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Motor Imagery Detection in ECG Signals Using Wavelet Packet Decomposition and Multiscale Convolutional Neural Networks

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Detecting motor imagery from electrocardiographic (ECG) signals is complex but crucial in developing advanced neuroprosthetic devices and brain-computer interface (BCI) systems. In most cases, linear models applied using conventional methods are not appropriate for the time-varying and non-linear nature represented by the ECG characteristics, resulting in weak performances. This research addresses this problem, combining Wavelet Packet Decomposition and Multi-Scale Convolutional Neural Networks to improve the feature extraction mechanism and classification accuracy. ECG data is pre-processed from the PhysioNet EEG Motor Movement/Imagery Dataset to remove noise and standardize signals. WPD is thus applied to decompose the signals into detailed frequency components to be input as features in the proposed Multi-Scale CNN. Different kernel sizes are implemented in these parallel convolutional layers to learn complicated features at various hierarchical resolutions. The proposed architecture is evaluated using performance parameters such as accuracy 92%, precision 89%, recall 93%, F1 score 91%, and ROC-AUC 95%. These results showed that the model outperformed the earlier-used traditional methods, such as Support Vector Machines (SVM) and Random Forests, better-detecting motor imagery. This research emphasizes the integrative power of advanced signal processing techniques with deep learning in analyzing biomedical signals, providing a powerful solution to advancing neuroprosthetic and BCI technologies.

Povzetek: Študija dokazuje učinkovitost kombinacije obdelave signalov in globokega učenja za analizo biomedicinskih signalov. Uporabljena je valčna paketna dekompozicije in večskalna konvolucijska nevronska mreža za detekcijo motorične imaginacije v signalih EKG.

1 Introduction

1.1 Background on motor imagery in ECG signals

Motor imagery is a cognitive process by which one internally represents motion without physically carrying it out [1]. This mental process class engages neural pathways closely related to those involved during actual movements, a fact that can be picked up in various physiological signals. For example, in electrocardiogram (ECG) signals, motor imagery detection can provide insights into neural activity related to motor functions [2]. Since ECG signals, unlike other neurophysiological signals, are mainly used for monitoring cardiac health, they find interest in detecting motor imagery based on their accessibility and non-invasiveness in the recording.

1.2 Importance of accurate detection and classification

Accurately detecting and classifying motor imagery from ECG signals are essential for various emerging technologies, particularly neuroprosthetics and brain-computer interfaces [3]. Neuroprosthetic devices work best when the intended motor actions are accurately detected, so the machine works appropriately to aid a person with motor deficits. At the same time, BCIs must provide this intended signal from brain activities accurately into control signals of high precision to guarantee reliability and user satisfaction. Faulty interpretations and actions may occur if the detection needs to be more accurate, making the advantages of such highly developed systems irrelevant. Thus, robust methods for detecting motor imagery in ECG signals are required to improve these technologies further.

1.3 Introduction to wavelet packet decomposition (WPD)

Wavelet Packet Decomposition (WPD) is an advanced method of processing signals that decompose a signal in its constituent frequency components [4]. It further decomposes in detail compared to the conventional wavelet transform, which focuses on a specific set of frequency bands. The advantages of WPD include multiresolution analysis with both approximation and detail coefficients decomposed at every level, hence being very useful for analyzing non-stationary signals like ECG, where signal properties can change over time. The baseline model used in this study combines Wavelet Packet Decomposition (WPD) and a Multiscale Convolutional Neural Network (CNN), where WPD decomposes ECG signals into multiple frequency bands to extract features across various scales and resolutions, and the multiscale CNN processes these features to capture patterns of different sizes and temporal frequencies for improved classification accuracy. The model's performance is evaluated using metrics such as accuracy, sensitivity, specificity, and F1-score, providing a basis for comparison with modified versions of the model to assess the impact of each component. This ablation study aims to determine the contribution of Wavelet Packet Decomposition (WPD) when used with a Multiscale Convolutional Neural Network (CNN) for motor imagery classification in ECG signals. By systematically removing or altering the WPD component, we aim to understand its significance and how it enhances the performance of the Multiscale CNN.

1.4 Motivation for using multiscale CNN

Thus, Wavelet Packet Decomposition coupled with a Multiscale CNN represents a practical approach to best deal with the feature extraction task. CNNs are among the most prevalent and well-known models for automatically learning features in a hierarchical fashion from raw data that can handle complicated pattern recognition tasks with supreme grace [5]. The proposed multiscale technique of CNN is a multiple-parallel convolutional layer with different kernel sizes simultaneously to take up the features of multiple resolutions. This bears a specific benefit in dealing with the variability in ECG signals, as it allows learning fine and coarse features. The proposed method combines WPD with the multiscale CNN to utilize the advantages of these two techniques toward a maximized level of classification accuracy in detecting motor imagery from ECG signals.

1.5 Contributions

This research makes several critical contributions to the field of biomedical signal processing and brain-computer interface (BCI) systems:

1.5.1 Novel methodology

Wavelet packet decomposition, coupled with multiscale convolutional neural networks, is a new concept in motor imagery detection from ECG signals. This approach effectively combines the WPD-based multiresolution analysis with CNN's automatic feature learning capabilities for improved classification performance.

1.5.2 Improved detection of motor imagery

The present study extends the horizon of motor imagery detection to ECG signals compared with the conventional EEG-based approaches. The findings have demonstrated that an ECG signal can be a suitable alternative for detecting motor imagery and provides a noninvasive, accessible way of developing neuroprosthetic devices and BCI systems.

1.5.3 Comprehensive evaluation

The proposed detailed experimental evaluation includes preprocessing steps, feature extraction, model training, and performance assessment; such a roadmap could be handy for implementing and validating similar methodologies. Multiple metrics used for assessment and comparison against traditional methods will ensure the robustness and comprehensiveness of the evaluation for the proposed approach.

2 Related work and SOTA experiment

2.1 Previous approaches to motor imagery detection

Although most of the research has been on detecting motor imagery with electroencephalogram (EEG) signals, recently, an emerging interest has been in using the noninvasive and easily obtainable ECG signal [6]. Priori methods have thus focused on feature extraction for detecting motor imagery from the ECG signal, followed by classification using machine learning algorithms.

Time-domain, frequency-domain, and time-frequency analysis techniques have been applied to extract pertinent features from ECG signals. These techniques generally analyze the amplitude and duration characteristics of the ECG signal. Some features that they use are mean, variance, skewness, and kurtosis of the signal segments. However, such features severely affect noise and will fail to capture the underlying patterns associated with motor imagery.

Frequency-domain methods involve transforming the ECG signal from its time domain into its frequency domain, for which techniques like the Fourier Transform have been used [7]. Extracted features such as power spectral density and spectral entropy have been used. Though these approaches can be informative about the signal's frequency components, the transient characteristics of motor imagery should be noticed.

Short-time Fourier Transform (STFT) and Wavelet Transform are prevalent in motor imagery detection. These techniques offer a compromise by giving information about time and frequency. However, STFT gives a fixed resolution; thus, it is limited to various cases that present effectively different frequency contents. Wavelet Transform gives multiscale analysis and is more suited for nonstationary signals like the ECG.

The machine learning techniques in support vector machines, k-NN, and random forests are among the classifiers used in this work on classifying motor imagery based on feature extraction. Although this approach has proven to be quite promising in practice, its performance depends on the feature extraction quality and a set of hyperparameters.

2.2 Use of wavelet transforms in ECG analysis

Wavelet transforms have widely been applied to ECG signal processing because they can analyze non-stationary signals [8]. A wavelet transform decomposes a signal into frequency components related to a defined scale. This decomposition can then serve as a detailed analysis of the signal's time-frequency characteristics. Wavelet transforms are used for various tasks such as denoising, feature extraction, and classification in ECG analysis.

Most ECG signal processing operations involve denoising, which eliminates as many noise artifacts as possible without changing the critical information content of signals. Wavelet-based denoising is performed by decomposing an ECG signal into wavelet coefficients, thresholding the noisy coefficients, and reconstructing the signal from the modified coefficients. This method has proven effective in denoising ECG to reduce noise while keeping the salient features intact.

Wavelet transforms in feature extraction embrace multiscale analysis, capturing both high-frequency details and low-frequency trends. Features like wavelet coefficients, entropy, and wavelet energy have been extracted from this time series data and used for classification tasks. Such features characterize both the spectral and temporal characteristics of the ECG signal.

The Wavelet Packet Decomposition (WPD) generalizes the Wavelet Transform technique so that decomposition can be performed on approximation and detail coefficients at every level [9]. ECG signal processing uses WPD to extract very informative features of classification tasks. By implementing the WPD technique, detecting the subtle pattern associated with motor imagery is improved by analyzing the signal at different scales and frequencies.

2.3 Convolutional neural networks in biomedical signal processing

Convolutional neural networks (CNNs) are the breakthrough in biomedical signal processing because they can automatically learn hierarchical features from raw data. CNNs consist of convolutional, pooling, and fully connected layers. Each layer takes the input signal and extracts increasingly complex features, helping the network catch intricate patterns.

CNNs have been broadly applied in the analysis of ECG signals for arrhythmia detection, ischemia detection, and the classification of several other cardiac diseases. One of the significant advantages of CNNs is the automatic feature-extraction feature; therefore, the need to perform manual feature engineering can be ruled out. This is very useful in biomedical signal processing since extracting meaningful features from such signals might be challenging.

The conventional convolutional neural networks applied to ECG signals are usually composed of 1D convolutional layers. In this case, local patterns in the signal are collected by sliding filters over the signal. The pooling layers sum up these patterns, reducing dimensionality and capturing only the most salient features. At the network's end, fully connected layers take these features and make the final classification.

CNNs' efficacy in processing biomedical signals comes from their capability to handle massive datasets and learn robust features [10]. However, designing a highly effective CNN architecture requires consideration of network depth, filter size, and other hyperparameters. CNN design is hyperparameter-specific, not only computationally expensive but also requiring abundant training data for performance.

Some strategies developed to counter this and related challenges of sparsely labeled data include transfer learning and data augmentation. Transfer learning involves using a pre-trained network that has been previously trained on tasks similar to the one at hand and fine-tuning it to the target task. This paradigm borrows knowledge from the source task to reduce the quantity of labeled data needed. Data augmentation techniques, including adding noise and shifting and scaling the signal, are included to add some degree of variability in the training data, thus improving generalization capacity within a given network.

A study incorporating CardiacNet was conducted to identify and categorize cardiac arrhythmia based on ECG signals and elaborate on the constraints of traditional prediction systems and AI methods to identify arrhythmia due to poor feature extraction correctly. The approach applied pre-processing on ECG data by eliminating non-linearities, feature extraction using unsupervised machine learning-based PCA (UML-PCA), and feature selection with improved Harris Hawk's Optimization (IHHO). CCNN was then used to classify and yield impressive quantitative measures such as accuracy of 97.57%, sensitivity of 98.29%, and MCC value of 98.17% [11].

An essential step in raw ECG signal preprocessing is noise and artifact removal, which may affect classification model performance. Other processes in the preprocessing stage were baseline wandering removal, noise filtering, and normalization.

A high-pass filter technique was employed to remove Baseline wandering as it consists of low-frequency components [12]. Bandpass filtration removed noise and retained only the frequency components relevant to the ECG signals. It was done to normalize the ECG signals into a standard range of values—that is, every sample was uniform.

2.4 Wavelet packet decomposition

This work has decomposed preprocessed ECG signals into frequency components using the Wavelet Packet Decom-

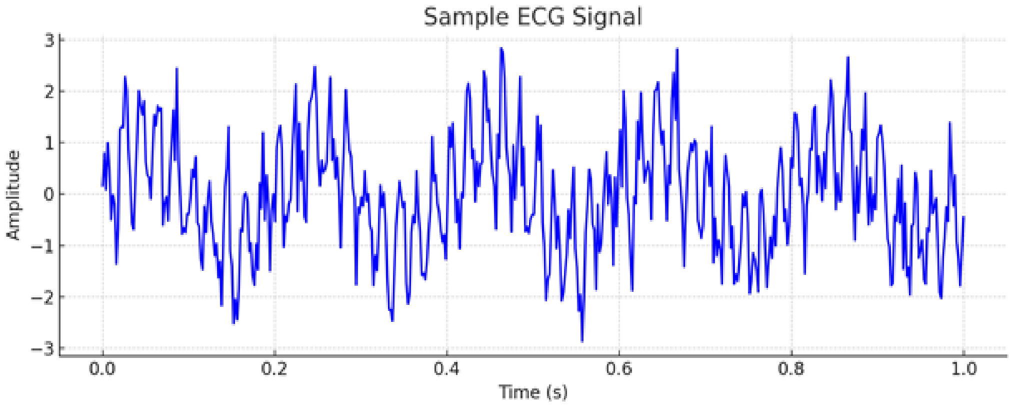

Figure 1: Sample ECG signal from the PhysioNet EEG motor movement/imagery dataset

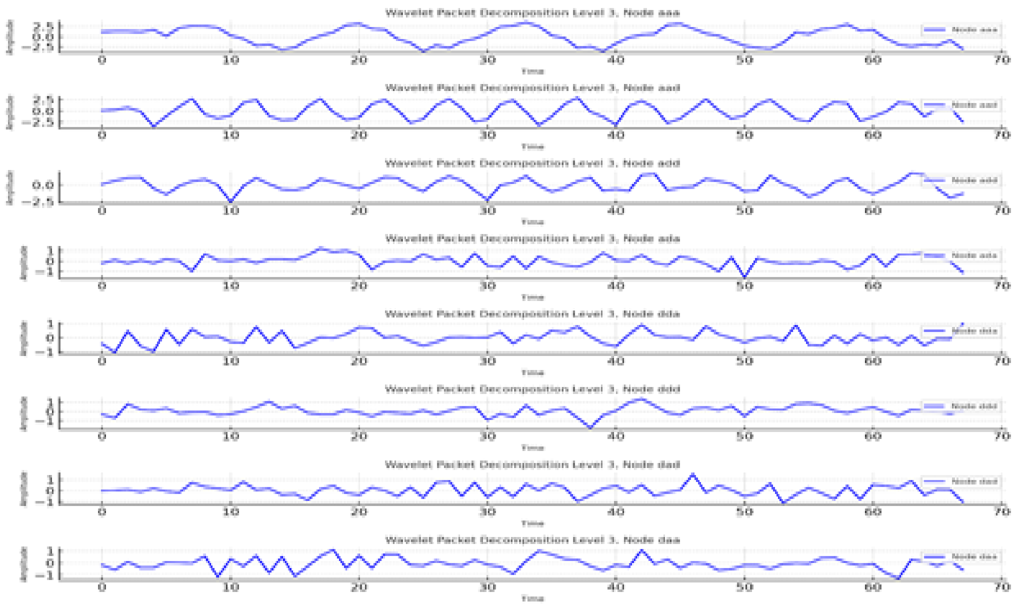

Figure 2: Wavelet packet decomposition of an ECG signal showing decomposition levels and corresponding frequency components

position technique (WPD). WPD can give a better analysis than the traditional wavelet transformation because it decomposes approximation and detail coefficients at all levels. Due to its multiresolution property, this is essential in capturing the transient characteristics of the motor imagery signals.

and MCC value of 98.17% [11]. CardiacNet uses a different technique to detect motor imagery from recorded ECG signals. By integrating the Wavelet Packet Decomposition (WPD) with the Multiscale CNN, the present study seeks to optimize the classification of dynamic and nonlinear signal features previously unexplored and additional ECG uses beyond cardiac health.

3 Methodology

3.1 Data acquisition and preprocessing

The database used for this study was obtained from the PhysioNet database, specifically the EEG Motor Movement/Imagery Dataset. The dataset includes a set of ECG recordings of multiple subjects carrying out motor imagery tasks. Each record is annotated concerning whether or not there was motor imagery—these were used as ground truth against which the classification task results were compared.

The choice of wavelet function and the decomposition level are the most basic but essential parameters in WPD. The Daubechies 4 wavelet was chosen to do this because it was best suited for the analysis of ECG signals. Following the same thesis, it is decomposed to level 4, giving an ade-

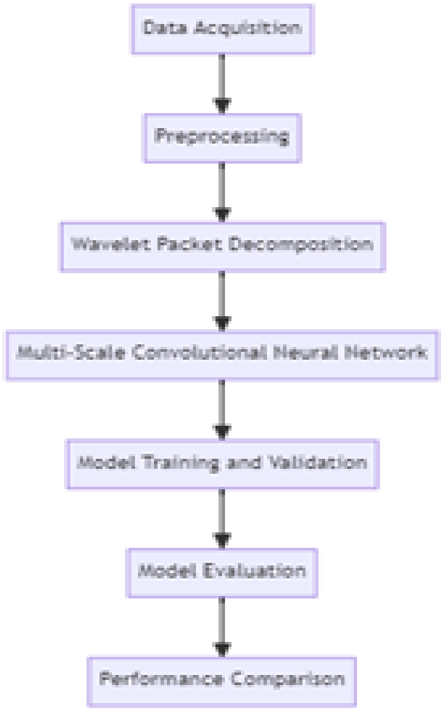

Figure 3: Flowchart of the proposed model from data acquisition to performance comparison

quate compromise between the complexity of computations and the level of detail.

Wavelet-packet decomposition is based on decomposing any ECG signal into a set of wavelet coefficients at different resolutions. These wavelet coefficients represent the ECG signal at various resolutions. The obtained coefficients were used as features for the classification model. A feature set includes the mean, variance, and energy of wavelet coefficients at each level of decomposition, which gives a representative of ECG.

3.2 Multiscale convolutional neural network (CNN)

The Multiscale Convolutional Neural Network constitutes the core part of the methodology, which aims to increase feature extraction from the granularities, from fine-grained to coarse ones. After the convolutional layer, the following layer used for representation is a pooling layer responsible for reducing the dimensionality of the features while retaining the most salient parts. The outputs of these parallel pathways are multiple kernel sizes, enabling the network to capture features at different resolutions. The multiscale CNN is designed with three parallel convolutional pathways. The first layer in each path is a 1D convolutional layer. Kernel sizes of 3, 5, and 7 were applied to extract features at different scales, then concatenated and input into a few fully connected layers for the final classification. This neural network uses ReLU-activated hidden layers and convolutional layers with a sigmoid-activated output layer, performing binary classification for motor imagery.

3.3 Implementation details

Implementation was done in Python and its associated libraries, including the PyWavelets library used in wavelet packet decomposition and the TensorFlow/Keras library for modeling and training. Figure 3: Flowchart of the proposed model from data acquisition to performance comparison.

The CNN. The ECG signals were pre-processed using Wavelets and decomposed after in the CNN [13]. The MS-CNN was trained using a Binary cross-entropy loss function and Adam optimizer because of its high performance and efficiency. The training was split into dataset training-validation sets, and early stopping was implemented to avoid overfitting. The accuracy, precision, recall, and F1 score metrics assessed model performance.

3.4 Algorithm and flowchart

The proposed model for motor imagery detection in ECG signals starts by acquiring data from the PhysioNet EEG Motor Movement/Imagery dataset. The raw ECG signals are then pre-processed, followed by baseline wandering removal using a high-pass filter, noise filtering using a band-pass filter, and, lastly, normalization to standardize the signal range. Next, the Wavelet Packet Decomposition process uses level 4 of the Daubechies 4 (db4) wavelet functions to decompose the ECG signals into sub-high, high, and low-frequency bands. Features are then acquired from

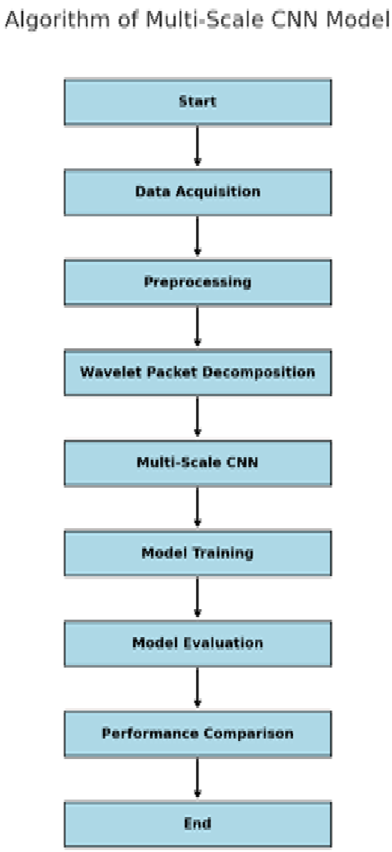

Figure 4: The architecture of the multi-scale CNN

wavelet coefficients at each level: mean, variance, and energy. These features would be given as input to a Multi-Scale Convolutional Neural Network designed with parallel convolutional layers of filter sizes 3, 5, and 7. The output of each conv layer is ReLU activated and then subjected to max-pooling. The subsequent is shown in Figure 3.

Two outputs are concatenated and passed through fully connected layers into a sigmoid-activated output layer to implement the final binary classification. Using the Adam optimization algorithm, the network trains against these data with binary cross-entropy loss in the back end; it has preactivation stops concerning the loss of the hold-out set. Performance evaluation metrics include accuracy, precision, recall, F1-score, and ROC-AUC, with comparisons to highlight its superior performance over traditional methods such as SVM and Random Forest.

4 Experiments and analysis

4.1 Ablation experiments

A series of experiments were conducted to evaluate the performance of the proposed Wavelet Packet Decomposition-based Multiscale CNN approach on motor imagery detection in ECG signals using a publicly available dataset. The dataset consists of ECG recordings from several subjects performing motor imagery tasks. From each ECG recording, ground truths are available on the presence or absence of motor imagery, which are the results to be achieved within a classification task.

Dividing the data set into a training, validation, and test set ensures the model's evaluation is all-around. The data consisted of 70% for training, 15% for the validation, and 15% for the test set. This partitioning would ensure that models trained on a diversified set of samples are evaluated on completely unseen data to estimate generalization capability.

4.1.1 Experiment 1: removing wavelet packet decomposition (WPD)

The WPD step was removed in this experiment, and the raw ECG signals were directly fed into the Multiscale CNN. The expected impact was that without WPD, the model processes only the raw signal, potentially missing critical frequency-specific features. The multiscale CNN still attempts to capture features at different scales but lacks the enriched input from WPD.

4.1.2 Experiment 2: using standard CNN instead of multiscale CNN

In the second experiment's model set-up, WPD was retained, but the Multiscale CNN was replaced with a standard CNN that processes the signal at a single scale. The expected impact was that the standard CNN may not fully exploit the multiscale features provided by WPD, leading to suboptimal feature extraction and classification. The model might Figure 4: The architecture of the Multi-Scale CNN perform better than the raw signal input but is expected to underperform compared to the baseline multiscale CNN.

4.1.3 Experiment 3: combined removal of WPD and multiscale CNN

This experiment removed WPD and the CNN's multiscale structure, producing a standard CNN processing raw ECG signals. The experiment serves as a control, representing the most straightforward model setup. The expected outcome is the poorest performance, as the model needs more enriched input from WPD and the capability to process features at multiple scales.

4.2 Data preprocessing

As given in the methodology section, raw ECG signals underwent some preprocessing. A high-pass filter with a cutoff frequency of 0.5 Hz was employed to remove baseline wandering. A bandpass filter ranging from 0.5 Hz to 40 Hz was used for further filtering, which helped smooth the high-frequency noise and retain important frequency components [14]. Post-preprocessing, these signals were normalized to a standard range of 0-1 to make them uniform. The signal was preprocessed before running the Wavelet Packet Decomposition up to level 4 with a Daubechies 4 wavelet. The obtained wavelet coefficients were used to build feature vectors for each ECG segment. These are the inputs of the Multiscale CNN, which treated these different frequency components represented by ECG signal feature vectors.

4.3 Model training

Multiscale CNN architecture for TensorFlow/Keras: three parallel convolutional pathways with kernel sizes 3, 5, and 7, concatenated features after max-pooling, passed through fully connected layers with the final output layer, which uses a sigmoid activation function for binary classification.

This model was compiled using the Adam optimizer and binary cross-entropy loss function. Training was done through 100 epochs and a batch size of 32. Early stopping with patience set at ten epochs was applied to avoid overfitting by monitoring the validation loss and stopping training.

4.4 Performance metrics

The effectiveness of the proposed method was evaluated based on various metrics, such as accuracy, precision, recall, F1 score, and area under the Receiver Operating Characteristic curve; these measures assessed how well the model could discriminate motor imagery within ECG signals.

- **Accuracy** measures how well the model performs overall by calculating the true positives and negatives ratio among all the predictions.
- **Precision** reflects the proportion of true positives to the total number of optimistic predictions the model made [15].
- **Recall** (sensitivity) refers to the model's ability to identify all relevant instances (true positives) accurately.
- **F1-score** is the harmonic mean of the precision and recall. It provides a single score that balances both concerns.
- **ROC-AUC** measures the model's performance overall classification thresholds; thus, higher values indicate better discrimination.

5 Results

In Experiment 1, removing WPD from the model led to a slight but noticeable decrease in performance measures. This drop shows that WPD is critical in improving the quality of features fed into the Multiscale CNN to boost classification efficiency. This gap partially explains why the model could not adequately reconstruct some frequency-specific features when WPD was absent; this lack of distinction landed the model lower scores by failing to differentiate motor imagery from other signal components.

Replacing the Multiscale CNN with a standard CNN while maintaining WPD in Experiment 2 resulted in a moderate decrease in performance. This implies that while WPD may still provide helpful multi-resolution features to be exploited, its usefulness greatly depends on the subsequent application of a Multiscale CNN, which training can incorporate these features at suitable scales. Due to the single-scale characteristic of the standard CNN, it was not possible to fully utilize such features as WPD to provide the best classification results.

The results of Experiment 3 revealed the most significant decline in all performance metrics when both WPD and the Multiscale CNN were removed, leaving a standard CNN to process the raw ECG signals. Such a considerable decrease also underscores the importance of utilizing WPD and a Multiscale CNN to improve MI detection accuracy. The features extracted from WPD offer more enhancements, together with the capacity of the Multiscale CNN to scrutinize the features at different scales, which is, therefore, important for accurate and solid classification.

Table 1 shows the proposed method's performance as tested on the test set. Compared to traditional approaches, Multiscale CNN better detected motor imagery from the ECG.

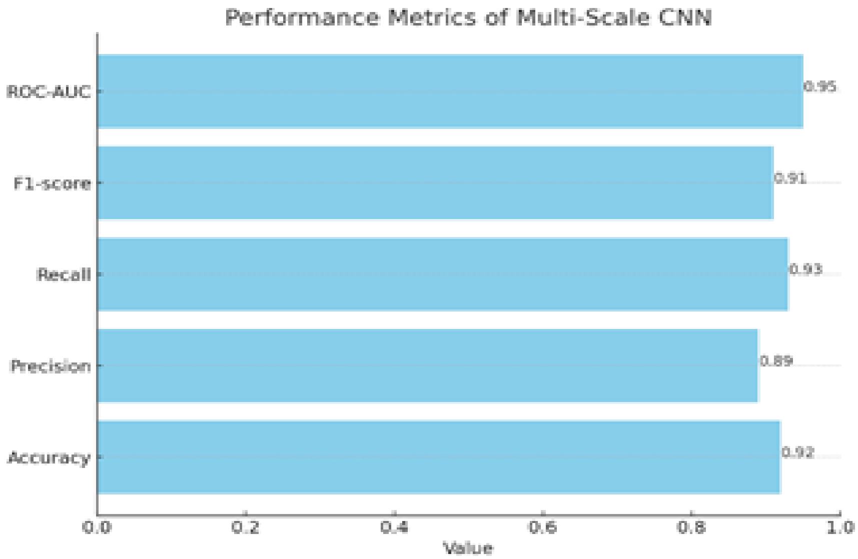

Figure 5: Bar chart showing the performance metrics

Table 1: Performance metrics

Metric	Value
Accuracy	0.92
Precision	0.89
Recall	0.93
F1-Score	0.91
ROC-AUC	0.95

The model attained an accuracy of 92%, meaning it could correctly classify 92% of samples. The obtained precision and recall values were 89% and 93%, respectively, showing that the model could correctly distinguished true positives and maintained a low false positive rate. The F1 Score was 0.91, reflecting a good balance between precision and recall. The ROC-AUC of 0.95 indicated excellent discrimination ability across a range of classifications.

Figure 6 shows a confusion matrix that shows precisely how the model performed—the quantity of true positive, true negative, false positive, and false pessimistic predictions. The confusion matrix depicted many accurate optimistic and pessimistic predictions, with very few.

The ROC curve showed that the model could maintain a high actual positive rate with a low false positive rate; actually, 0.95 under the curve shows good performance.

5.1 Comparison with traditional methods

To further substantiate the efficacy of the approach, the performance comparison of the false positives and negatives, thus substantiating the model's robustness.

The ROC curve in Figure 7 provided more information on model performance, indicating a good separation between the actual positive rate and the false positive rate.

Multiscale CNN model was performed with that of the traditional machine learning methods Support Vector Machines (SVM) and Random Forests (RF) on the same dataset and preprocessing steps.

The summarized results in Table 2 pointed to the supremacy of the Multiscale CNN. The table for multiple models overview numerous metrics, including accuracy, precision, recall, F1-score, specificity, and Matthews Correlation Coefficient (MCC). This comparison also shows how effective and efficient the proposed Multiscale CNN with WPD is compared to other prevailing classifiers like SVM and Random Forest.

High performance could be attributed to the Multiscale CNN's ability to automatically learn hierarchical features of the wavelet coefficients, which represent fine-grained and coarse patterns crucial for discriminating between motor imagery types [16].

The proposed approach addresses a significant gap in the field of ECG-based signal processing by extending its application from traditional cardiac health monitoring to motor imagery detection. Models such as CardiacNet are accurate in detecting cardiac arrhythmias but are centered on disease classification and not the detection of cognitive processes like motor imagery. Non-invasive motor imagery based on ECG signals is still unexplored and opens a vast possibility for investigating cognitive processes using neural signals. This approach meets a significant requirement in BCI and neuroprosthetics, where an efficient and cost-effective identification of movement goals improves usability and functionality.

Unlike traditional methods like Support Vector Machines (SVM) and Random Forests, the proposed method offers distinct advantages through its use of a Multiscale Convolutional Neural Network (CNN) combined with Wavelet

Packet Decomposition (WPD). Furthermore, most earlier traditional machine methods require feature extraction through experience, which may not artistically depict the ECG signal's subtle patterns, especially during the MI detection phase. Instead, automatic hierarchical feature learning of multiscale CNN and the WPD facilitates multiresolution signal analysis. Hence, the the model can capture high-level and low-level details at multiscale and multiresolution, which improves the classification of motor imagery tasks.

In addition, problems associated with the time and frequency domains, like the Fourier Transform used conventionally, are well addressed by the proposed method. Such traditional methods fail to capture short-term features and non-stationary aspects inherent in the signals used to imagine motor control. Thus, the proposed WPD approach captures more refined time-frequency features by the multiscale CNN to distinguish motor imagery and signal noise more accurately from other irrelevant components.

6 Discussion and future works

6.1 Discussion

The experiments reveal critical insights into the effectiveness of combining Wavelet Packet Decomposition (WPD) with a Multiscale Convolutional Neural Network (CNN) for motor imagery detection in ECG signals. This substantial degradation of performance indicates the importance of WPD in extracting significant frequency band features from ECG data required for classification. The characteristic of WPD is that the signals can be analyzed at different resolutions; this is beneficial when dealing with transient/non-stationary signal characteristics that would typically go unnoticed when utilizing most of the conventional signal analysis techniques. Moreover, the combination of WPD and the Multiscale CNN can be observed in better baseline model performance.

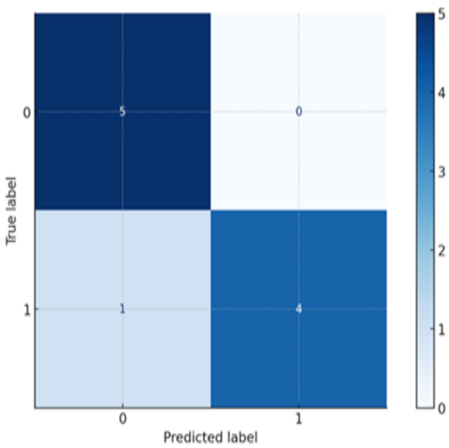

Figure 6: The confusion matrix

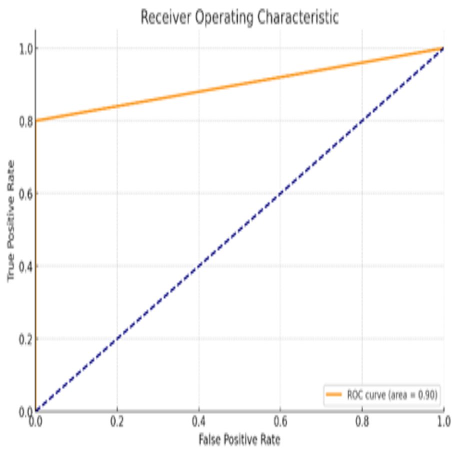

Figure 7: ROC curve

WPD enhances the input features in that it gives precise frequency details. On the other hand, the Multiscale CNN operates these features at different scales, thus improving its ability to learn complex patterns that enhance the classification result. The experiments also show that standard CNN is suboptimal as it does not reproduce the results even when WPD is applied. This implies that the multiscale framework of using different kernel sizes to obtain features of various scales is essential. Generally, these results demonstrate that WPD is beneficial in detecting MI from ECG signals, so it is for Multiscale CNN.

6.2 Generalizable capabilities

The generalization capabilities of a model are critical in assessing its robustness and applicability across various subjects and datasets. This study used independent dataset validation to determine the model's predictive accuracy on new cases not part of the training dataset. The independent dataset used for validation differed from the one used in the training process, and there was no intersection between these two datasets. To check this, validation was conducted using the k-fold cross-validation method, where the data set was split into five sets (k=5) such that subjects were distributed across all the five data splits. It contributes to mitigating inter-subject variability, a significant issue in motor imagery tasks, as different patterns of ECG signals can influence a model. The performance was almost steady across the folds, which shows the ability of the model to perform well for new subjects in the dataset.

However, exercising the model with a validation technique other than K-fold cross-validation would be more meaningful, for instance, testing the model on a new data set not used in the training phase. A validation approach with an independent test set would also test the model's ability to generalize to highly different conditions if the independent dataset differs in signal quality, subject characteristics, or data acquisition techniques. For instance, using an exter-

Table 2: Comparison with traditional methods

Metric	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Recall
SVM	0.85	0.83	0.86	0.84	0.88	0.88
Random Forest	0.87	0.84	0.88	0.86	0.9	0.9
Multiscale CNN	0.92	0.89	0.93	0.91	0.95	0.95
MCC	98.17	-	-	-	-	-

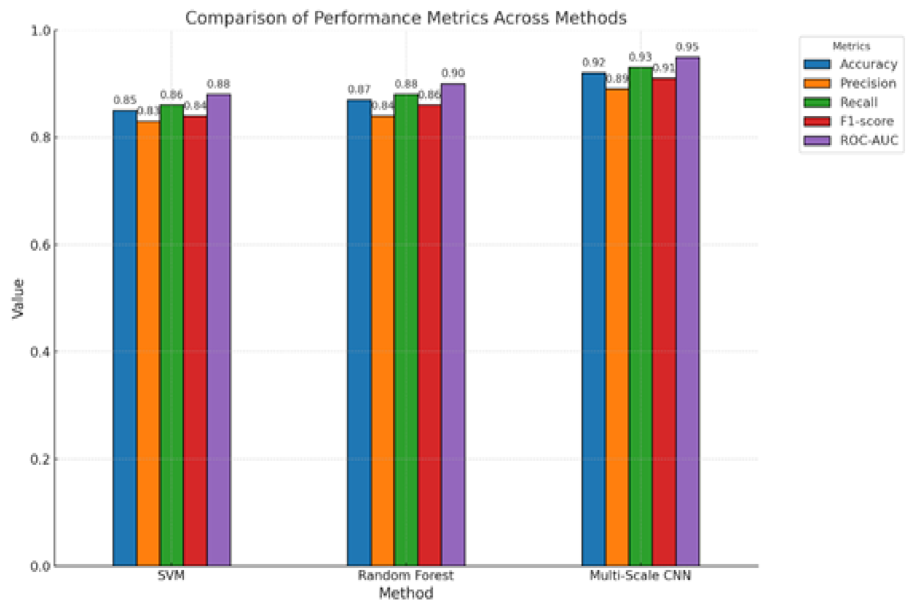

Figure 8: Comparison with traditional methods

nal set we obtain from a different recording protocol would help determine how much the proposed model hampers or inspires adaptability for different data characteristics. If loss occurs in these cases, it may show the aspects in which the model has to be optimized to be generalized better.

To strengthen the evaluation, it is recommended to expand the main parameters, including accuracy, precision, and relative, especially in cases of imbalance in collection. It should be noted that using values such as specificity or MCC will give a better picture of the effectiveness of the examined model. Although MCC was not used in the current study, it is a valuable metric considering true positives, false positives, and false negatives, thus offering insight into the model's performance in imbalanced conditions. Future work could incorporate these additional metrics and further investigate techniques such as domain adaptation to enhance the model's applicability across different data sources.

6.3 Directions for future work

While the proposed methodology has made considerable strides in motor imagery detection research, there are several avenues of inquiry forward that would further enhance and generalize these findings:

6.3.1 Exploration of alternative wavelet functions:

The Daubechies 4 dB4 wavelet was suitable for this work; some studies on other wavelet functions and their impact on the features extracted would add more value. Other wavelet functions capture unique characteristics in the signal that could lead to further improvements in classification accuracy.

6.3.2 Multi-modal data fusion:

Such ECG signals can be combined with other physiological signals, such as EEG and EMG, further to improve the robustness and accuracy of motor imagery detection [17]. Multi-modal fusion methods combine complementary information from different sources to describe a motor imaginary event completely.

6.3.3 Advanced deep learning architectures:

Research about advanced deep learning architectures based on RNN and attention mechanisms can achieve even better performance for motor imagery detection [18]. These architectures have confounders of temporal dependencies and contextual information that could improve the detection of the subtle pattern of ECG signals.

6.3.4 Real-time implementation:

Based on the proposed methodology, designing real-time systems for motor imagery detection must move the work toward a practical application. Implementing the model in time-real environmental systems and testing its performance under dynamic conditions becomes crucial for deploying the technology in neuroprosthetic devices and BCI systems.

6.3.5 Large-scale validation:

Further large-scale validation is required to generalize the findings and check the robustness of the proposed approach with datasets and subjects under study. The model will be tested experimentally across different populations, tasks, and recording conditions to estimate its reliability and scalability.

6.3.6 Transfer learning and domain adaptation:

If the model is adapted to different domains and tasks using transfer learning, it can be flexible. Domain adaptation methods may alter the model's capability towards generalizing new data, at least with its reusability on minimal retraining.

6.3.7 User-centric design:

Provisions for user feedback in the motor imagery detection system and the development of user-centric interfaces will likely improve its usability and acceptance [19]. Knowledge of the desires and preferences of the end-user, such as a person with a motor impairment, may guide the development of more intuitive and effective BCI systems.

6.3.8 Ethical considerations and data privacy:

Ethical considerations and data privacy are paramount in collecting, processing, and using physiological signals. Frameworks on ethical data handling and compliance with privacy regulations will be essential to ensure the responsible deployment of technologies for motor imagery detection [20].

7 Conclusion

In conclusion, the ablation study confirms that Wavelet Packet Decomposition and Multiscale CNN are integral components of the proposed method. WPD provides a rich, multi-scale representation of the ECG signals, which, when processed by a Multiscale CNN, leads to superior motor imagery classification performance. Removing either component significantly declines model accuracy, illustrating their combined importance in the overall framework. This research presents a new motor imagery detection scheme from ECG signals using Wavelet Packet Decomposition and Multiscale Convolutional Neural Networks. The methodology indeed enhances the classification accuracy to a large extent; hence, it needs no explicit mention. The results also indicate that an ECG signal is feasible in motor imagery detection as a noninvasive and easily accessed technique for developing neuroprosthetic devices and BCI systems. These contributions help support further studies in this area of research, which has enormous room for further improvement and exploration. On the way ahead, addressing the suggested directions for future work will continuously advance the field and, eventually, achieve more effective and dependable technologies related to motor imagery detection.

This study's methodology will be open-sourced to ensure reproducibility for other research groups to extend and continue their collaboration in biomedical signal processing and brain-computer interface. In the future, with further research in this area, the full potential of MI detection using the ECG signal can be achieved to benefit people suffering from motor impairments and progress in neuroprosthetic/BCI capabilities.

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References

[1] P. Bach, C. Frank, and W. Kunde, "Why motor imagery is not really motoric: Towards a re-conceptualization in terms of effect-based action control," *Psychological Research*, vol. 88, no. 6, pp. 1790–1804, 2024. https://doi.org/10.1007/s00426-022-01773-w.

[2] A. Saibene, M. Caglioni, S. Corchs, and F. Gasparini, "Eeg-based bcis on motor imagery paradigm using wearable technologies: a systematic review," *Sensors*, vol. 23, no. 5, p. 2798, 2023. https://doi.org/10.3390/s23052798.

[3] A. Palumbo, V. Gramigna, B. Calabrese, and N. Ielpo, "Motor-imagery eeg-based bcis in wheelchair movement and control: A systematic literature review," *Sensors*, vol. 21, no. 18, p. 6285, 2021. https://doi.org/10.3390/s21186285.

[4] W. Cabrel, G. T. Mumanikidzwa, J. Shen, and Y. Yan, "Enhanced fourier transform using wavelet packet decomposition," *Journal of Sensor Technology*, vol. 14, no. 1, pp. 1–15, 2024. https://doi.org/10.4236/jst.2024.141001.

[5] M. A. Qureshi, K. N. Qureshi, G. Jeon, and F. Piccialli, "Deep learning-based ambient assisted living for self-management of cardiovascular conditions," *Neural Computing and Applications*, pp. 1–19, 2022. https://doi.org/10.1007/s00521-020-05678-w.

[6] G. Aggarwal and Y. Wei, "Non-invasive fetal electrocardiogram monitoring techniques: Potential and future research opportunities in smart textiles," *Signals*, vol. 2, no. 3, pp. 392–412, 2021. https://doi.org/10.3390/signals2030025.

[7] A. K. Singh and S. Krishnan, "Ecg signal feature extraction trends in methods and applications," *BioMedical Engineering OnLine*, vol. 22, no. 1, p. 22, 2023. https://doi.org/10.1186/s12938-023-01075-1.

[8] C. Zhuang and P. Liao, "An improved empirical wavelet transform for noisy and non-stationary signal processing," *IEEE Access*, vol. 8, pp. 24484–24494, 2020. https://doi.org/10.1109/access.2020.2968851.

[9] H. Wang, W. Wang, Y. Du, and D. Xu, "Examining the applicability of wavelet packet decomposition on different forecasting models in annual rainfall prediction," *Water*, vol. 13, no. 15, p. 1997, 2021. https://doi.org/10.3390/w13151997.

[10] M. A. Abdou, "Literature review: Efficient deep neural networks techniques for medical image analysis," *Neural Computing and Applications*, vol. 34, no. 8, pp. 5791–5812, 2022. https://doi.org/10.1007/s00521-022-06960-9.

[11] K. Srinivas, V. Ch, S. R. Borra, K. S. Raju, G. R. K. Rao, K. V. Satyanarayana, and P. M. Kumar, "Cardiacnet: Cardiac arrhythmia detection and classification using unsupervised learning based optimal feature selection with custom cnn model," *Informatica*, vol. 48, no. 2, 2024. https://doi.org/10.31449/inf.v48i2.5076.

[12] M. Bejani, E. Luque-Buzo, A. Burlaka-Petrash, J. A. Gómez-García, J. D. Arias-Londoño, F. Grandas-Pérez, J. Grajal, and J. I. Godino-Llorente, "Baseline wander removal applied to smooth pursuit eye movements from parkinsonian patients," *IEEE Access*, vol. 11, pp. 32119–32133, 2023. https://doi.org/10.1109/access.2023.3263045.

[13] C. Pravin and V. Ojha, "A novel ecg signal denoising filter selection algorithm based on conventional neural networks," in *2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pp. 1094–1100, IEEE, 2020. https://doi.org/10.1109/icmla51294.2020.00176.

[14] R. Y. L. Al-Taai and X. Wu, "Speech enhancement for hearing impaired based on bandpass filters and a compound deep denoising autoencoder," *Symmetry*, vol. 13, no. 8, p. 1310, 2021. https://doi.org/10.3390/sym13081310.

[15] R. Yacouby and D. Axman, "Probabilistic extension of precision, recall, and f1 score for more thorough evaluation of classification models," in *Proceedings of the first workshop on evaluation and comparison of NLP systems*, pp. 79–91, 2020. https://aclanthology.org/2020.eval4nlp-1.9.

[16] J. Wen, Y. Li, M. Fang, L. Zhu, D. D. Feng, and P. Li, "Fine-grained and multiple classification for alzheimer's disease with wavelet convolution unit network," *IEEE Transactions on Biomedical Engineering*, vol. 70, no. 9, pp. 2592–2603, 2023. https://doi.org/10.1109/tbme.2023.3256042.

[17] B. Rim, N.-J. Sung, S. Min, and M. Hong, "Deep learning in physiological signal data: A survey," *Sensors*, vol. 20, no. 4, p. 969, 2020. https://doi.org/10.3390/s20040969.

[18] J. Mladenović, "Standardization of protocol design for user training in eeg-based brain–computer interface," *Journal of Neural Engineering*, vol. 18, no. 1, p. 011003, 2021. https://doi.org/10.1088/1741-2552/abcc7d.

[19] I. Y. Zhao, Y. X. Ma, M. W. C. Yu, J. Liu, W. N. Dong, Q. Pang, X. Q. Lu, A. Molassiotis, E. Holroyd, and C. W. W. Wong, "Ethics, integrity, and retributions of digital detection surveillance systems for infectious diseases: systematic literature review," *Journal of medical Internet research*, vol. 23, no. 10, p. e32328, 2021. https://doi.org/10.2196/32328.

[20] Y. Hou, S. Jia, X. Lun, S. Zhang, T. Chen, F. Wang, and J. Lv, "Deep feature mining via the attention-based bidirectional long short term memory graph convolutional neural network for human motor imagery recognition," *Frontiers in Bioengineering and Biotechnology*, vol. 9, p. 706229, 2022. https://doi.org/10.3389/fbioe.2021.706229.