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Multidomain Wavelet–CST Representation for Deep Learning Classification of Coma Brain Signals

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Abstract: For diagnostic and treatment purposes brain activity in comatose patients must be accurately classified. Existing classification method use Support Vector Machines that often cause problems in processing high-dimensional and complex brain signal data. On the other hand this study proposes a new method by integrating Convolutional Neural Network(CNN)-based analysis with features of Wavelet Transform(WT) and Continuous Stock well Ttransform(CST). While CST functions to capture spatiotemporal dynamics improving the representation of brain activity, WT effectively divides brain signals into multiple frequency bands and CNN model is used to classify brain activity and detect complex patterns. Experimental results show that our proposed model performs much better in classification than SVM-based techniques. This method appears promising for real-time monitoring of comatose patients and may be extended to other neurological disorders. We anticipate upcoming initiatives that will attempt to improve the integration of the model into the clinical setting.

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

I. INTRODUCTION

Classifying the brain activity of comatose patients is essential for making an accurate diagnosis, predicting their chances of recovery, and guiding treatment options. The brain's ability to respond to external stimuli is severely impaired in a coma, a state of deep unconsciousness usually caused by severe brain injury, stroke, or other neurological disorders. The electrical activity of the brain can be monitored non-invasively using an electroencephalogram, or EEG for short—an indispensable tool for understanding the brain activity of comatose patients. By analyzing electroencephalogram data doctors can assess brain function level of consciousness and possible indicators of recovery. Electroencephalogram data are complex high-dimensional and, noisy making their accurate classification difficult. This is especially true in comatose patients whose brain activity patterns are often subtle and difficult to detect.

It's difficult to use standard techniques because EEG data from comatose patients often contain non-stationary features and mixed-frequency components. More advanced approaches to solving these problems have attracted more attention among researchers especially those using deep learning algorithms and signal processing techniques. The continuous Stockwell transform and the wavelet transform techniques that have proven particularly successful in improving the classification of brain activity. Convolutional neural networks are deep learning models that enhance the effectiveness of these methods. In complex cases such as comatose patients these techniques provide a more reliable framework for evaluating and classifying EEG data.

One of the effective methods of time-frequency analysis is the wavelet transform. It, allows the signal to be analysed on multiple time scales by splitting it, into multiple frequency components. WT is ideal for analyzing non-stationary signals such as EEG as it provides time and frequency information unlike the standard Fourier transform that only provides frequency domain information. The ability of WT to capture the periodic and non-stationary nature of brain activity allows better feature extraction from EEG signals. WT is particularly suitable for the treatment of comatose patients whose brain activity may fluctuate dynamically at times. EEG signals are divided into different frequency bands using the WT method such as delta theta alpha beta and gamma bands. To understand how the brain works in different states of consciousness it's necessary to understand these areas. These frequency bands are useful for distinguishing between comatose states and other neurological diseases because they are closely related to different levels of brain activity.

For example, EEG analysis is further enhanced by the continuous Stockwell transform as well as WT properties. Conventional approaches often ignore the spatiotemporal dimensions of brain activity captured by CST features. WT is useful for analyzing the frequency components of EEG signals, but considering the correlations between spatial patterns of brain activity and the temporal evolution of these patterns, CST properties can provide a more comprehensive representation. Coma states sometimes produce subtle and complex changes in brain activity over, over time and across multiple regions that CST properties are amenable to recording. CST functions provide a richer picture of brain activity by taking into account the spatial and temporal dimensions of the EEG signal. This allows for more accurate classification and better separation of coma, coma and no comatose states.

Although WT and CST excel at feature extraction, their full potential is revealed when combined with deep learning models such as convolutional neural networks. Deep learning algorithms, known as CNNs, have shown impressive results in analyzing high-dimensional data such as signals and images. The tedious process of manually designing features can be avoided as convolutional neural networks are well suited to automatically recognize complex patterns from, from raw data. You know what? This is particularly useful when analyzing electroencephalogram (EEG) signals, where the underlying patterns can be complex and difficult to clearly identify. CNNs identify patterns at different levels of abstraction by applying a series of convolutional filters to the input data. You, know what? This ability to, learn from raw data and extract features makes CNNs suitable for EEG signal identification, especially when combined with WT and CST features that can input rich multidimensional data into a CNN model.

This strategy not only overcomes the drawbacks of traditional techniques such as SVM, but also improves the detection of subtle changes in brain activity that may indicate recovery or remission in comatose patients.

This study proposes a unique framework for classifying brain activity in comatose patients that combines CNN-based analysis with WT and CST features. Seriously, our proposed approach is based on taking advantage of these multiple approaches to improve the classification accuracy. Yes, WT provides an efficient technique to split EEG signals into different frequency bands, allowing us to capture high and low frequency components. A more comprehensive picture of brain activity is provided by the characteristics of CST, that records the temporal and spatial dynamics of the signals. Seriously, the better classification performance is the, result of the CNN model later learning the hierarchical patterns of the feature space. The proposed approach is expected to outperform traditional SVM-based methods, especially in dealing, with complex, high-dimensional, and often noisy EEG data from comatose patients.

The primary goal of this paper is to present and evaluate a deep learning method for classifying brain activity in COMATOSE patients. To increase accuracy and reliability, the proposed approach combines CNN-based analysis with WT and CST features. We aim to show through experimental evaluation, this integrated approach outperforms SVM-based techniques, especially when detecting small variations in brain activity that indicate different comatose states. This approach may have important implications for real-time monitoring and clinical decision-making by increasing classification accuracy, leading to better treatment plans for comatose patients.

In the following sections, we describe the process of integrating the CNN, WT and CST functions. Use of SVM, WT, CST, and CNN in the EEG classification of comatose patients in II. The III. section provides a detailed explanation of the proposed methodology, including a detailed examination of the CNN architecture and feature extraction procedures. The experimental results and the comparison between the proposed method and traditional SVM-based techniques are presented in Section IV. Section V the conclusion of the study, deals with the possible implications of the research and suggests further development of the classification of, brain activity.

II. RELATED WORKS

He and Wu (2019) present a novel approach to brain-computer interfaces using transfer learning [1], focusing on matching data in Euclidean space. A major obstacle has been identified: the distribution of signals at face-to-face interfaces is different between different people, that makes it difficult to transfer knowledge from one person to another. This issue is critical in applications such as EEG-based BCI systems, where training data from one person may not generalize well to another. To improve the transfer efficiency of learning models, this paper presents a new method for fitting EEG data from different subjects, into a common Euclidean space. The, work shows that this alignment approach can significantly improve the accuracy of a BCI system, eliminate the need for subject-specific models, and promote better generalization. Seriously, Seriously, this work is essential to, improve the usability of brain-to-brain interfaces (BCIs), especially in real-world situations where access to an individual's data is limited or non-existent.

According to the study [2], the need to correctly identify mental states for applications such as neurofeedback, cognitive training, and brain-computer interfaces was emphasized by Liu, Sorina, and, Nguyen (2009), who focused on real-time monitoring of brain waves in EEG to classify mental states. The authors propose a method for real-time monitoring and interpretation of different mental states by analyzing EEG waves. The research presents a, method for classifying mental states, from EEG, data using machine learning algorithms and signal processing techniques. Seriously, do you know the study highlights the difficulty of managing computational complexity and ensuring accuracy in real-time implementation of such systems. do you, knownIn order to create more interactive and personalized BCI applications, the authors showed that their approach works well in distinguishing between different mental states. The development of real-time EEG-based monitoring system applications in a, bunch of fields such as healthcare, entertainment, and education will greatly benefit from this research.

The book by Niedermeier and da Silva (2004) is a comprehensive resource that explains the principles [3] of EEG, its clinical applications, and its relevance to various neurological disorders. Provides a comprehensive examination of the basics of EEG signal acquisition, the different types of, brain wave patterns (including alpha, beta, theta, and delta signals), and their importance in the diagnosis of neurological disorders. The, authors provide a detailed overview of the practical application of EEG, particularly in diseases such as epilepsy, sleep disorders, and comatose states, discussing various EEG procedures, signal processing methods, and clinical interpretations. guess? And oh yeah, covering both basic and advanced applications, the, book is an essential resource for academics and clinicians who use EEG in, both diagnostic and therapeutic settings. The study improves the efficiency of transfer learning, models by introducing a new method for aligning EEG data from different subjects into a common Euclidean space.

And oh yeah, Similar to [4], Liao, Lee and Wang (2012) investigated the use of brain-computer interface devices in stroke rehabilitation, Motor impairments after stroke is common, and one of the biggest challenges in rehabilitation is regaining lost functions. To aid patient recovery by providing real-time feedback and restoring motor control, this research examines how brain-computer interfaces can be used in rehabilitation programs. Guess what? The authors suggest that using electroencephalography-based cognitive brain interfaces, stroke patients may benefit from activities that involve movement-related brain activity. Patients can receive input from a BCI, system that enhances brain plasticity and restores motor function. The study provides experimental evidence that BCI-based rehabilitation can significantly accelerate the recovery of stroke patients by stimulating the reorganization of their brain networks. The, field of brain-computer interface applications in medical rehabilitation is growing, and this study contributes to this. Emphasizes how these techniques can improve patient outcomes and aid the recovery of those with neurological diseases.

III. METHODOLOGY

Classification of the brain activity of comatose patients is essential for understanding, their neurological condition, guiding treatment options, and predicting their chances of recovery. For example, electroencephalography (EEG) signals are often used to provide a non-invasive way to monitor brain activity. However, because the EEG patterns of comatose patients are, complex and unstable, their classification can be difficult. Robust and accurate classification algorithms are needed due to small changes in brain, brain states, such as between coma, minimal consciousness, and normal wakefulness. Although widely used, traditional methods such as Support Vector Machines have limitations in feature extraction, model generalization, and interpretability. For example, the proposed approach combines CNN, wavelet transform, and continuous wavelet transform to more accurately classify the brain functions of comatose patients and solve these problems.

Since the wavelet transform simultaneously provides information in the time and frequency domain, it’s an effective tool for time-frequency analysis and is particularly suitable for processing EEG signals. The traditional Fourier transform only records frequency information; It's the opposite. The division of EEG, data into different frequency bands is supported by discrete wavelet transformation., These include theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), gamma (30-40 Hz) and, delta (0.5-4 Hz). A patient's level of consciousness or coma severity can be determined based on differences in these frequency bands, each of that is associated with different states of brain activity. Seriously, the multi-resolution signal analysis provided by DWT allows, allows the recording of high and low frequency data, that is essential for viewing subtle patterns of brain activity. Statistical parameters such as energy, variance, and entropy are calculated from the wavelet coefficients to create a, feature set that can be used to classify states of brain activity.

For example, wavelet transform and continuous, stack is used to improve the spectral representation of EEG signals. Like, CST calculates the cumulative sum of the, power spectrum within a frequency range. This method draws attention to differences in spectral content. Yes, it can be difficult to detect using standard spectroscopic techniques. CST provides a more comprehensive and differentiated representation of the EEG signal by integrating the cumulative energy over multiple frequency ranges. This is useful in classifying subtle changes in brain states, such as those seen in coma, Brain activity in patients with reduced consciousness often shows, subtle or irregular patterns, that CST is particularly good at detecting. The global feature representation of the EEG signal is improved by combining the spectral data recovered, with CST and the features derived from the wavelet transform. do you know After feature extraction using WT and CST, a convolutional neural network is used to classify brain activity.

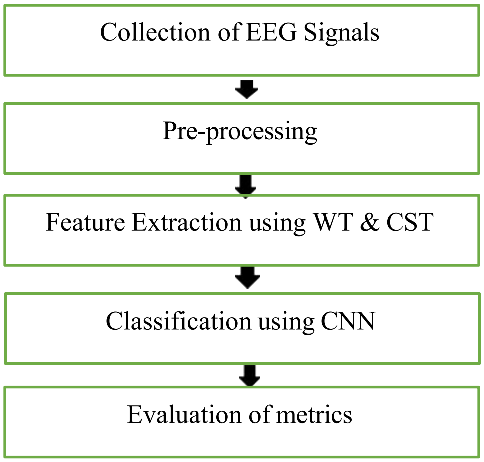


Figure 1: Flow of Proposed Method

CNNs have proven to be very effective in a bunch of fields, especially in signal and image processing. do you know Part of this is their ability to automatically recognize complex patterns and feature hierarchies from raw data. CNNs excel at classifying EEG data because they automatically identify key features, saving you from the time-consuming, task of manual feature design. Like, is revolutionary, especially when dealing, with the complex and high-dimensional nature of EEG data. multiple convolutional layers use filters to identify local features in the input data, pooling layers help reduce the amount of data, and fully connected layers handle the final classification in CNN. Essentially, CNN learns how to identify features in a hierarchical manner, where the, deeper layers focus on understanding more complex representations of the input, while the lower layers identify simple patterns. Thanks to hierarchical learning, CNNs are able to identify complex relationships between different states of brain activity.

The features retrieved from WT and CST are fed into the CNN as input to the proposed technique. For example, based on these features, a CNN learns to classify brain activity and distinguish, between different states, including coma, simple consciousness, and regular wakefulness. The ability of CNNs to identify complex non-linear relationships in data is one of their biggest advantages. They are therefore ideal for classifying electroencephalographic signals that often contain complex and subtle patterns that are difficult to interpret. Also, because CNNs detect complex patterns from large datasets, they are less susceptible to overfitting than traditional machine learning models such as SVM. You know what? This makes them very flexible and able to generalize to new, unseen data.

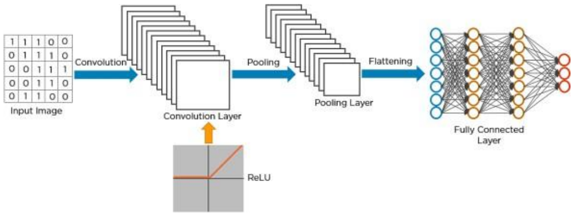


Figure 2: CNN NETWORK ARCHITECTURE

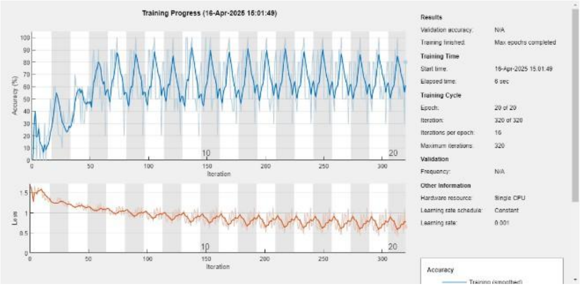
WT and CST are often combined with CNN-based analysis, that has a bunch of advantages, over traditional classification techniques of brain activity in comatose patients. This technique enables comprehensive imaging of the electroencephalographic signal using WT and CST, efficiently collecting data from both the frequency and temporal domains. Thanks to the model's multidimensional feature set, it’s better able to capture subtle changes in brain activity, that traditional techniques may miss. Second, by focusing on the cumulative power of a bunch of frequencies, CST improves the discriminative power, power of features, making the set of features more distinguishable and better able to discriminate between different brain states. Third, CNNs automatically recognize hierarchical patterns in raw data, making them excellent models for deep learning. Seriously, this improves the model's ability to adapt and work well with new data while reducing the need for manual feature selection. And oh yeah, Finally, since raw EEG data are often contaminated by electrical interference, muscle activity, and eye movements, the proposed method takes advantage of the robustness of WT and CST against noise and artifactsThis is an important aspect in the classification of EEG signals.

Like, despite its a bunch of advantages, the proposed approach has some, some drawbacks that need to be addressed for real-world application. The preparation of the data necessary for the cleaning of the EEG signals before they, they are used for classification is a significant disadvantage. Noise and artifacts are commonly found in electroencephalography signals, that can degrade feature extraction and lead to incorrect classification. Effective pre-processing techniques such as filtering, normalization and artifact rejection should be used to minimize this and ensure the accuracy and clarity of the data provided. Another difficulty is the interpretability of the CNN model. Like, CNNs, CNNs are sometimes criticized for being “black box” models, making it difficult to understand how a model, model arrives at a particular result, despite their impressive performance in automatic, feature learning. Interpretability is essential for, medical applications such as triage of comatose patients so that clinicians can trust the results and make wise decisions., Future studies should therefore explore ways to improve the interpretability of CNN, such as creating emphasis maps or emphasizing important features through attentional mechanisms. Availability of comprehensive datasets is another challenge we face. And oh yeah, CNNs and other deep learning models require large amounts of labeled data for training. Seriously, However, it can be difficult to collect this type of data from comatose patients due to privacy concerns and difficulties in obtaining electroencephalogram data. Transfer learning is a viable strategy to address this problem. This method allows the model to learn from existing datasets an, adapt them to the specific task of classifying comatose patients. Finally, another critical factor in clinical use is real-time classification. Since real-time classification is often required in clinical settings such as intensive care units, the proposed method should be improved for real-time deployment.

The proposed technique provides a reliable and efficient method to classify brain activity in comatose patients by combining wavelet transform, continuous Stockwell transform and convolutional neural networks. This method efficiently captures the complex, complex and multidimensional properties of electroencephalogram data by integrating state-of-the-art deep learning techniques and traditional signal processing techniques. Because of this, it provides higher classification accuracy than traditional techniques such as Support Vector Machines. Seriously, the approach we propose has great potential for improving clinical decision-making and management of patients in coma and other altered states of consciousness, although, there are undoubtedly some challenges to overcome such as pre-processing the data, understanding how the models work, selecting the, right datasets, and running everything in real-time. Like, Future research will focus on addressing these issues, improving the real-time application approach, and investigating the use of transfer learning to, improve model performance in a clinical setting. Data sets are collected from Kaggle for pre-processing.

IV. RESULTS AND DISCUSSIONS

The outcomes shown in Figure 3 illustrate the CNN model's development over training, showing both accuracy and loss across a number of iterations. During the first iterations, the accuracy curve (top plot) shows a sharp rise in classification performance, which steadies at a high level of accuracy as training goes on. This suggests that the suggested approach successfully extracts distinctive characteristics from the EEG data.



Results
Validation accuracy: N/A
Training finished: Max epochs completed
Training Time
Start time: 16-Apr-2025 15:01:49
Elapsed time: 6 sec
Training Cycle
Epoch: 20 of 20
Iteration: 320 of 320
Iterations per epoch: 16
Maximum iterations: 320
Validation
Frequency: N/A
Other Information
Hardware resource: Single CPU
Learning rate schedule: Constant
Learning rate: 0.001

Figure 3:Training progress of the CNN model

METHOD	ACCURACY (%)
SVM	**83.15 %**

WT + CST + CNN	**86.96 %**

Table1:Comparison Table for Classification Methods

The implementations above result, which is displayed in Table 1, demonstrates the classification accuracy following the application of Wavelet Transform, Continuous Stockwell Transform and Convolutional Neural Networks.

V. CONCLUSION

This study deployed a Convolutional Neural Network to analyze brain activity and create an EEG categorization framework. Discrete Wavelet Transform and Continuous Stockwell Transform were used to extract features from the EEG data after they had been pre-processed using a band pass filter to eliminate unwanted noise. Subsequently, these characteristics were employed to categorize brain states and differentiate between various activity levels. Gaussian noise was included to the collected features to increase resilience and decrease overfitting, and a more difficult data split was used to improve model generalization.

The CNN model is a feasible method for EEG data analysis since it showed good feature learning and classification accuracy. Reliable classification was supported by the network's ability to recognize complex patterns in electroencephalography (EEG) data thanks to the inclusion of convolutional layers... We can certainly explore further development using various deep learning models. Like For example long-term, memory networks are an excellent choice because they handle sequential EEG data much better. Feature selection, methods such as principal component analysis can be incorporated to maximize feature representation. In order to improve generalizability and performance in practical EEG-based applications, future study may potentially entail adjusting hyperparameters and evaluating the model on bigger datasets.

REFERENCES

[1] A. Bhardwaj,, . A. Tiwari,, . D. Gupta,, ,. P. Tripathi, Jhanjhi and . J. N. Z., , ""A novel deep learning framework for classification of EEG brain signals"," *Applied Sciences,* Vols. 11(17),, p. 8026, 2018.

[2] L. Y, . S. O and . N. M., "Real-time EEG brainwave monitoring for mental state recognition," *Proc. Int. Conf. Cyber World,* pp. 153-159, 2009.

[3] N. E and d. S. . L. F., "Electroencephalography: Basic Principles, Clinical Applications, and Related Fields," *Lippincott Williams & Wilkins,* vol. 5th, 2004.

[4] D. . L. L. , L. L. P. and . W. . F. Y., "Brain-computer interface-based stroke rehabilitation,," *" IEEE Trans. Biomed. Eng,* vol. 59, pp. 2836-2844, 2012.

[5] . H. H. and . W. D, "Transfer learning for brain-computer interfaces: A Euclidean space data alignment approach," *IEEE Trans. Biomed. Eng,* vol. 66, pp. 424-432, 2019.

[6] . Z. Y., .. L. T and . S. J., "An fMRI-based approach for brain state classification in coma patients," *Neuroimaging,* vol. 118, pp. 124-131, 2015.

[7] Schirrmeister, . T. . S. R., T. F. J. , D. G. L. , E. M., and T. K., , ""Deep learning with convolutional neural networks for EEG decoding and visualization," *Human Brain Mapping,* Vols. 38(11),, pp. 5391-5420..

[8] ,. I. Ullah, ,. M. Hussain, E. U. Qazi, and Aboalsamh, "An automated system for epilepsy detection using EEG brain signals based on deep learning approach," *Expert Systems with Applications,* vol. 107, pp. 61-71, (2018).

[9] Bashar and S. K, "Deep learning for EEG-based brain activity classification A review," *Biomedical Signal Processing and Control,* p. 104172, 2023.

[10] A. . H. Craik and . J. . L. Contreras-Vidal,, "Deep learning for electroencephalogram (EEG) classification tasks: A review," *Journal of Neural Engineering,* vol. 16(3), p. 031001, 2015.

[11] S. e. a. Fazli, "Enhanced performance by hybrid EEG-NIRS brain-computer interface," *NeuroImage,* vol. 49(1), p. 519–532, 2009.

[12] X. e. a. Gao, "Deep learning for EEG-based brain-computer interfaces: A review," *IEEE Transactions on Neural Networks and Learning Systems,* vol. 33(4), p. 1449–1465, 2022.

[13] Z. e. a. Guo, "EEG-based motor imagery classification using a deep convolutional neural

network with efficient kernel normalization," *Sensors,* vol. 20(5), p. 1288, 2020.

[14] H. e. a. He, "Wavelet transform and CNN-based EEG classification for brain state monitoring," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 29, p. 1205–1216., 2021.

[15] H. e. a. Yang, "Brain activity classification using wavelet transform and CNN for coma patient monitoring," *IEEE Access,* vol. 9, p. 12845–12858, 2021.

[16] R. e. a. Sharma, "Wavelet-based EEG feature extraction for coma state classification using deep learning," *Biomedical Signal Processing and Control,* vol. 86, p. 104938, (2023).

[17] J. e. a. Stender, "Diagnostic precision of PET imaging and functional MRI for detecting consciousness in vegetative and minimally conscious states," *The Lancet,* vol. 384(9942), p. 514–522, 2014.

[18] S. e. a. Mitra, ""Wavelet-based EEG feature extraction and deep learning for brain activity classification in comatose patients," *IEEE Journal of Biomedical and Health Informatics,* vol. 26(8), p. 3742–3751, 2022.

[19] J. W. Y. e. a. Kam, "Brain state classification using deep learning on EEG signals," *Journal of Neuroscience Methods,* vol. 328, p. 108387, 2019.

[20] J. e. a. Pan, "Motor imagery brain-computer interface using common spatial patterns and convolutional neural networks," *Journal of Neural Engineering,* vol. 15(6), p. 066017, 2018.