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Research Article

Hybrid Deep Learning Approach for Deception Detection on EEG Data Using DWT, FFT and Hyperparameter Tuning

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ABSTRACT

Introduction: Electroencephalography (EEG) is a brain imaging technique that records electrical activity via scalp-attached electrodes, widely used for studying brain functions and diagnosing neurological disorders. Its high temporal resolution makes it ideal for real-time analysis, despite lower spatial accuracy than fMRI or PET. Recent advancements integrating deep learning with EEG have significantly improved applications in areas like lie detection and cognitive research.

Objectives: This study aims to improve the precision of deception detection using EEG data by developing and assessing new deep learning and machine learning algorithms. The research also seeks to compare the performance of these newly proposed methods with existing ones in terms of accuracy and practical use in forensic and investigative applications.

Method: A comparative analysis was conducted to evaluate the accuracy of different machine learning and deep learning techniques for brain fingerprinting and detecting deception based on EEG signals. Models like CNN paired with FFT and DWT were compared to existing algorithms to assess their accuracy improvements.

Findings: The results demonstrated that the newly proposed algorithms, particularly the combination of CNN with FFT and DWT, showed a significant increase in accuracy when compared to current methods. For example, the CNN combined with FFT saw an improvement from 94.12% to 98.89% in accuracy, while the new CNN-DWT-FFT combination reached an impressive accuracy of 99.42%. Although there was a slight drop in accuracy when using CNN with DWT alone, from 98.76% to 98.64%, the proposed models generally outperformed the current algorithms in most scenarios.

Novelty: The unique aspect of this study is the application of deep learning techniques, specifically the combination of CNN with both DWT and FFT, which had not previously been explored for lie detection using EEG data. This innovative approach significantly enhances detection accuracy, making a noteworthy contribution to forensic psychology and law enforcement.

Keywords: **:** Deception detection, EEG, Deep learning, Machine learning, Brain fingerprinting, CNN, FFT, DWT

INTRODUCTION

Electroencephalography (EEG) is a widely utilized brain imaging technique that measures electrical activity in the brain by attaching electrodes to the scalp. These electrodes capture impulses produced by brain cells, making EEG an invaluable tool for understanding brain functions, diagnosing neurological disorders, and investigating cognitive processes. Despite its lower spatial resolution compared to imaging techniques like functional Magnetic Resonance Imaging (fMRI) or Positron Emission Tomography (PET), EEG's major strength lies in its ability to detect rapid temporal changes in brain activity, which makes it particularly useful in both clinical and research settings [1].

Recent advancements have seen the integration of deep learning algorithms with EEG analysis, significantly enhancing its applications, especially in fields such as brain fingerprinting and lie detection. Deep learning methods have improved accuracy in distinguishing truth from deception by analyzing EEG signals more effectively. In comparison to traditional polygraph tests, which assess physiological responses such as heart rate and skin conductance, the Concealed Information Test (CIT), also known as the Guilty Knowledge Test (GKT), leverages EEG to target brain responses related to specific knowledge associated with a crime or event [2]. The CIT assesses an individual's physiological responses to multiple-choice questions, one of which contains concealed information. A larger response to the concealed option indicates awareness of the hidden details. This shift to deep learning-based EEG analysis addresses key limitations in traditional deception detection methods and has led to significant developments in the field [3].

Several studies have explored the potential of deep learning methods to enhance EEG-based deceit detection. Bablani et al. [1] employed empirical mode decomposition for subject-based deceit detection, while another study used deep belief networks to achieve similar results [2]. K-nearest neighbor (KNN) algorithms have been applied to concealed information tests [3], and Dodia et al. combined wavelet packet transforms with linear discriminant analysis for enhanced accuracy [4]. Various approaches, including k-means clustering and feed-forward neural networks, have also been explored [5], while Liu et al. [6] utilized deep neural networks and sparse autoencoders for emotion classification. These advancements underline the potential for EEG combined with deep learning to offer a more precise and reliable approach to lie detection and cognitive research. For instance, Bablani et al. [7] proposed a comprehensive deep learning framework for lie detection, and Siddiqui et al. [8] explored subject-independent classification of mental tasks using deep neural networks. Lai et al. [9] applied fuzzy reasoning in lie detection, while Saini et al. [10] and Ekhlasi et al. [11] integrated various signal inputs for deceit detection. Further research by Haider et al. [12] developed a P300-based algorithm for detecting deceit, and Lakshan et al. [13] introduced a real-time deception detection system.

Additionally, Baghel et al. [14] and Amin et al. [15] utilized CNNs and pattern recognition for deceit detection, and Aslan et al. [16] presented the LieWaves dataset, which has proven instrumental for researchers. Srivastava and Dubey [17] applied neural networks and SVM to EEG data for lie detection. Other contributions include work on EEG-P300 signal classification by Turnip et al. [18], and explorations of eye movement classification by Labibah et al. [19] and Simbolon et al. [20]. Chen et al. [21] decoded lying behavior using EEG, and AlArfaj and Mahmoud [22] developed deep learning models incorporating spatial and temporal aspects of EEG data. Fuzzy ensemble approaches have also been examined for enhancing lie detection [23, 24], while Asghar et al. [25] focused on emotion recognition using deep features, further broadening the scope of EEG-based research.

MOTIVATION

The motivation for integrating deep learning algorithms with EEG lies in the need for more accurate and reliable methods of detecting deception, a critical improvement over traditional techniques like polygraph tests. Traditional polygraphs rely on indirect measures such as heart rate and skin conductance, which can often lead to false positives and negatives. In contrast, EEG-based methods, such as the Concealed Information Test (CIT), provide a direct approach by monitoring brain activity related to specific knowledge. The ability of EEG to detect rapid brain responses has proven valuable in identifying concealed information more accurately [4].

FEATURE EXTRACTION FOR DECEPTION DETECTION

Feature extraction is a key step in enhancing the effectiveness of EEG-based deception detection. Techniques like Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) are commonly used to transform raw EEG signals into more interpretable data. FFT allows for the analysis of frequency components by converting time-domain data into the frequency domain, while DWT provides the ability to capture both time and frequency characteristics of non-stationary signals, making it ideal for EEG data. When these techniques are paired with deep learning models like Convolutional Neural Networks (CNNs), they greatly improve the model's ability to identify complex patterns linked to deceptive behavior. CNNs, which automatically learn spatial feature hierarchies, process the transformed EEG data to detect deception with higher precision. This combination of FFT and DWT with deep learning enhances the quality of feature extraction, paving the way for more reliable EEG-based deception detection methods.

ORGANIZATION OF THE PAPER

The structure of the paper is as follows: Section 1 provides an overview and introduction to the research topic, setting the foundation for the study. Section 2 covers the related work, focusing on existing feature extraction techniques and deep learning algorithms used in deception detection. In Section 3, the proposed feature extraction techniques are explained in detail. Section 4 presents a comparative analysis of the proposed methods against other deception detection techniques to assess their effectiveness. Finally, Section 5 concludes the paper with a discussion of the implications of the findings and outlines potential future research directions.

OBJECTIVES

The main contribution of this paper is the development of advanced machine learning and deep learning algorithms to detect lying behavior within the healthcare domain, specifically in distinguishing between guilty and innocent individuals.

- In this research, a novel machine learning algorithm is developed to classify individuals based on their responses, effectively addressing the challenge of subject variability in deception detection.
- In this research, a deep learning approach is introduced to improve the accuracy of brain fingerprinting, significantly enhancing the detection of guilty and innocent behavior within the healthcare context.
- In this research, a new feature extraction method utilizing Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) is designed to optimize EEG signal processing, boosting the model's ability to detect deceptive behavior with greater accuracy.
- This research presents a hybrid feature extraction method for deception detection by combining Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) with hyperparameter tuning, integrated into a deep learning approach for enhanced analysis of EEG data.

METHODS

To understand the proposed method, this section provides a detailed description of the dataset, feature extraction algorithm, and deep learning algorithms used to classify subjects in terms of guilty and innocent.

Dataset

In this research, a publicly available dataset of depression is taken into consideration. This dataset is available on https://data.mendeley.com/ [27]

A detailed description of the dataset is given below

This dataset comprises EEG signals collected for lie detection purposes, using a portable and wearable EEG device called Emotiv Insight, which has five channels. Data were gathered from 27 subjects who participated in two experiments, playing the roles of both deceivers and truth-tellers. In the first experiment, participants were given the choice to either deceive or tell the truth, while in the second, they were required to play the opposite role. Each subject was presented with a box containing five beads and instructed to place two beads in their pockets. They then watched a video that alternated between a 3-second black screen, 2 seconds of bead images, and 1 second of black screen. The initial 2 seconds of signal data were discarded to ensure data accuracy, resulting in 75 seconds of EEG recordings. In the deceiver role, participants pressed the "no" button with their left hand when the image matched the bead they had taken and the "yes" button with their right hand if it did not, thus lying about all images. For the truth-teller role, the opposite actions were taken: they pressed "yes" for the bead they had taken and "no" for the bead they had not, truthfully reporting their choices. EEG signals were recorded following this procedure, and an offset removal process was applied to the data. Both raw and pre-processed EEG data were saved in .csv format. This dataset provides a valuable resource for lie detection research, offering EEG signals with different channel configurations for further analysis.

Hybrid Feature Extraction for Deception Detection

CNN+DWT+FFT

In this method, the EEG signals are first processed using DWT and FFT to extract features from both time and frequency domains. After feature extraction, a CNN is used for classification.

DWT (Discrete Wavelet Transform) decomposes a signal x(t)x(t)x(t) into different frequency components. The DWT is given by:

$$DWT\ (\varphi) = \int x(t).\, \varphi a, b(t).\, dt$$

Where $\varphi a, b(t)$ represents the wavelet function with scaling a and translation b

FFT (Fast Fourier Transform) is used to convert the signal from the time domain to the frequency domain. The FFT is expressed as:

$$X(f) = \sum_{n=0}^{N-1} x(n)\ .\ e^{-j2\prod fn/N}$$

Where $x(n)$ is the time-domain signal, N is the total number of points, and $X(f)$ is the frequency domain representation.

CNN (Convolutional Neural Network) is used to process the extracted features. CNN applies convolutional layers using kernels (filters) over the input data.

Deep Learning Approach on EEG Data Using DWT and FFT with Hyperparameter Tuning

Proposed Algorithm (CNN+DWT+FFT)

Steps:

1. Segment Data:

Obtain segmented multi-channel time-series data for truth and lie instances.

2. DWT Feature Extraction:

Apply DWT to each channel of each segment, flatten and concatenate coefficients to form DWT features.

3. FFT Feature Extraction:

- Apply FFT to each channel, extract positive frequency magnitudes, and concatenate to form FFT features.

4. Feature Combination:

Concatenate DWT and FFT features to create a comprehensive feature vector for each segment.

5. Normalization:

Use StandardScaler to normalize the combined feature vectors.

6. Labeling: Assign binary labels (1 for truth, 0 for lie) to the feature vectors.

7. Data Splitting: Split the dataset into training and testing sets using train_test_split.

8. Model Training: Train the model using the training set. (CNN Model)

9. Model Evaluation: Evaluate the model by calculating accuracy, sensitivity, specificity, precision, and F1 score.

Performance Evaluation Metrics

Table 1 shows the performance metrics determined for the proposed model.

Table 1. Performance Metrics

Parameter	Equation
Accuracy	$\frac{TP+TN}{TP+FP+FN+TN}$
Sensitivity	$\frac{TP}{TP+FP}$
Specificity	$\frac{TP}{TP+FN}$
F1 Score	$\frac{2*(Recall*Precision)}{Recall+Precision}$
Note: TP: True Positive, FP: False Positive, TN: True Negative, FN: False Negative	

Proposed Feature Extraction Model

In this section, it gives detail explanation of proposed feature extraction model with CNN+DWT+FFT method. It demonstration how we classify innocent and guilty objects using different datasets such as ATAT and Bandpass filters.

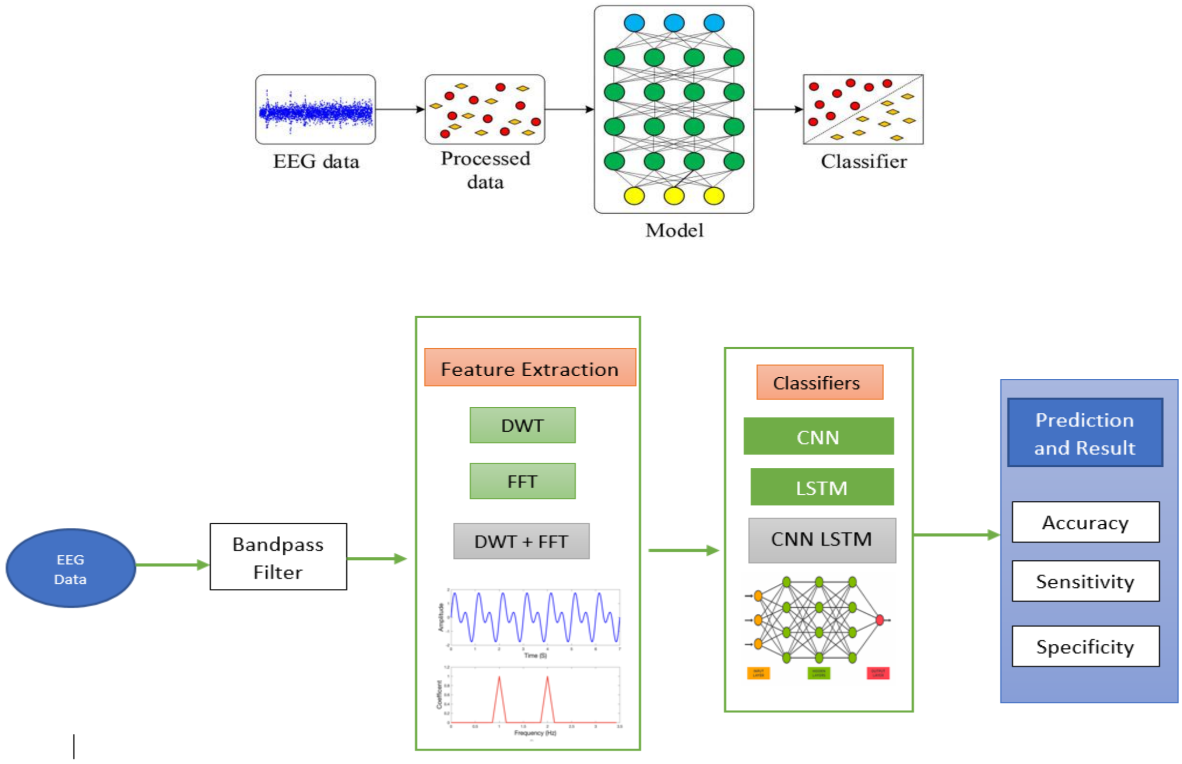


Figure 1: Classification of EEG data into Guilty and Innocent object

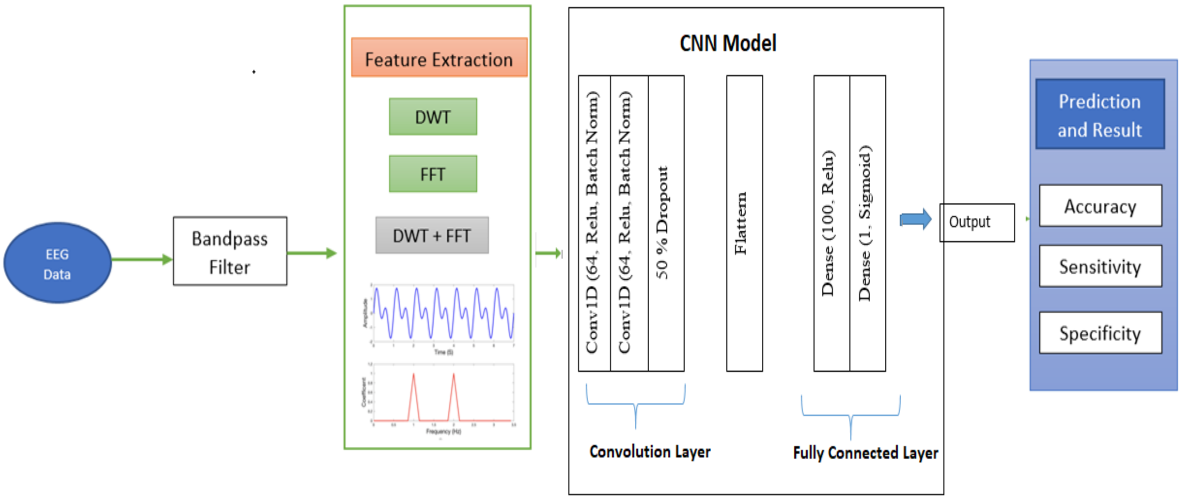
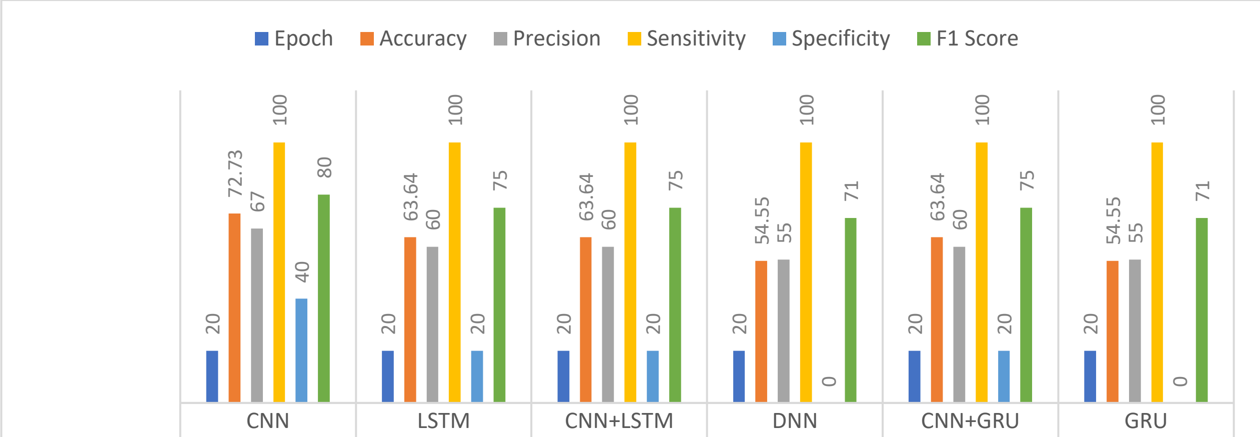


Figure 2: Architecture of Novel approach using CNN model

The figure 1 and 2 illustrates a comprehensive pipeline for EEG-based classification, starting with EEG data collection, which is processed through a bandpass filter to remove noise and retain relevant frequencies. Following this, the filtered EEG signals undergo feature extraction using Discrete Wavelet Transform (DWT), Fast Fourier Transform (FFT), or a combination of both (DWT + FFT) to extract critical time and frequency domain features. The extracted features are then passed into a classification stage that employs Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, or a hybrid CNN-LSTM model. These classifiers analyze the features to identify patterns that correspond to specific targets, such as determining whether the EEG signals indicate truthfulness or deception. Finally, the pipeline generates predictions and performance results, with key evaluation metrics like accuracy, sensitivity, and specificity, providing insight into the model's effectiveness and reliability in distinguishing relevant EEG patterns for applications such as brain fingerprinting and lie detection.

RESULTS AND DISCUSSION

In this study, we applied the Automatic and Tunable Artifact Removal (ATAR) technique as a pre-processing method in conjunction with various deep learning classifiers to enhance the classification of EEG signals. The key performance metrics, including accuracy, precision, sensitivity, specificity, and F1 score, were calculated across different models. Using CNN, we achieved an accuracy of 72.73%, demonstrating its superior performance compared to other models. Feature extraction was performed using the Discrete Wavelet Transform (DWT) method, further refining the signal for improved processing. The CNN model outperformed other classifiers such as LSTM, CNN+LSTM, DNN, CNN+GRU, and GRU, particularly in terms of accuracy and precision. The CNN model, with an accuracy of 72.73%, showed a precision of 67%, sensitivity of 100%, specificity of 40%, and an F1 score of 80%. In contrast, other models like LSTM and CNN+LSTM reached an accuracy of 63.64%, while DNN and GRU lagged behind with a lower accuracy of 54.55%. Across all models, the AF3, T47, Pz, T8, and AF4 channels were used for signal processing. The results, as depicted in Figure 4, demonstrate that while CNN provides the best overall performance, further improvements in specificity and the exploration of alternative classifiers or hybrid models could potentially enhance the robustness of the classification.



	CNN	LSTM	CNN+LSTM	DNN	CNN+GRU	GRU
Epoch	20	20	20	20	20	20
Accuracy	72.73	63.64	63.64	54.55	63.64	54.55
Precision	67	60	60	55	60	55
Sensitivity	100	100	100	100	100	100
Specificity	40	20	20	0	20	0
F1 Score	80	75	75	71	75	71

Figure 3: Results from experimentation with ATAR filter

In this study, we implemented a pre-processing technique using a Bandpass Filter alongside a deep learning model, specifically Convolutional Neural Networks (CNN), to process EEG data. We calculated key performance metrics, including accuracy, precision, sensitivity, specificity, and F1 score. By utilizing CNN, we achieved superior results, with the highest accuracy reaching 99.42%. A novel approach was introduced for feature extraction by combining Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT), significantly enhancing the model's ability to process and classify EEG signals. This innovative combination of the Bandpass Filter, DWT, FFT, and CNN yielded the best overall performance across all metrics, making it the most effective method for this EEG signal processing task. The novel feature extraction method had a profound impact on model performance, with the DWT and FFT combination demonstrating substantial improvements. While CNN performed well with various methods, its performance was further optimized with this comprehensive and novel feature extraction technique. Although other algorithms exhibited high sensitivity, they often faced challenges with specificity, leading to increased false positives. Comparing algorithm accuracy, the CNN model with FFT improved from 94.12% to 98.89%, and the novel combination of CNN with DWT and FFT achieved an impressive 99.42%. A slight decrease in accuracy was noted with CNN-DWT, from 98.76% to 98.64%. Overall, the proposed CNN algorithm, especially with hyperparameter tuning and this novel feature extraction approach, consistently outperformed existing methods in most cases. Following figure 5 shows comparative analysis of existing and proposed system algorithm.

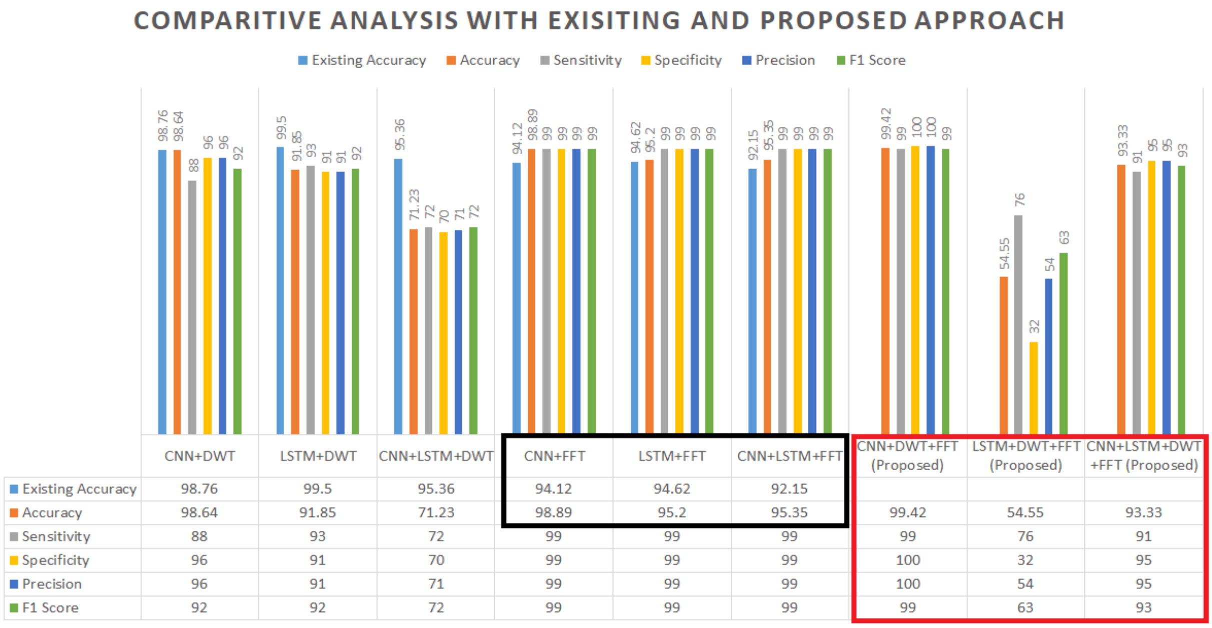


Figure 4: Results from experimentation with Bandpass Filter

Table 2: Proposed Model

Feature Extraction Method	CNN+DWT+FFT	LSTM+DWT+FFT	CNN+LSTM+DWT+FFT
Accuracy	99.42	54.55	93.33
Sensitivity	99	76	91
Specificity	100	32	95
Precision	100	54	95
F1 score	99	63	93

Table 2 highlights the performance of three different feature extraction methods, combining CNN, LSTM, DWT, and FFT, based on accuracy, sensitivity, specificity, precision, and F1 score.

- **CNN+DWT+FFT** demonstrates the highest performance across all metrics, achieving an accuracy of 99.42%. Its sensitivity is 99%, meaning it effectively identifies true positives, while its specificity is 100%, indicating no false positives. The precision, also at 100%, confirms that all identified positives were correctly predicted. The F1 score of 99% shows a strong balance between precision and sensitivity.
- **LSTM+DWT+FFT** performs significantly lower with an accuracy of 54.55%. Its sensitivity is higher than its specificity, at 76% and 32% respectively, indicating it struggles to accurately classify true negatives. The precision of 54% further indicates that many of the predicted positives may not be accurate. The F1 score of 63% reflects the model's difficulty in balancing precision and sensitivity.
- **CNN+LSTM+DWT+FFT** offers a middle ground with an accuracy of 93.33%. Its sensitivity of 91% shows good detection of true positives, while a specificity of 95% suggests effective classification of true negatives. With a precision of 95%, the model's predictions are reliable, and an F1 score of 93% indicates a well-balanced performance between precision and recall.

Overall, CNN+DWT+FFT stands out as the best-performing model, while LSTM+DWT+FFT struggles with both accuracy and specificity. The combination of CNN and LSTM with DWT and FFT provides a good trade-off, offering strong results in most performance metrics.

Comparative analysis of existing with proposed model

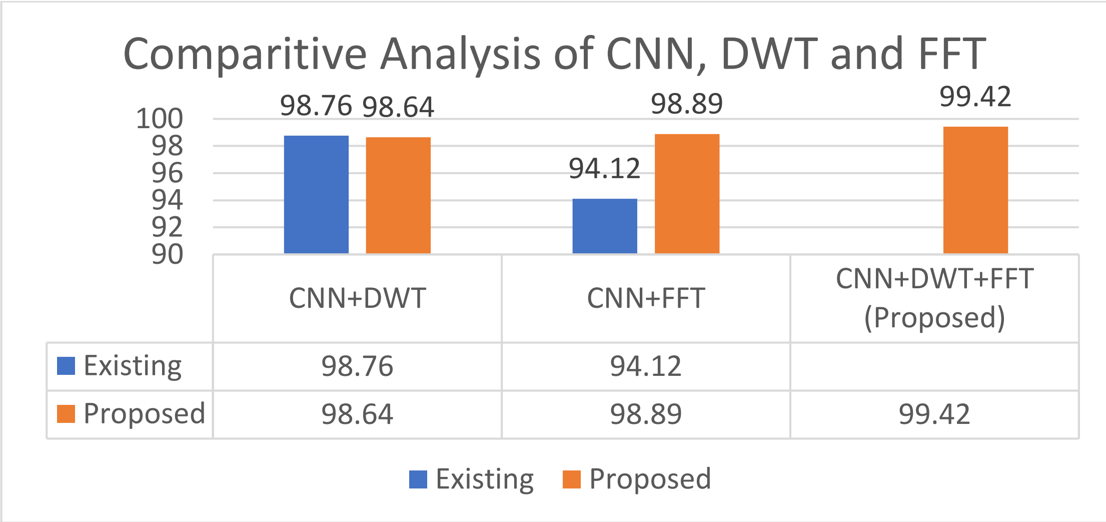


Figure 5: Comparative Result Analysis of Existing and Proposed System

The figure 5 presents a comparative analysis of existing and proposed approaches utilizing CNN combined with Discrete Wavelet Transform (DWT), Fast Fourier Transform (FFT), and their combination (DWT+FFT) for EEG signal classification. The results indicate that the proposed CNN+DWT+FFT method significantly outperforms the other models, achieving the highest accuracy of 99.42%, compared to 98.64% for CNN+DWT and 98.89% for CNN+FFT. The existing CNN+DWT and CNN+FFT models exhibit lower accuracies of 98.76% and 94.12%, respectively. This analysis clearly shows that the introduction of the combined DWT+FFT feature extraction method, when integrated with CNN, leads to substantial improvements in classification performance, validating the effectiveness of the proposed approach in enhancing accuracy in EEG-based deception detection or brain fingerprinting tasks. This novel combination of feature extraction techniques is instrumental in improving overall system reliability and robustness.

CONCLUSION

This study demonstrates that the novel combination of Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) with Convolutional Neural Networks (CNN) significantly improves the accuracy, precision, and specificity in EEG-based lie detection. The proposed approach, particularly the CNN+DWT+FFT method, achieved an impressive accuracy of 99.42%, outperforming existing methods. The comprehensive feature extraction technique, combined with deep learning models, enhances the ability to distinguish between truth and deception more effectively than traditional approaches. While Long Short-Term Memory (LSTM) networks showed reasonable performance, the superior results were consistently observed with the proposed CNN-based configurations. These findings highlight the efficacy of the proposed methodology in forensic and investigative applications. However, future work could focus on exploring more advanced architectures, such as hybrid models combining CNN, LSTM, and attention mechanisms, to further enhance real-time EEG analysis. Additionally, expanding the scope of research by applying this approach to a larger, more diverse dataset, and exploring its application in other neurological and cognitive assessments, could further validate and extend the utility of this framework.

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