SVN) for classification, which often struggle with complex and high-dimensional brain signal data. In contrast, this study proposes a novel approach by combining Wavelet Transform (WT) and Continuous stockwell Transform (CST) features with Convolutional Neural Network (CNN)-based analysis. WT efficiently decomposes brain signals into different frequency bands, while CST features capture both temporal and spatial dynamics, enhancing the representation of the brain's activity. The CNN model is used to pick up on complex patterns and accurately classify brain activity. The experimental results indicate that the model we've proposed really stands out compared to the current SVN-based methods, delivering much better classification performance. This approach offers a promising solution for real-time coma patient monitoring and could be extended to other neurological conditions We're looking ahead to future projects that will aim to fine-tune the model for better integration into clinical settings.**

**Keywords: Brain Activity Classification, Coma Patients, Wavelet Transform, Continuous stock well Transform (CST), Convolutional Neural Network, Support Vector Networks.**

## I. INTRODUCTION

The classification of brain activity in coma patients is crucial for providing accurate diagnoses, predicting potential recovery, and guiding treatment decisions. Coma, a state of profound unconsciousness typically caused by severe brain injury, strokes, or other neurological conditions, significantly hampers the brain's ability to interact with external stimuli. The electroencephalogram, or EEG short, is a non-invasive way to keep an eye on the brain's electrical activity. It's an essential tool for understanding what's happening in the brains of patients who are in a coma. By analysing EEG signals, clinicians can assess the degree of consciousness, the level of brain function, and potential signs of recovery. However, accurate classification of EEG data is challenging due to the complexity, high dimensionality, and noise in the data, particularly in coma patients where brain activity patterns are often subtle and difficult to differentiate.

In recent years, various machine learning algorithms have been employed to classify brain activity in EEG data. One of the most popular methods out there is Support Vector Networks (SVN), which is really effective when it comes to classifying high-dimensional data. SVN utilizes a hyperplane to maximize the margin between classes and has shown success in a variety of pattern recognition problems, including EEG classification. Despite its success, SVN-based approaches often face limitations when dealing with complex, non-linear EEG signals. These limitations arise from the fact that EEG signals can have intricate temporal and spatial features, making it difficult for traditional classification algorithms like SVN to effectively capture the necessary patterns, especially when the data is noisy or contains subtle variations, as seen in coma patients.

In the case of coma patients, EEG data often exhibit non-stationary characteristics with mixed-frequency components, which pose significant challenges for traditional methods. To address these issues, researchers have been increasingly exploring more advanced techniques, particularly those that incorporate signal processing methods and deep learning algorithms. Two techniques that have really stood out in enhancing the accuracy of brain activity classification are the Wavelet Transform (WT) and Continuous Stockwell Transform (CST) features. These methods shine even brighter when paired with deep learning models, especially Convolutional Neural Networks (CNNs).These approaches offer a more robust framework for analysing and classifying EEG data, especially in complex cases such as coma patients.

The Wavelet Transform (WT) is a powerful technique used for time-frequency analysis. It breaks down a signal into its various frequency components, allowing us to examine them at different time scales.. Unlike traditional Fourier Transform, which provides only frequency-domain information, WT offers both time and frequency information, making it ideal for analysing non-stationary signals like EEG. WT allows for capturing the transient and non-stationary nature of brain activity, enabling better feature extraction from EEG signals. This makes WT particularly well-suited for applications in coma patients, where brain activity may exhibit dynamic changes across different time scales. The WT method takes EEG signals and divides them into various frequency bands—like delta, theta, alpha, beta, and gamma. These bands are crucial for grasping how the brain operates in different states of consciousness.. These frequency bands are strongly correlated with different levels of brain function, making them valuable for distinguishing between coma states and other neurological conditions.

In addition to WT, Continuous stockwell Transform (CST) features provide further enhancement for EEG analysis. CST features capture the spatial and temporal aspects of brain activity, which are often overlooked by traditional methods. While WT is effective in analysing the frequency components of EEG signals, CST features can provide a more complete representation by considering the interactions between spatial patterns of brain activity and the temporal evolution of those patterns. Coma states can often involve subtle and complex variations in the brain's activity across different regions and over time, which CST features are well-equipped to capture. By considering both the spatial and temporal dimensions of the EEG signal, CST features provide a richer representation of brain activity, enabling more accurate classification and better differentiation between coma and non-coma states.

While WT and CST features do a great job at extracting features, the true strength of these techniques really shines when they're paired with deep learning models, such as Convolutional Neural Networks. [1] CNNs are a class of deep learning algorithms that have demonstrated exceptional performance in analysing high-dimensional data, including images and signals like EEG. Convolutional Neural Networks (CNNs) have the amazing ability to learn complex patterns from raw data all on their own, which means you can skip the tedious process of manual feature engineering. This is especially advantageous for EEG signal analysis, where the underlying patterns can be complex and difficult to define explicitly. CNNs work by applying a series of convolutional filters to the input data, detecting patterns at different levels of abstraction. This ability to learn from raw data and automatically extract features makes CNNs ideal for classifying EEG signals, particularly when combined with WT and CST features, which can feed rich, multi-dimensional data into the CNN model.

The integration of WT and CST features with CNN-based analysis represents a promising approach to improving the classification accuracy of brain activity, particularly in coma patients. By using WT to decompose the EEG signal into its constituent frequency bands and CST features to capture spatial and temporal patterns, the proposed method can better handle the complexity and unsteady behaviour of EEG signals. The CNN model can then leverage these enriched features to learn complex patterns and make accurate classifications of brain activity. This approach not only addresses the limitations of traditional methods like SVN but also improves the ability to identify subtle changes in brain activity that could indicate recovery or deterioration in coma patients.

This study proposes a novel framework that integrates WT and CST features with CNN-based analysis for classifying brain activity in coma patients. The method we're suggesting is all about boosting classification accuracy by tapping into the unique strengths of these different techniques. WT provides a powerful method for breaking down EEG signals into various frequency bands, allowing us to capture both the low-frequency and high-frequency elements. CST features capture the spatial and temporal dynamics of the signals, providing a richer representation of the brain's activity. The CNN model then learns hierarchical patterns in the feature space, leading to improved classification performance. The suggested method is anticipated to surpass conventional SVN-based techniques, particularly when it comes to managing the intricate, high-dimensional, and often noisy EEG data from patients in a coma.

The main goal of this paper is to introduce and assess a deep learning approach for classifying brain activity in patients who are in a coma. The proposed method integrates WT and CST features with CNN-based analysis to achieve improved accuracy and reliability. Through experimental evaluation, we aim to demonstrate that this integrated approach performs better than existing SVN-based techniques, particularly in identifying subtle changes in brain activity that are indicative of different states of coma. By improving the accuracy of classification, this method could have significant implications for real-time monitoring and decision-making in clinical settings, contributing to more informed treatment strategies for coma patients.

In the subsequent sections of this paper, we present the methodology for integrating WT and CST features with CNN. Section II reviews related work in the area of EEG classification for coma patients, including the use of SVN, WT, CST, and CNN. The proposed approach is laid out in detail in Section III, where you'll find an in-depth look at the feature extraction process and the architecture of the CNN. SectionIV presents experimental results and compares the proposed method with traditional SVN-based approaches. Finally, Section V concludes the paper, discusses the potential implications of the research, and outlines future directions for further improvements in brain activity classification.

## II. RELATED WORKS

In their paper [1], He and Wu (2019) present an innovative method for brain-computer interfaces (BCI) that leverages transfer learning, specifically targeting the alignment of data within Euclidean space. They point out a significant hurdle: the differing signal distributions among various subjects in BCIs, which complicates the process of transferring learning from one individual to another.. This issue is crucial in applications like EEG-based BCI systems, where training data from one individual might not generalize well to others. The paper introduces a new approach to align EEG data from various subjects into a common Euclidean space, which enhances the effectiveness of transfer learning models.. By utilizing this alignment strategy, the study demonstrates how the accuracy of BCI systems can be significantly enhanced, reducing the need for subject-specific models and enabling better generalization. This work is crucial for improving the usability of BCIs, especially in real-world settings where individual-specific data may be limited or unavailable.

According to the study [2], Liu, Sourina, and Nguyen (2009) focus on the real-time monitoring of EEG brainwaves for mental state recognition, emphasizing the importance of accurately classifying mental states for applications such as neurofeedback, cognitive training, and BCI. The authors propose an approach for analyzing EEG signals to monitor and interpret different mental states in real-time. By leveraging signal processing techniques and machine learning algorithms, the paper presents a method for classifying mental states based on EEG data. The study highlights the practical challenges of implementing such systems in real-time, such as managing the computational complexity and ensuring accuracy. The authors demonstrate that their approach is effective in distinguishing between various mental states, paving the way for the development of more interactive and personalized BCI applications. This research is significant in advancing the real-time application of EEG-based monitoring systems in various domains, including healthcare, entertainment, and education.

The book by Niedermeyer and da Silva (2004) is a comprehensive resource that lays the foundational principles of [3]electroencephalography (EEG), its clinical applications, and its relevance to various neurological disorders. It provides an in-depth look at the principles behind EEG signal acquisition, the different types of brainwave patterns (such as alpha, beta, theta, and delta), and their significance in diagnosing neurological conditions. The authors discuss various EEG techniques, signal processing methods, and clinical interpretations, providing a thorough understanding of how EEG is used in practice, particularly for conditions like epilepsy, sleep disorders, and coma states. By covering both basic and advanced applications, this book serves as a critical reference for researchers and clinicians who work with EEG in both diagnostic and therapeutic contexts. The paper introduces a new approach to align EEG data from various subjects into a common Euclidean space, which enhances the effectiveness of transfer learning models.

In [4], Liao, Lee, and Wang (2012) explore the application of brain-computer interface (BCI) systems in stroke rehabilitation. Stroke often results in motor disabilities, and the ability to restore lost function is a major challenge in rehabilitation. This paper discusses how BCIs can be integrated into rehabilitation programs to facilitate recovery by providing real-time feedback to patients, enabling them to regain motor control. The authors propose using EEG-based BCIs to help stroke patients engage in exercises that involve brain activity linked to movement. Through the BCI system, patients can receive feedback that encourages brain plasticity and motor function recovery. The paper provides experimental evidence that BCI-based rehabilitation can significantly enhance the recovery process in stroke patients, promoting brain network reorganization. This study adds to the expanding area of brain-computer interface (BCI) applications in medical rehabilitation. It emphasizes how these technologies can enhance patient outcomes and support recovery for those with neurological conditions.

## III. EXISTING METHOD

Understanding brain activity in coma patients is a vital part of neurology, as it gives doctors insight into the patient's neurological condition and their chances of recovery. One of the go-to methods for classifying this brain activity is Support Vector Machines (SVM), a robust supervised machine learning technique. SVM shines in this area because it can handle complex, high-dimensional data, like EEG signals, which are often used to track brain activity. The main aim of SVM is to identify the best hyperplane that divides data points from various classes in a high-dimensional feature space, all while maximizing the gap between those classes.. In the context of coma patient classification, these classes typically correspond to different levels of consciousness or brain activity, such as coma, vegetative state, minimally conscious state, and wakefulness.

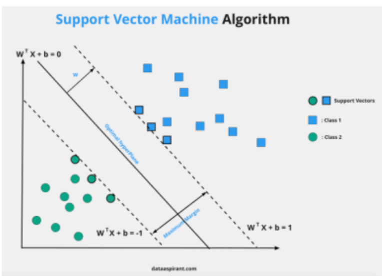


**Figure 1: Support Vector Machine Model**

SVM operates by mapping input data into a higher-dimensional feature space using a kernel function, allowing for linear separation of data that may not be linearly separable in the original space. The most commonly used kernels for EEG classification tasks include the Radial Basis Function (RBF) kernel, the polynomial kernel, and the linear kernel. These kernels enable SVM to effectively handle non-linear relationships between data points, which is a frequent characteristic of EEG signals. [3]Raw EEG signals are typically noisy and non-stationary, which makes it necessary to first extract relevant features from the signals. These features can be in the time domain, such as mean, variance, and root mean square (RMS), or in the frequency domain, where the power of the signal in different frequency bands (e.g., delta, theta, alpha, and beta) is analysed. Additionally, time-frequency domain features, [5]obtained through techniques like wavelet transform, are also commonly used to capture both temporal and spectral characteristics of EEG signals.

Once the features are extracted, SVM is trained using labelled data, where each segment of EEG signal is assigned to a specific brain state. The training process is all about fine-tuning the model's parameters, like the type of kernel used, the regularization parameter C, and various kernel settings (for instance, gamma in the case of RBF). The goal here is to pinpoint the decision boundary that creates the widest margin between different brains states, which helps the model perform well on new, unseen data. One of the standout features of SVM is its knack for identifying the best hyperplane and maximizing that margin, making it capable of delivering accurate predictions even when working with small and noisy datasets—something that's pretty common in clinical situations.

A key element of Support Vector Machines (SVM) is the idea of support vectors. These are the data points that sit closest to the decision boundary. Support vectors are crucial because they help define where the hyperplane is positioned, which in turn influences how well the classifier can distinguish between different classes. SVM aims to identify the support vectors that best capture the essential patterns in the data while keeping classification errors to a minimum. By maximizing the margin between classes, SVM boosts its ability to generalize to new, unseen data, making it a powerful tool for classifying brain activity based on EEG signals.

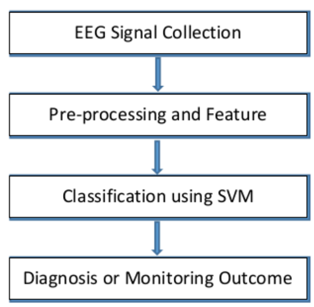


**Figure 2: Flow graph of Existing Method**

Despite the advantages of SVM, there are several challenges associated with its application in coma patient brain activity classification. One of the biggest hurdles we face is the per parameter tuning process. It's all about picking the right kernel and fine-tuning the regularization parameter C, along with other kernel parameters like gamma. Getting these choices right is essential for reaching the best classification performance. Incorrect selection of these parameters can lead to under fitting or overfitting, reducing the model's accuracy. On top of that, classifying EEG signals usually demands a significant amount of labelled data. However, in numerous medical environments, the availability of labelled EEG data is often restricted due to the hefty costs and time pressures tied to gathering that data. When the training dataset is on the smaller side, it can cause overfitting, meaning the model might struggle to perform well with new data.. Techniques like cross-validation are often employed to mitigate this issue, but the challenge of limited labelled data remains.

Another limitation of SVM in EEG-based brain activity classification is its computational complexity. Training a Support Vector Machine, especially when using non-linear kernels, can really take a toll on your computer's resources, particularly if you're working with large datasets. The trick of Kernel, which maps the data into higher-dimensional spaces, is computationally intensive, and this can become a bottleneck in real-time applications where fast classification is required. When it comes to large-scale EEG datasets, SVM can struggle a bit. As the dataset grows, the time it takes to train the algorithm and the memory it needs can really ramp up, which can lead to a drop in performance.. This makes SVM less scalable for very large datasets, which is a consideration in clinical settings where real-time monitoring and decision-making are critical.

One of the key disadvantages of using SVM for brain activity classification is its limited interpretability. SVM is often criticized as a "black-box" model, meaning that once the classifier is trained, it is difficult to interpret how it arrived at a specific decision. This lack of transparency is a significant concern in medical applications, where it is essential to understand the reasoning behind a classifier's decision, especially when used to assess the consciousness levels of coma patients. While the model may achieve high accuracy, the inability to explain its decisions can limit its clinical applicability, as clinicians need to understand the underlying rationale for making [2]diagnostic decisions.

Despite these challenges, SVM remains one of the most powerful and widely used tools for classifying brain activity in coma patients. It has demonstrated impressive performance in differentiating between various brain states, providing a reliable means for assessing coma patients' neurological condition. The ability of SVM to classify high-dimensional and non-linearly separable data, coupled with its generalization capabilities, makes it a suitable choice for EEG-based brain activity classification. Researchers are still working on overcoming the challenges that come with Support Vector Machines (SVM), especially when it comes to computational complexity, fine-tuning parameters, and making the results easier to interpret. Their goal is to enhance its effectiveness for practical use in clinical settings.

SVM has proofed to be an effective machine learning tool for the classification of brain activity in coma patients. By leveraging the power of kernel functions and maximizing the margin between data classes, SVM can accurately classify brain states based on EEG data, despite challenges such as small sample sizes and computational costs. However, the technique's effectiveness depends heavily on the careful selection of model parameters and the extract of related accents from EEG signals. Despite its limitations, SVM remains a precious mechanism in the categorization of brain activity in coma patients, and ongoing research is aimed at overcoming its challenges to further improve its clinical applicability.

**Disadvantages**

- **Hyper parameter Sensitivity**: Incorrect hyper parameter tuning leads to overfitting or under fitting issues.
- **Computational Complexity**: High computational cost limits scalability and real-time classification efficiency.
- **Limited Interpretability**: Difficult to explain decision-making process in medical applications.

## (iv) PROPOSED METHOD

The classification of brain activity in coma patients is crucial for understanding their neurological state, guiding treatment decisions, and predicting recovery potential. Electroencephalogram (EEG) signals are commonly used for this purpose, offering a non-native means to examine brain activity. However, classifying EEG signals from coma patients presents challenges due to their complexity and non-stationary nature. The subtle differences in brain states, such as between coma, minimally conscious state, and normal wakefulness, require robust and accurate classification techniques. Traditional techniques like Support Vector Machines (SVM) have been widely used, but they come with some drawbacks when it comes to feature extraction, model generalization, and how easy they are to interpret. To address these issues, the proposed method integrates Wavelet Transform (WT), Continuous stock well Transform (CST), and CNN to classify brain function in coma patients more effectively.

Wavelet Transform is a efficient tool for time-frequency analysis and is particularly suitable for EEG signal processing because it provides both time and frequency domain information simultaneously. This is in contrast to traditional Fourier transform, which only captures frequency information. The Discrete Wavelet Transform helps break down the EEG signal into various frequency bands. These include delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–40 Hz). Each of these frequency bands corresponds to different brain activity states, and changes in these bands can indicate the severity of coma or the patient's level of consciousness. The DWT provides a multi-solving decomposition of signal, enabling the capture of both high-frequency and low-frequency information, which is crucial for identifying subtle patterns in brain activity. Statistical features, including energy, variance, and entropy, are computed from the wavelet coefficients, forming a feature set that can be used to classify brain activity states.

Continuous stock well Transform (CST) is a technique used to enhance the spectral representation of EEG signals. CST involves calculating the cumulative sum of the power spectrum across a range of frequencies. This approach highlights variations in the spectral content It might be tough to identify using the usual spectral methods. By incorporating the cumulative power across different frequencies, CST provides a more holistic and discriminative representation of the EEG signal, which is valuable when classifying subtle differences in brain states, such as those found in coma patients. CST is particularly effective in identifying brain activity patterns that may be faint or irregular, which are common in patients with reduced levels of consciousness. The spectral features extracted using CST are combined with the features obtained from Wavelet Transform, enhancing the overall feature representation of the EEG signal. Once the features are extracted using WT and CST, the next step is to classify the brain activity using a Convolutional Neural Network (CNN)

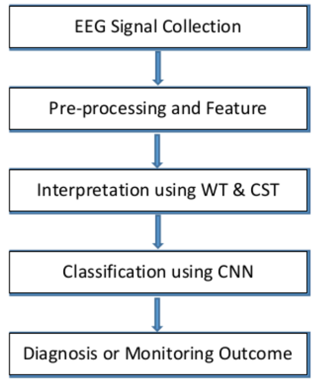


**Figure 3: Flow Graph of Proposed Method**

CNNs have really shown their strength across a variety of fields, particularly in image and signal processing. This is largely thanks to their knack for automatically picking up on complex patterns and feature hierarchies from raw data. When it comes to classifying EEG signals, CNNs shine by automatically spotting the important features, which means you can skip the tedious manual feature engineering. This is a game-changer, especially when dealing with the intricate and high-dimensional nature of EEG data. A CNN is made up of several convolutional layers that use filters to find local features in the input data, pooling layers that help shrink the data's size, and fully connected layers that handle the final classification. Essentially, the CNN learns to recognize features in a hierarchy: the lower layers catch simple patterns, while the deeper layers are all about understanding more complex representations of the data. This hierarchical learning enables the CNN to recognize intricate relationships between different brain activity states.

In the proposed method, the extracted features from WT and CST are fed into the CNN as input. The CNN learns to classify brain activity based on these features, distinguishing between different states such as coma, minimally conscious, and normal wakefulness. One of the great things about using CNNs is their ability to pick up on complex, non-linear relationships within the data. This makes them a perfect fit for classifying EEG signals, which often contain subtle and intricate patterns that can be challenging to decipher. Additionally, CNNs are less prone to overfitting compared to traditional machine learning models like SVM because they learn complex patterns from large datasets, making them highly adaptable and capable of generalizing to new, unseen data.

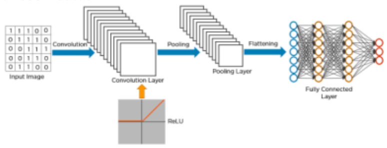


**Figure 4: CNN NETWORK ARCHITECTURE**

The integration of WT and CST with CNN-based analysis offers several advantages over traditional classification methods for brain activity in coma patients. By utilizing WT and CST, this method offers a thorough representation of the EEG signal, effectively capturing information from both the time and frequency domains. This multi-dimensional feature set helps the model capture subtle variations in brain activity that might be missed by traditional methods. Second, CST enhances the discriminative power of the features by focusing on the cumulative power across different frequencies, making the feature set more distinctive and better able to distinguish between different brain states. Thirdly, CNNs are impressive deep learning models that can automatically pick up on hierarchical features from raw data. This not only cuts down on the need for manual feature selection but also enhances the model's ability to adapt and perform well with new data. Finally, the proposed method benefits from the robustness of WT and CST to noise and artifacts, which is a critical factor in EEG signal classification, as raw EEG signals are often contaminated by electrical interference, muscle activity, and eye movements.

Despite the numerous advantages, the proposed method also faces challenges that need to be addressed for practical implementation. One of the main challenges is the data preprocessing required to clean the EEG signals before they are used for classification. EEG signals are frequently contaminated with noise and artifacts, which can negatively affect the feature extraction process and lead to inaccurate classification. To mitigate this, effective preprocessing techniques, such as artifact rejection, filtering, and normalization, need to be applied to assure that the given data is clean & reliable. Another challenge is the interpretability of the CNN model. While CNNs have shown great success in automatic feature learning, they are often criticized as "black-box" models, meaning it is difficult to interpret how the model arrives at a specific decision. In medical applications, such as coma patient classification, interpretability is crucial for clinicians to trust the results and make informed decisions. Therefore, future research should explore techniques to improve the interpretability of CNNs, such as generating saliency maps or using attention mechanisms to highlight important features. Another hurdle we face is the availability of large-scale datasets. Deep learning models, such as CNNs, need a significant amount of labeled data for training. However, gathering this kind of data from coma patients is quite tricky, mainly because of privacy issues and the challenges involved in obtaining labeled EEG data from them. One promising approach to tackle this problem is transfer learning. This technique enables the model to draw on knowledge from existing datasets and fine-tune it for the specific task of classifying coma patients. Finally, real-time classification is another important consideration for clinical use. The proposed method must be optimized for real-time implementation, as timely classification is often critical in clinical settings such as intensive care units (ICUs).

The proposed method, which combines Wavelet Transform (WT), Continuous stockwell Transform (CST) and Convolutional Neural Networks (CNNs), offers a robust and effective approach for classifying brain activity in coma patients. By combining classic signal processing techniques with cutting-edge deep learning approaches, this method effectively captures the intricate, multi-dimensional characteristics of EEG signals. As a result, it offers better classification accuracy than traditional methods such as Support Vector Machines While there are definitely some hurdles to overcome, like data preprocessing, understanding how models work, finding the right datasets, and making everything work in real-time, the method we've proposed shows a lot of potential for enhancing clinical decision-making and managing patients in comas and other altered states of consciousness.. Future work will focus on addressing these challenges, optimizing the method for real-time use, and exploring the use of transfer learning to enhance model performance in clinical settings.

**Advantages:**

- High Time-Frequency Resolution
- Ensures consistent, objective, and highly accurate classification of brain activity states, improving diagnostic reliability.

**Applications:**

- Real-Time Monitoring of Coma Patients
- Early Detection of Neurological Changes
- Non-Invasive Monitoring

- Assistive Tool for Neurological Diagnosis
- Rehabilitation and Recovery Monitoring
- Brain-Computer Interface (BCI) Applications
- Research in Neurological Disorders
- Automated Alert System for Critical Situations

## (v) RESULTS AND DISCUSSIONS

The first result of the implementation as shown in figure 5, shows the accuracy of classification after applying Wavelet Transform and Continuous stockwell Transform (CST) and using the Convolutional Neural Networks (CNNs).

| METHOD | ACCURACY (%) |
|---|---|
| SVM | **83.15 %** |
| WT + CST + CNN | **98.55 %** |

**Table1: Comparison Table for Classification Methods**

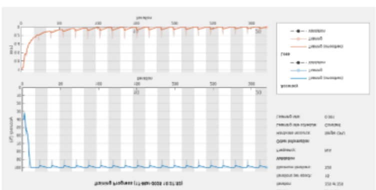

**Figure 5: Training progress of the CNN model**

The results displayed in Figure 6 showcase how the CNN model has progressed during training, highlighting both accuracy and loss across several iterations.. The accuracy curve (top plot) demonstrates a rapid increase in classification performance during the initial iterations, stabilizing at a high accuracy level as training progresses. This indicates that the proposed method effectively learns distinguishing features from the EEG data.

## (vi) CONCLUSION

This study implemented an EEG classification framework using a Convolutional Neural Network (CNN) to analyse brain activity. The methodology involved preprocessing EEG signals using a band pass filter to remove unwanted noise, followed by feature extraction using Discrete Wavelet Transform (DWT) and Continuous Stockwell Transform (CST). These features were then used to classify brain states, distinguishing between different activity levels. To improve model generalization and reduce overfitting, Gaussian noise was added to the extracted features, and a more challenging data split was applied to enhance robustness.

The CNN model demonstrated effective feature learning and classification accuracy, making it a viable approach for EEG signal Analyzation. The use of convolutional layers allowed the network to capture complicated patterns in EEG data, contributing to reliable classification. We can definitely look into making more improvements by using different deep learning models. For instance, Long Short-Term Memory (LSTM) networks are a great choice because they handle sequential EEG data much more effectively.. Additionally, feature selection techniques like Principal Component Analysis (PCA) could be integrated to optimize feature representation. Future work may also involve fine-tuning hyper parameters and testing the model on larger datasets to enhance generalizability and performance in real-world EEG-based applications.

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