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Optimizing EEG Signal Classification in BCI Systems: A Comparative Study of Hybrid Transfer Learning and Advanced Machine Learning Approaches



Abstract: - Electroencephalogram (EEG) data can be challenging to classify for motor imagery (MI) tasks in brain-computer interfaces (BCI) due to low signal-to-noise ratios, complex patterns, and subject variability. This study aims to overcome these issues by evaluating various Transfer Learning (TL) and advanced machine learning models to improve EEG data classification accuracy. We pre-processed raw EEG signals into scalogram images by Continuous Wavelet Transform (CWT) and fed them into TL models like DenseNet, VGG19, ResNet, and InceptionV3. Features from these models were classified using advanced machine learning classifiers, including Random Forest, K-Nearest Neighbours, Decision Tree, and XGBoost. Using the BCI Competition IV 2a raw dataset, DenseNet combined with XGBoost achieved 99.2% classification accuracy on both training and validation datasets. According to the study, TL-based architecture can be used for controlling rehabilitation devices using EEG data for post-stroke patients, improving their quality of life and facilitating a more convenient way for individuals with severe physical disabilities to manage their healthcare via hybrid TL and advanced ML integrated BCI systems.

Keywords: Transfer Learning, Machine Learning, Motor-Imagery (MI), Brain-Computer Interface (BCI), Electroencephalogram EEG Signal.

I. INTRODUCTION

With a brain-computer interface that uses an electroencephalogram (EEG), a computer can interpret the brain's electrical activity into commands. In cases of people with severe physical limitations, such as stroke victims, it offers a promising solution that offers them a chance of recovery. These limitations significantly impact their quality of life, making daily tasks and therapeutic exercises challenging. BCIs enable these individuals to communicate and control devices through brain signals, gaining some degree of control and independence [1]. However, BCIs heavily depend on the accurate extraction and classification of these signals. This is inherently complex due to EEG signals' noisy and variable nature [2]. Despite advancements in BCI technology, feature extraction and signal classification remain challenging tasks. Traditional methods often struggle to achieve accuracy and reliability for effective real-world applications. There are many challenges to an accurate and reliable MI classification, including subject-to-subject variability, low signal-to-noise ratios, and EEG patterns that are complex in nature. This study strives to improve those challenges. Existing methods struggle to address these issues comprehensively, leading to suboptimal performance in real-world applications [3]. A notable research gap exists in the application of Transfer Learning (TL) for EEG signal classification within BCI systems. While TL has demonstrated success in various fields by utilizing pre-trained models to extract relevant features, its use in BCI applications, especially with EEG data, is still underexplored [4]. EEG signal classification needs to be enhanced in terms of accuracy and efficiency using TL models to close this gap. Bridging this gap could significantly improve the performance of BCI systems and expand their practical utility. In this work, the goals are to assess the effectiveness of many different TL models in terms of extracting features from wink-based EEG data and to categorise these features using a variety of machine learning classifiers once the evaluation has been completed [5]. Specifically, the study examines TL models such as DenseNet, VGG19, ResNet, and InceptionV3. To begin, we use Continuous Wavelet Transform (CWT) to convert the raw EEG signals into scalogram pictures. This gives us a better idea of the signal's time-frequency properties. In order to extract features, the TL models are fed these modified signals. The extracted features are classified using Random Forest, K-Nearest Neighbors, and XGBoost classifiers, with hyperparameter optimization to enhance performance [6]. This research is essential because it addresses a critical need in the development of BCI technology for stroke rehabilitation. By integrating advanced TL models and ensemble learning techniques, the study aims to improve the precision and reliability of EEG signal classification. Enhanced classification accuracy directly translates to more effective control of rehabilitative devices, offering stroke patients better management of their physical limitations and a higher quality of life [7]. The use of scalogram images and advanced TL models represents a novel approach in this field, potentially setting a new standard for BCI systems [8]. The study's findings are

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expected to make a significant contribution to the field of BCI technology. By demonstrating the effectiveness of TL models and ensemble learning in classifying EEG signals, the research advocates for the broader adoption of these techniques in BCI applications. This integration has the potential to revolutionize the way stroke rehabilitation is approached, providing patients with more reliable and precise control over assistive devices [9]. The advancements proposed in this study could lead to substantial improvements in the autonomy and well-being of individuals with severe physical disabilities [10].

A. Motivation

As a consequence of the development of the brain-computer interface technology (BCI), individuals with severe physical disabilities, such as stroke survivors, can greatly enhance the quality of their lives through increased functionality [11]. Stroke often results in debilitating motor impairments, leaving patients unable to perform basic daily tasks or control assistive devices. BCIs offer a non-invasive method for these individuals to regain control by translating brain signals, EEG signals converted into commands for external devices are a critical topic [12]. Effective control of devices using EEG signals can enhance independence and rehabilitation outcomes for stroke survivors [13][14]. However, accurately extracting and classifying EEG signals remains a challenge. EEG signals are inherently noisy and complex, requiring sophisticated techniques to decode the intended commands reliably. Traditional methods for feature extraction and signal classification often fall short, leading to suboptimal performance in real-world applications. Transfer Learning (TL), one of the most recent advancements in machine learning, have shown promise in improving the accuracy of signal classification by leveraging pre-trained models to extract relevant features from complex data [15][16]. Despite these advancements, the application of TL in BCI, especially for EEG signal classification, remains relatively unexplored. Transfer Learning (TL) has the potential to revolutionize EEG signal classification by utilizing the knowledge gained from large, pre-trained models on diverse datasets. TL models such as DenseNet, VGG19, ResNet, and InceptionV3 have demonstrated exceptional performance in various domains, including image and speech recognition. Applying these models to EEG signal classification can potentially improve the accuracy and reliability of BCIs, making them more effective for stroke rehabilitation. This study aims to fill the research gap by evaluating the performance of these TL models in classifying wink-based EEG data, thereby contributing to the development of more efficient BCI systems.

B. Contributions

As a result of this study, the following contributions have been made:
 To improve the quality and interpretability of EEG data classification tasks, the study generated scalogram images from raw EEG signals by using Continuous Wavelet Transform (CWT).
 To investigate advanced Transfer Learning (TL) models, including DenseNet, VGG19, ResNet, and InceptionV3, for EEG feature extraction, and to fill a significant research gap.
 With the combination of TL and advanced classification techniques (Random-Forest, K-Nearest Neighbors, Decision Tree, and XGBoost), features were classified using hybrid ensemble learning classifiers.
 Implemented hyperparameter optimization for the classifiers, enhancing their performance and robustness in EEG signal classification tasks. It used a well-known benchmark dataset, BCI Competition IV-2a, for experimental evaluations, ensuring reliability and relevance of the study's findings.
 To classify both the training and validation datasets with high accuracy using DenseNet and XGBoost. We achieved a classification accuracy of 99.2%, demonstrating that this combination of techniques allows for highly accurate EEG signal classification.

C. Paper structure

The paper is structured as follows: Section II provides a literature review, examining various studies and methodologies that contribute to current knowledge. Section III outlines the study's methodology, detailing the experimental design and data analysis approaches. Section IV presents an in-depth discussion of the study's results, including comparisons with state-of-the-art approaches. Finally, Section V concludes the study by summarizing the key findings and identifying potential future research opportunities.

II. RELATED WORKS

There have been recent advances in the field of Brain-Computer Interface (BCI) which have improved the accuracy of the classification of EEG signals, largely due to the implementation of machine learning and transfer learning techniques. Studies have shown that integrating these approaches can significantly improve the performance of motor-imagery (MI) BCIs by leveraging pre-trained models to extract relevant features and reduce calibration time. Despite these improvements, challenges remain in effectively applying these methods across different datasets and user populations. A transfer learning-based algorithm was introduced by Zheng et al. [17] for enhancing the motor-imagery brain-computer interface (MI-BCI) system by expanding the set of commands and decreasing the calibration times of the system. This was achieved by creating combinations of traditional motor imagery (MI) commands as distinct commands and designing a feature extractor using data from these traditional commands. The learned patterns were transferred to the updated commands, improving

system accuracy, especially for low-quality datasets. Additionally, this approach significantly reduced the time required for collecting EEG signals and training the model, enabling quicker system use. However, limitations include varying performance with high-quality datasets, implementation complexity requiring substantial computational resources, and the need for further validation across diverse user groups and tasks.

As part of a study done by Turnip et al. [18] a comparison of 3 different EEG processing methods was conducted in order to determine which one is the best one for optimized brain-computer interfaces (BCIs). NPCA proved effective in reducing noise, JADE excelled in identifying independent components, and SOBI was particularly good at separating sources with time-delayed correlations. However, despite these advantages, the classification accuracy was often limited by unforeseeable signal variations caused by artifacts and the feedback loop between the recognizer and the subject, highlighting the need for more robust methods to handle such variability. For the classification of motor imagery EEG data using a transfer learning algorithm, Zheng, M., et al. [19] have proposed an approach that can be applied across sessions and subjects and takes advantage of the unique feature of motor imagery EEG data. EEG data is analyzed to analyze shared features among sessions or subjects, such as the variance and mean of model parameters. Following that, it updates these shared features based on Euclidean distances between relevant datasets. With these shared features combined with subject- or session-specific features, an algorithm allows for greater accuracy. Advantages of this approach include superior performance over traditional algorithms, effective application across sessions and subjects, and robust model creation by utilizing both shared and specific features. However, limitations include the substantial computational resources needed for analyzing and selecting relevant datasets, and the algorithm's variable effectiveness depending on the quality and consistency of EEG data.

According to Zanini et al. [20], an affine transformation can enhance transfer learning for EEG-based BCI classification across sessions or between subjects. They use SPD matrices derived from the Riemannian manifold of EEG data, employing spatial covariance matrices to represent EEG data, thereby improving classification accuracy. It also involves applying an affine transformation to center these matrices around a reference covariance matrix estimated separately for each session and subject. This approach models task-related changes in covariance matrices as shifts from a reference (resting) state, aligning data from different sessions and subjects for better classification. Advantages of this method include significant improvements in classification accuracy, consideration of the Riemannian structure of the covariance matrix manifold, and avoidance of dependencies on task order and unknown class structures, which were limitations in prior work. However, the limitations of the current method include computational complexity and the need for precise estimation of reference covariance matrices. A study by Ilyas, M.Z., and colleagues [21] identified logistic regression (LR) and support vector machines (SVMs) as the most accurate classifiers for analyzing EEG signals in brain-computer interface (BCI) applications. Using data from BCI Competition IV, they evaluated and compared four different techniques: SVM, Nearest Neighbor (k-NN), Multilayer Perceptron Artificial Neural Network (MLP-ANN), and LR. Thus, LR achieved 73.03 % classifier accuracy and SVM reached 68.97 % classifier accuracy as a result of this study. Advantages include LR and SVM's high accuracy and the study's clear comparison of classifiers, aiding researchers in selecting effective algorithms. The study is limited by the fact that it only assessed a specific dataset, which might limit its generalizability. In addition to that, the accuracy rates of the proposed algorithm indicate that further advancements are required to be able to achieve better results in real-life scenarios.

According to Dose, H., et al. [22], a new method using deep learning has been introduced for classifying motor imagery EEG signals in brain-computer interfaces, achieving high classification accuracy and outperforming previous methods. The researchers employed a convolutional neural network (CNN) with two convolutional layers: the first layer applied a linear pre-filter to each EEG channel, and the second layer combined information across channels by performing 2D convolutions along the channel axis. In the final stage, a fully connected layer is applied to turn these generalized features into classifications. Gradient descent optimization and backpropagation were used to train the model. Advantages include high classification accuracy and effective dimensionality reduction, showcasing the potential of deep learning in enhancing EEG signal classification for BCIs. Limitations are the potential for further improvement in the neural network architecture. In particular, LSTMs are suitable for real-time applications involving online feedback, and it is essential to validate them using datasets other than the Physionet dataset.

A method of processing and classifying motor imagery (MI) EEG signals was introduced by Sreeja, S.R., et al. [23]. For feature extraction, the method uses Common Spatial Pattern (CSP) and employs two methods for feature selection. It involves selecting EEG channels, applying a band-pass filter, and applying two different feature selection techniques. Gaussian Naive Bayes (GNB) classifier is used for the final classification. This approach effectively addresses inter-subject variability in MI-based BCIs by extracting user-specific features, which improves classifier accuracy. Notably, this proposed methodology had not been previously applied to MI-based BCI applications. Advantages include improved accuracy through user-specific feature extraction, enhanced feature quality using CSP and multiple selection techniques, and promising performance with the GNB classifier. As well as the complexity and computational demands of the method, additional refinement and testing will be required to determine whether the method is effective and reliable in practical applications, as well as the need for further validation across diverse datasets and real-world scenarios.

To find characteristics that may be used to operate brain-computer interfaces (BCIs) made for people with disabilities or paralysis, the authors of Rashid, M., et al. [24] analysed EEG data from various cognitive states. The entropy, standard deviation, power spectral density, and spectral centroids were calculated using electroencephalogram (EEG) signals captured during mental workouts such as relaxation and rapid arithmetic solutions. K-Nearest Neighbours (k-NNs), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVMs) were among the classification techniques used in the research. Advantages include the identification of relevant EEG features for BCI control, the use of diverse mental exercises to capture a broad range of cognitive states, and the robust evaluation of multiple classification methods. Limitations involve the need for further validation with larger and more diverse datasets, potential limitations of the study's specific mental exercises to other tasks, and the necessity for more comprehensive testing to ensure the consistency and quality of EEG data in real-world scenarios.

He, H., et al. [25] proposed a novel Euclidean space data alignment (EA) approach to tackle the challenge of individual differences in EEG-based BCIs, aiming to enhance learning performance for new subjects with minimal or no subject-specific data, thereby facilitating transfer learning in BCIs. The technique makes advantage of any signal processing, feature extraction, and machine learning methods by directly matching EEG data from several participants in Euclidean space. EA outshines the Riemannian space alignment (RA) method due to its use of the arithmetic mean rather than the Riemannian mean, its cheap computing cost, and the fact that it works unsupervised without requiring labelled data from fresh subjects. However, EA only addresses covariate shift and ignores prior probability shift and concept shift, which may lead to large discrepancies in per-class input data distributions among different subjects. The use of EA to compensate for covariate shift may increase concept shift for some participants, resulting in decreased differentiation between classes. EA's performance can also be affected by bad trials and outliers in the data used to compute the reference matrix R , potentially reducing classification accuracy. Due to the fact that the simulated online supervised classification studies did not fully generalize to real-world online trials, it is possible that the findings will not be completely relevant in real-world circumstances.

III. PROPOSED METHODOLOGY

The process of categorizing EEG data involves four primary steps: signal collection, pre-processing, feature extraction, and classification. Initially, EEG signals are collected using standardized electrode placement systems to ensure consistent and reliable data across different sessions and subjects. In the pre-processing step, signals are amplified and filtered to remove noise and artifacts, with wavelet transforms applied to capture both time and frequency information, enhancing signal quality. Feature extraction is then performed using pre-trained neural networks built with transfer learning methods to identify meaningful patterns in the EEG data. Finally, the extracted features are classified using optimized machine learning algorithms and pre-trained transfer learning models. This comprehensive approach aims to enhance brain-computer interface (BCI) performance, making BCI applications more effective and reliable.

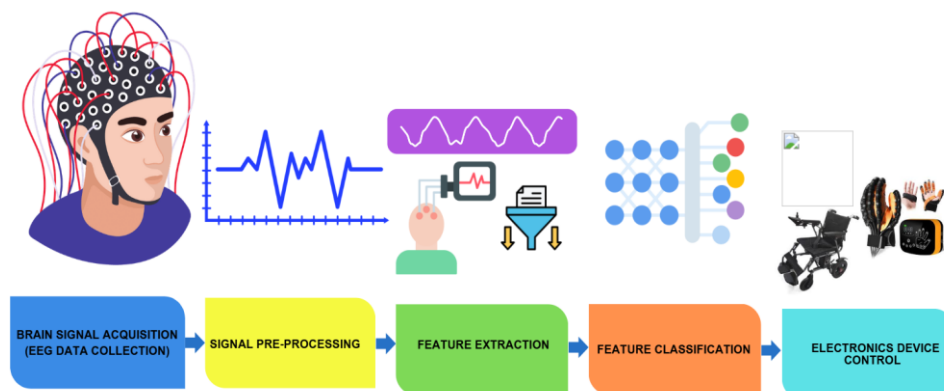


Figure 1. The basic work flow of an EEG-based MI-BCI system

Figure 1 illustrates the basic process of analyzing EEG signals from the BCI Competition IV 2a dataset using EEG-based MI-BCI. The raw EEG data is pre-processed using Continuous Wavelet Transforms (CWT), which provide time-frequency representations of the raw EEG data that can be used to further interpret the results. In a feature extraction phase, scalogram images are fed into neural networks that have been trained to extract relevant features using transfer learning techniques. Finally, the extracted features are input into an combined machine learning and transfer learning classifiers to accurately classify the EEG signals into their respective categories. Several techniques are integrated into EEG-based brain-computer interfaces for improving classification performance, such as advanced signal processing, deep learning, and machine learning. Figure. 2 illustrates the architecture of the proposed scheme.

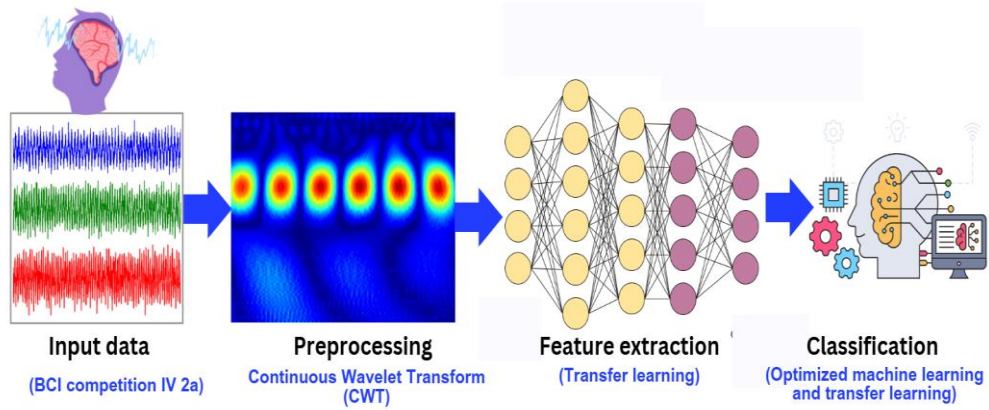


Figure 2. Overview architecture of proposed scheme

A. Data collection

This study's EEG signals were acquired using the well-recognised BCI Competition IV-2a Dataset, which is a standard for research on brain-computer interfaces (BCIs). The nine participants in this study recorded their electroencephalograms as they imagined moving their left and right hands, feet, and tongues, among other motor imagery activities. In order to ensure that all patients had identical electrode placement, the data were gathered using 22 Ag/AgCl electrodes that were positioned according to the worldwide 10-20 system. The signals were first filtered to eliminate baseline drift and high-frequency noise after being captured at 250 Hz. Each subject participated in several sessions, providing a comprehensive set of data for training and evaluating BCI systems. The dataset's rigorous collection protocol and variety of motor imagery tasks make it ideal for developing and testing machine learning algorithms for EEG signal classification.

B. Preprocessing method

Data loading and filtering are the first steps in preprocessing raw EEG signals from the BCI Competition IV 2a dataset. First, the EEG data is loaded using appropriate libraries such as MNE, which provides tools to handle EEG data formats efficiently. The raw signals are then subjected to filtering to remove noise and artifacts. A common approach is to apply a bandpass filter within the frequency range of interest (e.g., 0.5 Hz to 40 Hz) to eliminate power line noise and other irrelevant frequencies. It is also possible to detect and eliminate ocular or muscle artefacts that could skew EEG data by using methods like Independent Component Analysis (ICA). Consistent amplitude ranges between channels and participants are achieved by data normalisation as well. The next stage, after data pre-processing, is to use the Continuous Wavelet Transform (CWT) to convert the cleaned EEG signals into scalogram pictures. In order to extract the time-frequency components from the filtered EEG data, the CWT is used, providing detailed information about the signal's frequency content over time. By selecting an appropriate wavelet, such as the complex Morlet wavelet ('cmor'), and defining a range of scales corresponding to the frequencies of interest, the CWT generates coefficients that represent the signal's energy distribution across time and frequency.

These coefficients are then used to create scalogram images, which visually depict the power of the signal in different frequency bands over time. Normalization adjusts the amplitude of the signals to a standard range, reducing variability caused by differences in electrode placement or individual subject characteristics. This step is essential for maintaining the integrity of EEG data throughout the analysis and classification process. By ensuring that the EEG signals are clean and standardized, the preprocessing method sets a solid foundation for accurate feature extraction and classification. A brain-computer interface (BCI) is a system that allows a person to use their brain to interact with a computer.

The EEG signals $x(t)$ can be convoluted with the impulse response of bandpass filters $h(t)$ in order to obtain the bandpass filter. As a result of filtering $y(t)$, we get:

$$y(t) = x(t) * h(t) \tag{1}$$

where $*$ denotes the convolution operation. For a digital implementation, the discrete-time version of the convolution is:

$$y[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n - k] \tag{2}$$

A mixed signal X is separated into independent components S using Independent Component Analysis (ICA). The following can be expressed in this way:

$$X = AS \quad (3)$$

In this case, A represents the mixing matrix and S represents the source matrix. As a result of ICA, the unmixing matrix W should be estimated as follows:

$$S = WX \quad (4)$$

Normalization involves scaling the EEG signal $x[n]$ the mean should be zero and the variance should be one. The normalized signal $z[n]$ is given by:

$$z[n] = \frac{x[n] - \mu_x}{\sigma_x} \quad (5)$$

where μ_x is the mean and σ_x sigma is the standard deviation of the signal $x[n]$.

The CWT of a signal $x(t)$ is defined as the convolution of $x(t)$ with a scaled and translated version of the mother wavelet $\psi(t)$:

$$C(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (6)$$

In signal processing using Continuous Wavelet Transform (CWT), the scale parameter a adjusts the wavelet's frequency, while the translation parameter b shifts it along the time axis. The complex conjugate of the mother wavelet, ψ , is used to capture localized signal features.

It is possible to write the CWT for discrete signals $x[n]$ as follows:

$$C(a, b) = \sum_{n=-\infty}^{\infty} x[n] \psi^* \left(\frac{n-b}{a} \right) \quad (7)$$

A scalogram represents the energy distribution in the time-frequency domain of a signal as its squared magnitude of CWT coefficients:

$$\text{Scalogram}(a, b) = |C(a, b)|^2 \quad (8)$$

In the Continuous Wavelet Transform (CWT), EEG signals are transformed into scalogram images by means of these equations.

C. Feature extraction

By using Continuous Wavelet Transform (CWT) to transform raw EEG signals into scalogram images, the BCI Competition IV 2a dataset is processed for features, which provides a rich time-frequency representation of the data. These scalogram images are resized to meet the input requirements of pre-trained convolutional neural networks (CNNs) such as DenseNet, VGG19, ResNet, and InceptionV3. By removing the fully connected layers and retaining the convolutional bases of these CNNs, high-level feature maps are extracted from the scalogram images. The output feature maps are then flattened or pooled to form feature vectors, capturing the essential characteristics learned by the CNNs. These feature vectors are combined if multiple CNN architectures are used, and subsequently fed into an optimized machine learning classifier for effective EEG signal classification, leveraging the sophisticated feature extraction capabilities of the pre-trained CNNs.

D. Classification

The classification of EEG signals utilizes advanced machine learning classifiers and transfer learning models to categorize extracted features. This approach involves methods like k-nearest neighbors (KNN) for generating classifications based on the majority class among nearest data points and ensemble methods such as Random Forest, which employs multiple decision trees. Additionally, XGBoost, an optimized gradient boosting

algorithm, is known for its superior performance. Pre-trained convolutional neural networks (CNNs) like DenseNet, VGG19, ResNet, and InceptionV3 are also employed for feature extraction, capitalizing on their capability to learn high-level features from EEG signals.

IV. EXPERIMENTAL DESIGN

To ensure a thorough and robust analysis, several key steps are involved in the experimental setup for evaluating our classification models. Multi-metric metrics including accuracy, precision, recall, and F1-score are used to evaluate the classifiers' performance, particularly their ability to cope with imbalanced datasets. Moreover, we use confusion matrices and Receiver Operating Characteristics (ROC) curves to provide a visual representation of the true versus predicted classification results, providing a deeper understanding of the performance of our models. Using k-fold cross-validation, the dataset is divided into k subsets and the model is trained and validated k times with different subsets each time, ensuring robust evaluation. This method ensures that our models are rigorously tested across various scenarios, providing a reliable assessment of their generalizability and performance. By implementing this comprehensive evaluation framework, we can confidently determine the effectiveness of our classification models in accurately classifying EEG signals using transfer learning and ensemble methods.

A. Experimental setup

The experiments were conducted using a high-performance computing setup, which included an Intel Xeon E5-2698 v4 @ 2.20GHz processor, an NVIDIA Tesla V100 GPU with 32GB of VRAM, 128GB DDR4 RAM, and a 2TB SSD for storage. The software environment consisted of Ubuntu 20.04 LTS, Python 3.8, and deep learning frameworks TensorFlow 2.4 and PyTorch 1.8. A number of libraries were utilized during the data manipulation, model training, and visualization process, including NumPy, Pandas, SciPy, Scikit-Learn, Matplotlib, Seaborn, Keras, and XGBoost. GPU acceleration was enabled through CUDA 11.2 and cuDNN 8.1. Jupyter Notebook served as the interactive development environment. This robust hardware and software configuration ensured the efficient processing of large datasets and complex models, facilitating rigorous testing and validation of the classification models for EEG signal classification in BCI applications.

B. Performance evaluation metrics

Based on a number of performance evaluation metrics, including accuracy, precision, recall, F1-score, and Receiver Operating Characteristics (ROC) curves, we evaluated the performance of the classifiers. Each metric provides a unique perspective on model performance, especially when dealing with imbalanced datasets. Here are the details and formulas for these metrics:

Accuracy: The accuracy of the classification can be defined as the percent of instances out of all instances which fall into the correct category.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

Precision: As a result of selecting only accurate predictions out of all the possible predictions, the precision of the model is measured.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (10)$$

Recall: The proportion of true positive predictions within the dataset is called recall. It is also interesting to note that true positive rate is also referred to as sensitivity, although it is more commonly used as a term.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (11)$$

F1-Score: This metric provides a balanced measure between precision and recall.

There is a measure known as the AUC-ROC that evaluates the performance of ROC analyses across various classification thresholds. The area under the curve (AUC) is calculated by plotting the true positive rate (Recall) against the false positive rate (False Positive Rate) as part of the ROC analysis.

$$\text{AUC - ROC} = \int_0^1 \text{TPR}(x) dx \quad (12)$$

Based on these metrics, multiple classification models were evaluated, such as DenseNet, VGG19, ResNet, and InceptionV3, also using Random Forest, K-Nearest Neighbors, Decision Tree and XGBoost. These models were

combined with machine learning and transfer learning architectures. In this study, comprehensive metrics were employed to assess how accurate each model was at identifying BCI signals based on EEG data.

C. Experimental analysis and discussion

The Continuous Wavelet Transform (CWT) is used in the analysis to transform raw EEG signals from BCI Competition IV 2a into scalogram images. Using this transformation, brain-computer interface (BCI) applications can extract and classify features based on a rich time-frequency representation of the data. Figure 3 illustrates nine different EEG signals, each with distinct frequencies ranging from 8 Hz to 40 Hz, presented in a time-domain format showing amplitude variations over one second. Each subplot represents a different EEG signal: Signal 1 (8 Hz) shows smooth oscillations indicative of low-frequency brain activity; Signal 2 (10 Hz) has slightly more complex, higher frequency components; Signal 3 (12 Hz) exhibits further complexity and variability; Signal 4 (15 Hz) shows increased oscillations typical of higher frequency brain activities; Signal 5 (20 Hz) increases in complexity with more frequent oscillations; Signal 6 (25 Hz) demonstrates higher frequency and greater variability; Signal 7 (30 Hz) displays rapid oscillations; Signal 8 (35 Hz) is densely packed with high-frequency oscillations, and Signal 9 (40 Hz) presents the highest frequency with very rapid oscillations and high complexity. The transformation into scalogram images via CWT maps these time-domain signals into a time-frequency domain, capturing both temporal and spectral information. This detailed representation aids in identifying patterns and features not easily discernible in the raw time-domain signals, enhancing the effectiveness of subsequent feature extraction and classification processes in BCI systems.

We used advanced machine learning classes and transfer learning models for classifying these extracted features. In addition to Random Forest, K-Nearest Neighbors (k-NN), decision trees and XGBoost, there are several other traditional classifiers. To improve classification performance, Random Forest employed an ensemble method that used multiple decision trees. Data points were classified based on the majority class among the k closest neighbors and based on XGBoost, a gradient boosting algorithm optimized for high performance. We also used pre-trained neural networks, such as DenseNet, VGG19, ResNet, and InceptionV3, for obtaining high-level features from the scalogram images using the capabilities of these networks.

We converted EEG signals into scalograms via CWT, and then divided each dataset into training, validation, and test scenarios using a stratified ratio of 60:20:20. Each dataset was stratified in such a way that a balance was maintained between the classes that were evaluated. A combination of CNNs and conventional machine learning models was used to classify the images following feeding them into Transfer Learning models (TL). The figure 4 illustrates raw EEG signals and figure 5 illustrates scalogram transformed images. The raw images provide a visual of the original EEG signals, while the scalogram-transformed images showcase the enriched time-frequency representation used for training the models. This comprehensive approach ensured that the models were rigorously tested and validated, resulting in improved classification performance and robust evaluation of the EEG signals for BCI applications.

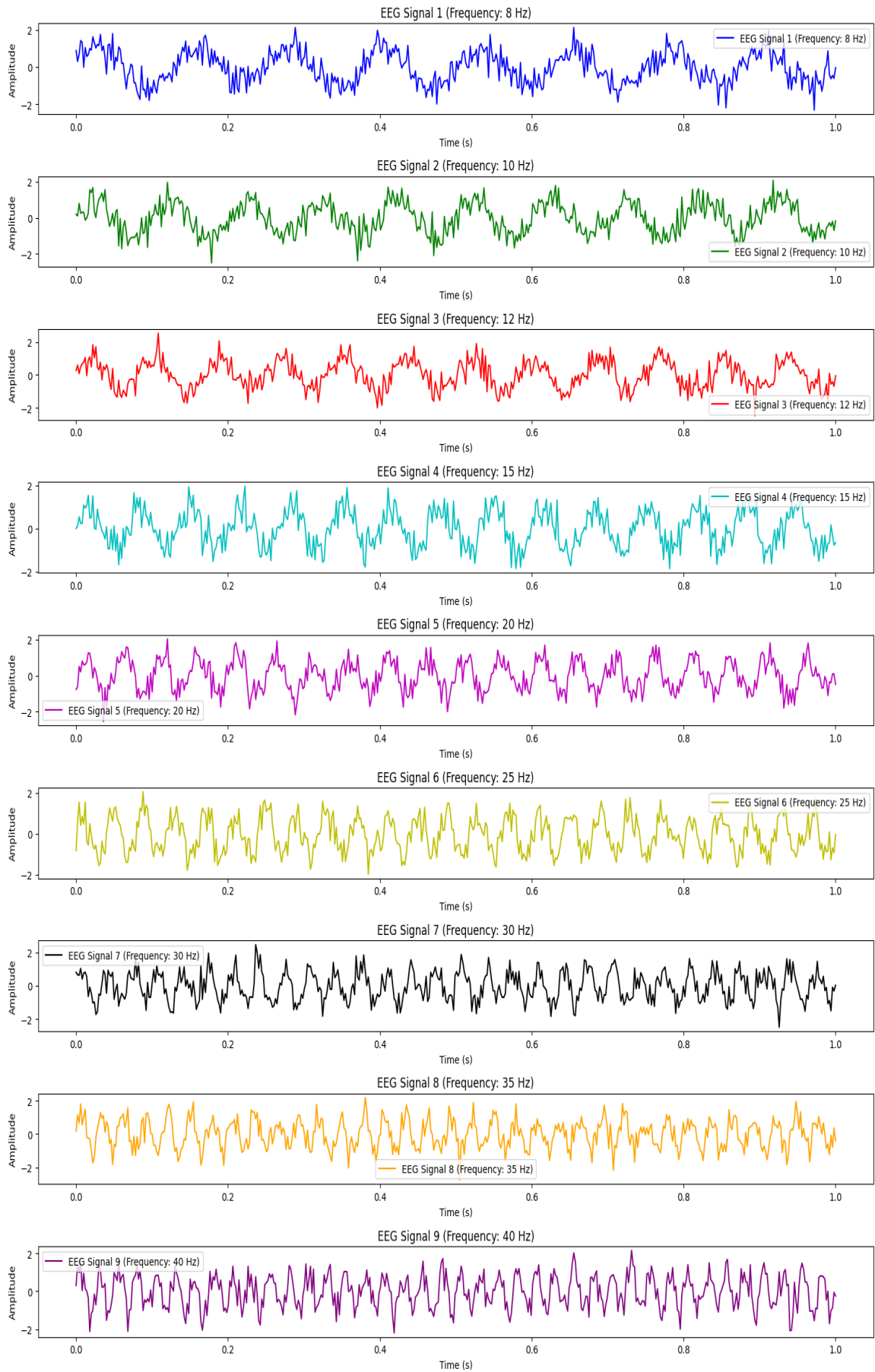


Figure 3. EEG signals with distinct frequencies ranging from 8 Hz to 40 Hz

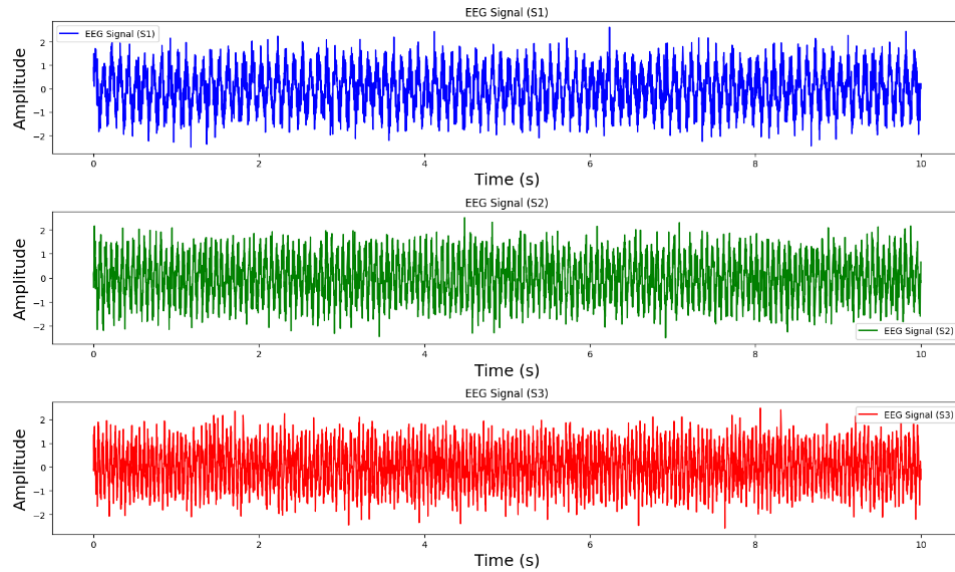


Figure 4. Raw EEG Signals

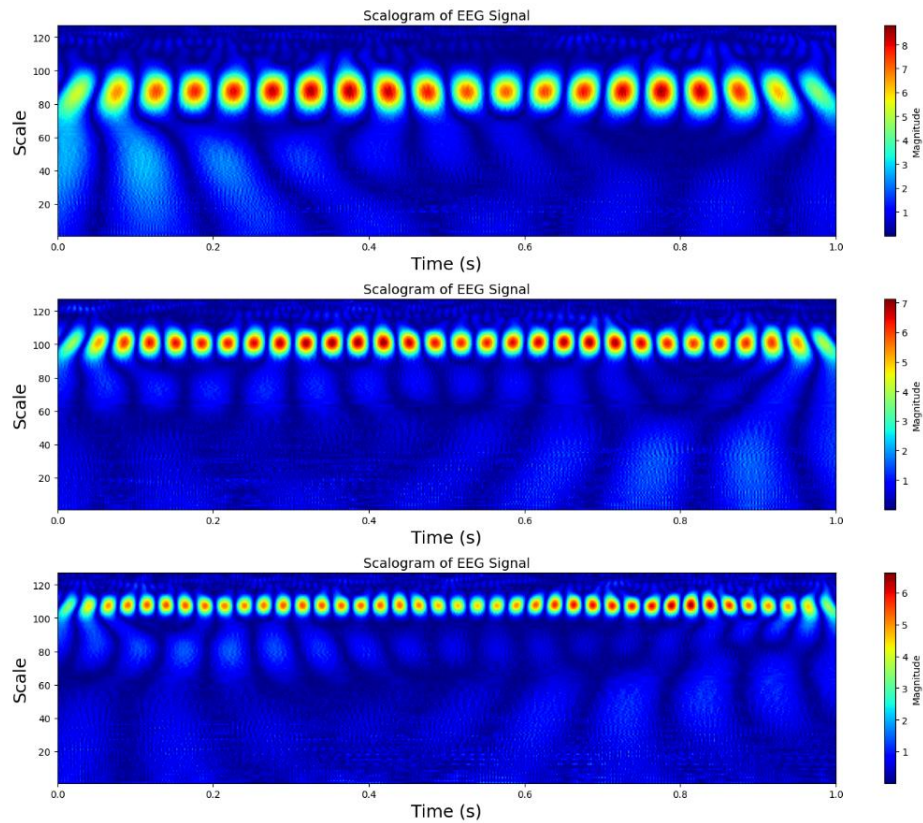


Figure 5. Scalogram Transformed Images

Figure 4 shows the original EEG signals as they were recorded. The raw images highlight the complexity and variability inherent in EEG data, demonstrating the need for effective preprocessing and feature extraction methods to make the data suitable for classification. **Figure 5** depicts the EEG signals after being transformed into scalograms using CWT. In addition to capturing temporal and spectral information, scalograms exhibit a representation of the EEG signals in terms of time and frequency. It is crucial to carry out this transformation in order to enhance the feature extraction process, which will then allow TL models to learn and classify the patterns present in EEG signals effectively. The transformation to scalogram images is a key step in the methodology, as it leverages the strengths of wavelet analysis to provide a richer, more informative representation of the EEG signals. By converting the raw data into a format that captures both time and frequency characteristics, the TL models can better identify and learn from the underlying patterns, leading to improved classification performance.

D. Performance comparison and discussion

There are several machine learning models, transfer learning models, and hybrid models discussed in this section. In evaluations, methodology merit is assessed based on important measures like F1-score, accuracy, precision, and recall. Using machine learning models, we investigated four classifiers and presented their results in Table 1. Its accuracy rating is 96.58%, the precision rating is 95.59%, its recall rating is 94.23%, and F1 rating is 96.65%. A Random Forest has impressive accuracy, precision, recall, and F1-score scores of 92.7%, 93.0%, 91.5%, and 92.5%, respectively. On the other hand, KNN achieves 89.1% accuracy, 88.5% precision, 86.4% recall, and 88.9% F1-score. The accuracy, precision, recall, and F1-score of a decision tree is 85.8%, 86.3%, and 84.6%, respectively. The analysis also takes into account additional evaluation metrics. Figure 6 visually represents these metrics, highlighting XGBoost's superior performance across all metrics compared to the other classifiers. This visual and tabular data collectively emphasize the effectiveness of XGBoost in the given classification tasks.

Table 1. Performance comparison of the ML models

Comparison of ML model performance				
Metrics	Random Forest	KNN	Decision Tree	XGBoost
Accuracy	92.7	89.1	85.8	96.58
Precision	93.0	88.5	86.3	95.89
Recall	91.5	86.4	84.6	94.23
F1 score	92.5	88.9	85.3	96.56

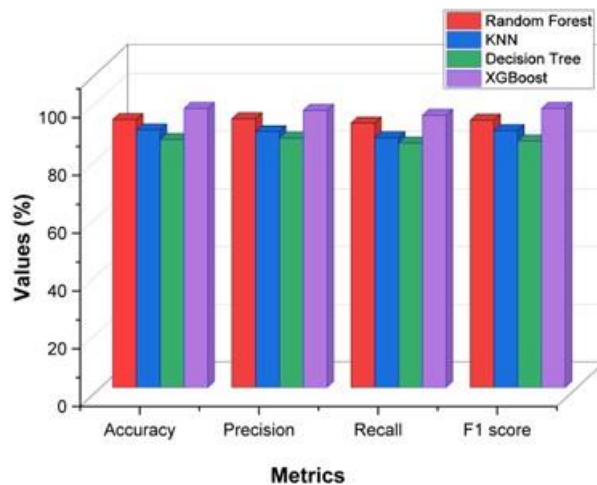


Figure 6. Performance comparison of the ML models

Table 2 presents a comparative analysis of transfer learning (TL) model performance using four different models: DenseNet, VGG19, ResNet, and InceptionV3. When evaluating classification performance, several factors are considered, including accuracy, precision, recall, and F1-score. DenseNet achieved the highest scores with an accuracy of 98.7%, precision of 98.3%, recall of 98.6%, and an F1-score of 98.5%. VGG19 also performed well, with scores of 95.6% accuracy, 94.5% precision, 94.1% recall, and a 95.4% F1-score. ResNet showed strong results with 95.8% accuracy, 89.3% precision, 91.6% recall, and a 94.23% F1-score. InceptionV3 achieved an accuracy of 96.58% and an F1-score of 96.56%. Figure 7 visually represents these metrics, highlighting DenseNet's superior performance across all evaluation criteria, followed closely by InceptionV3, VGG19, and ResNet. This visual and tabular data collectively emphasize the effectiveness of DenseNet in transfer learning applications for EEG signal classification.

Table 2. Performance comparison of the transfer learning models

Comparison of TL model performance				
Metrics	DenseNet	VGG19	ResNet	InceptionV3
Accuracy	98.7	95.6	95.8	96.58
Precision	98.3	94.5	89.3	95.89
Recall	98.2	94.1	91.6	94.23
F1 score	98.6	95.4	95.7	96.56

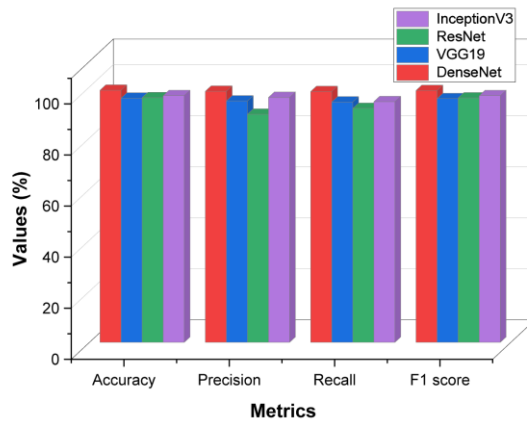


Figure 7. A comparison of the TL models' performance

Table 3 demonstrates that the XGBoost classifier was used to create hybrid models with DenseNet, VGG19, ResNet, and InceptionV3. Among these models, DenseNet+XGBoost outperformed the others, achieving an accuracy of 99.2%, precision of 99.0%, recall of 99.1%, and an F1-score of 99.1%. The InceptionV3+XGBoost model also showed strong performance with an accuracy of 98.6%, precision of 97.5%, recall of 97.3%, and an F1-score of 98.7%. Additionally, ResNet+XGBoost delivered impressive results with an accuracy of 98.6%, precision of 98.3%, recall of 98.2%, and an F1-score of 98.5%. Lastly, the VGG19+XGBoost model showed effective results with an accuracy of 98.5%, precision of 98.4%, recall of 98.0%, and an F1-score of 98.4%.

Figure 8 visually represents these metrics, highlighting DenseNet+XGBoost's superior performance across all evaluation criteria, followed by the other combinations, emphasizing its effectiveness in combined model applications for EEG signal classification. This visual and tabular data collectively emphasize the robustness and high classification capability of DenseNet+XGBoost in handling EEG signal data.

Table 3. Performance comparison of the combined models

Comparison of combined model performance				
Metrics	DenseNet+XGBoost	VGG19+XGBoost	ResNet+XGBoost	InceptionV3+XGBoost
Accuracy	99.2	97.8	98.6	98.5
Precision	99.0	97.5	98.3	98.4
Recall	98.9	97.3	98.2	98.0
F1 score	99.1	97.7	98.5	98.4

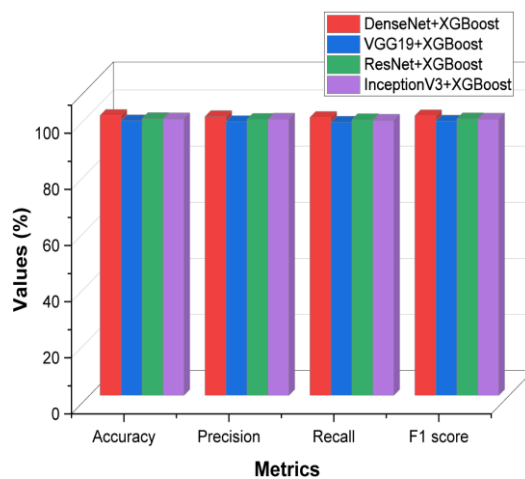


Figure 8. Performance comparison of the hybrid models

Figure 9 presents a Receiver Operating Characteristic (ROC) curve comparing the True Positive Rates (sensitivity) and False Positive Rates (1-specificity) for the hybrid DenseNet+XGBoost model. The blue curve illustrates the model's performance, with an Area Under the Curve (AUC) of 0.99, indicating excellent classification capability for the DenseNet+XGBoost model. The red dashed line signifies the performance of a random guess classifier, serving as a baseline. The substantial area under the ROC curve for the DenseNet+XGBoost model highlights its superior accuracy and effectiveness in distinguishing between different

classes in the EEG-based motor imagery task. In the context of brain-computer interfaces (BCIs), this high AUC value reinforces the model's robustness and reliability.

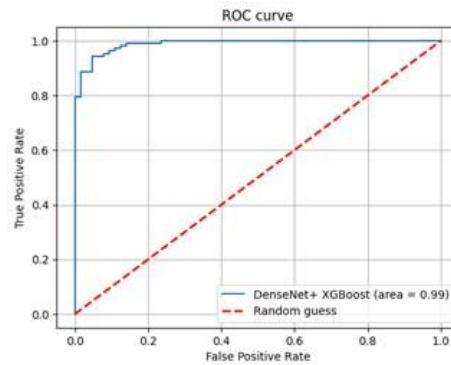


Figure 9. ROC-AUC performance of hybrid DenseNet+ XGBoost model

V. CONCLUSION

This study proposed a technique for converting raw EEG signals into scalogram images using Continuous Wavelet Transform (CWT) to enhance feature extraction and classification in EEG signal analysis. By employing models such as DenseNet, VGG19, ResNet, and InceptionV3, the study demonstrated the superior performance of the DenseNet and XGBoost combination, which achieved an impressive 99.2% accuracy. These results highlight the potential of transfer learning (TL) applications to support individuals with severe physical disabilities by providing precise and reliable control over rehabilitative devices, thereby improving their quality of life. Future research could explore the application of TL models to other types of brain signals, the integration of real-time processing capabilities, and the development of adaptive algorithms to further enhance the robustness and customization of BCI systems.

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