The 2025 IEEE Signal Processing in Medicine and Biology Symposium
Science Education and Research Center, Temple University, 1925 North 12th Street, Philadelphia, Pennsylvania, 19122, USA

CNN Based EEG Signal Analysis for Decoding Motor Activities

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Contents

Abstract

- The detection of motor movements using EEG signals is a promising field that can significantly benefit individuals with motor disabilities.

- By using advanced algorithms, deep learning, and the fusion of EEG with other bio-signals, researchers are developing highly accurate and real-time systems for interpreting motor intentions.

- These advancements have great potential to improve communication, control, and rehabilitation for patients with motor impair.

- This paper aims to leverage EEG technology to detect motor movements by analysing brainwave patterns associated with physical actions.

Abstract contd..

- The Gramian Angular Summation Field approach is used for extracting temporal significant features and converts 1-D EEG signals into 2-D Images which is fed to Convolution Neural Network model.

- CNN algorithm using Google net is employed to train the GASF images and the performance accuracy obtained is about 94.4% across both real and imagined movement tasks.

- The model is able to classify actual movements with a greater accuracy than imagery movements.

Introduction

- The primary objective of this research lies in decoding the motor intentions from EEG data, and to enable control of external devices or communication for those unable to perform physical movements.

- EEG is a non-invasive method used for recording electrical activity of the brain.

- BCIs used in motor imagery research help researchers to understand how the brain controls movement, both real and imagined.

- This knowledge can be used for development of more effective treatments for motor impairments.

- EEG-based motor BCIs is categorized as executed and imagery movements and motor imagery (MI) is vastly used for physically disabled persons for controlling external devise such as prosthetics or moving a cursor in computer, wheelchair, limbs. etc

Related Work

- A comprehensive review of recent advances in EEG-based motor movement and motor imagery (MI) detection shows significant progress toward building reliable and practical brain–computer interface (BCI) systems.

- Across studies, deep learning architectures—particularly CNNs, LSTMs, capsule networks, and connectivity-aware models—have consistently improved the extraction of spatio-temporal EEG features essential for decoding motor intent.

- Wearable systems with dry electrodes further demonstrate the feasibility of deploying BCIs in real-world and tele-rehabilitation environments.

- Collectively, performance outcomes ranging from 69% to over 84% accuracy across different datasets and task configurations underscore the promise of EEG-driven BCIs for motor control, rehabilitation, and assistive technologies.

Related Work contd..

- Moreover, recent datasets focusing on multi-session variability and subject-independent prediction expand the understanding of generalization challenges in MI-based systems.

- Overall, the literature strongly indicates that deep learning, multimodal feedback, and evolving EEG acquisition technologies are driving substantial improvements in BCI usability and performance.

- Despite these advancements, several critical limitations persist, hindering the transition of MI-based BCIs from controlled laboratory settings to reliable real-time deployment:

- The literature highlights persistent challenges in addressing inter and intra-subject variability, achieving consistent cross-session performance, and enhancing the interpretability of neural responses in diverse motor tasks.

- Furthermore, limitations remain in the comprehensive analysis of EEG data representations across one-dimensional (1D), two-dimensional (2D), and three- dimensional (3D) formats, which are essential for robust and generalizable BCI system.

Problem Statement

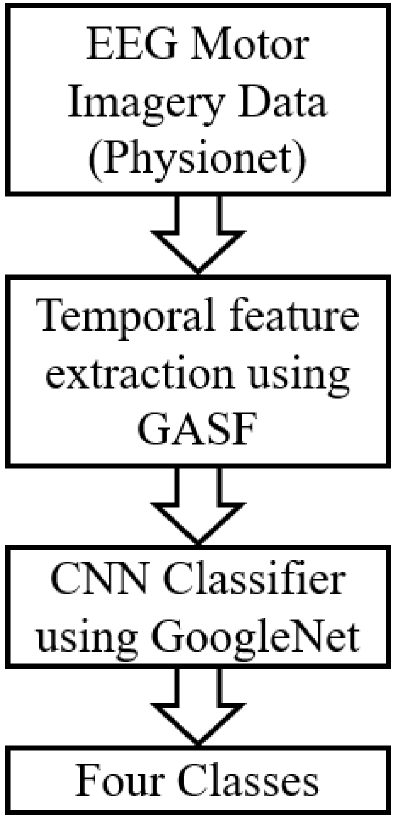
- The project's aim is to develop a system that enables physically challenged people to operate or control devices using their brain signals.
- This involves integrating neuroscience to understand brain activity, advanced signal processing to filter and enhance EEG signals, and convolutional neural networks (CNNs) to translate these signals into commands for the application.

The contributions of our proposed work are as follows:

Extraction of Temporal Correlations: We propose to leverage the Gramian Angular Field (GAF) technique to transform 1D EEG time- series signals into 2D images, effectively capturing the temporal correlations inherent in EEG dynamics for enhanced feature representation.

Development of a CNN-based Classification Framework: We aim to design a convolutional neural network (CNN) architecture based on GoogleNet to classify EEG data into four distinct motor imagery classes, thereby improving the accuracy and robustness of motor intention detection in BCI systems.

Material and Methods



Proposed Methodology

Dataset:

- The publicly available database for EEG movement /imagery signals are used . The data comprises of 1500 EEG recordings, each lasting for one or two minutes, collected from 109 participants using 64-channel EEG signals on the BCI2000 platform with a sampling rate of 160Hzs.
- Task 1 : open and close left or right fist
- Task 2 : imagine opening and closing left or right fist
- In Task 3: open and close both fists or both feet
- Task 4 : imagine opening and closing both fists or both feet.

Material and Methods contd..

Preprocessing of EEG Signals :

- To improve the signal-to-noise ratio, a referencing method employing a moving average filter is utilized.

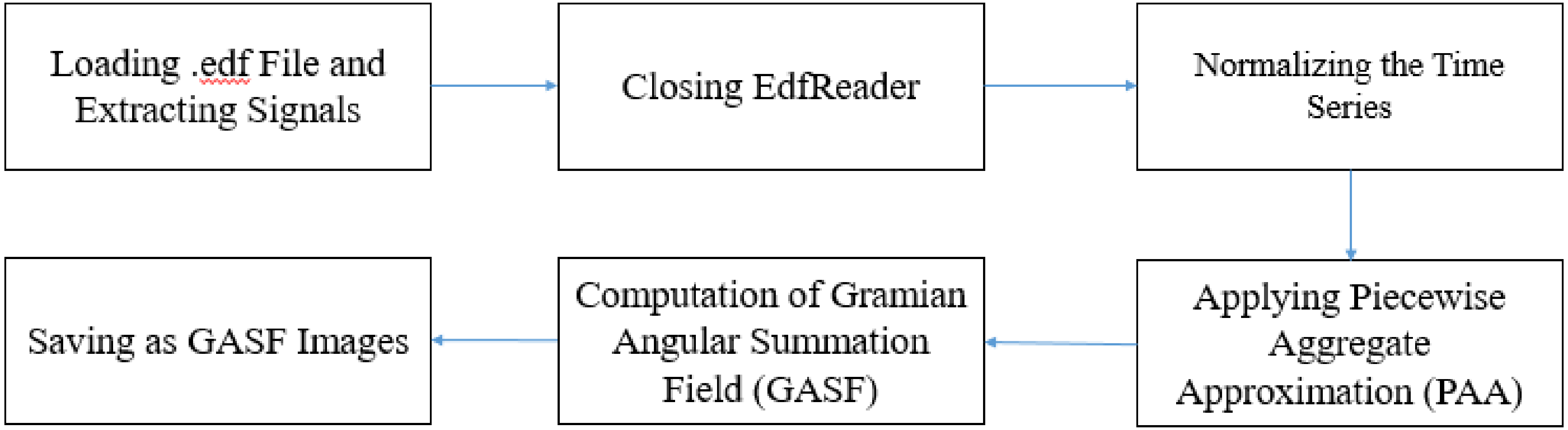
- Additionally, a 10th-order median filter is applied to smooth the signal, followed by a 20th-order FIR bandpass filter that band limits the signal from 0 to 60 Hz.

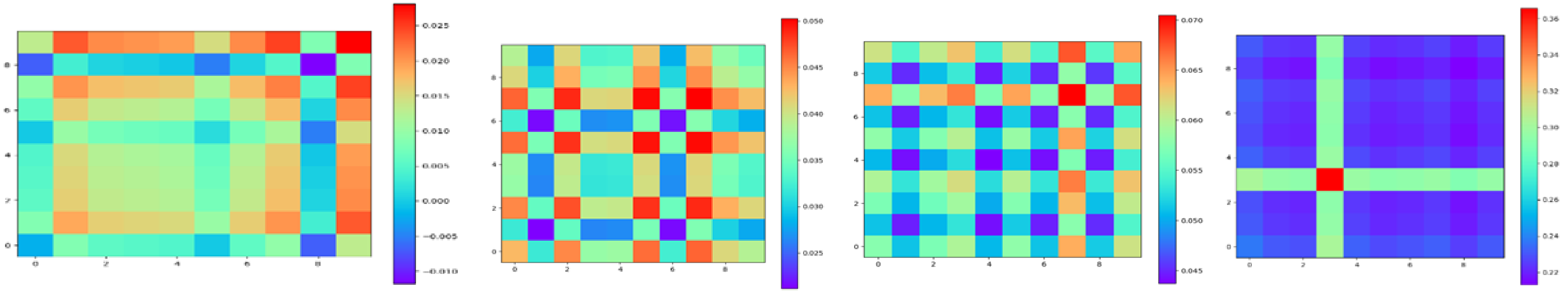
- A band-pass filter was employed to isolate the most relevant frequency bands associated with motor activity, specifically the 8–30 Hz range encompassing the mu and beta rhythms.

- This step effectively attenuates low-frequency drifts and high-frequency noise unrelated to motor processes.

Material and Methods contd..

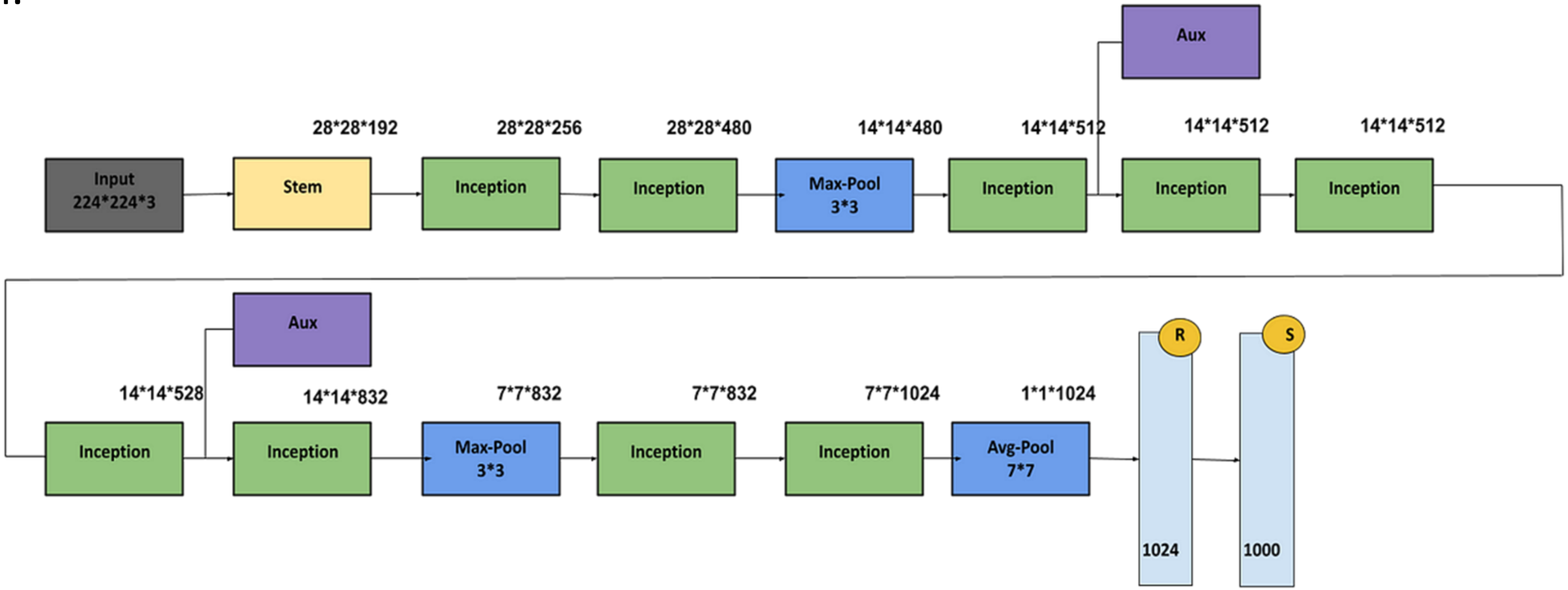
- Feature extraction : The Gramian Angular Summation Field is a robust technique for converting time-series data, into visual representations





Material and Methods contd..

Deep Learning Classification using Google net : In the present work, Google net model is used to train and classify the data into 4 classes based on the task mentioned in section A. The input layer holds the raw pixel values of the image, such as a 32x32x3 RGB image. Google net with "no weights" algorithm is implemented using MATLAB 2024A version.



Results & Discussions

- This procedure yielded a total of 7680 images per class through GASF transformation of the recorded EEG signals.

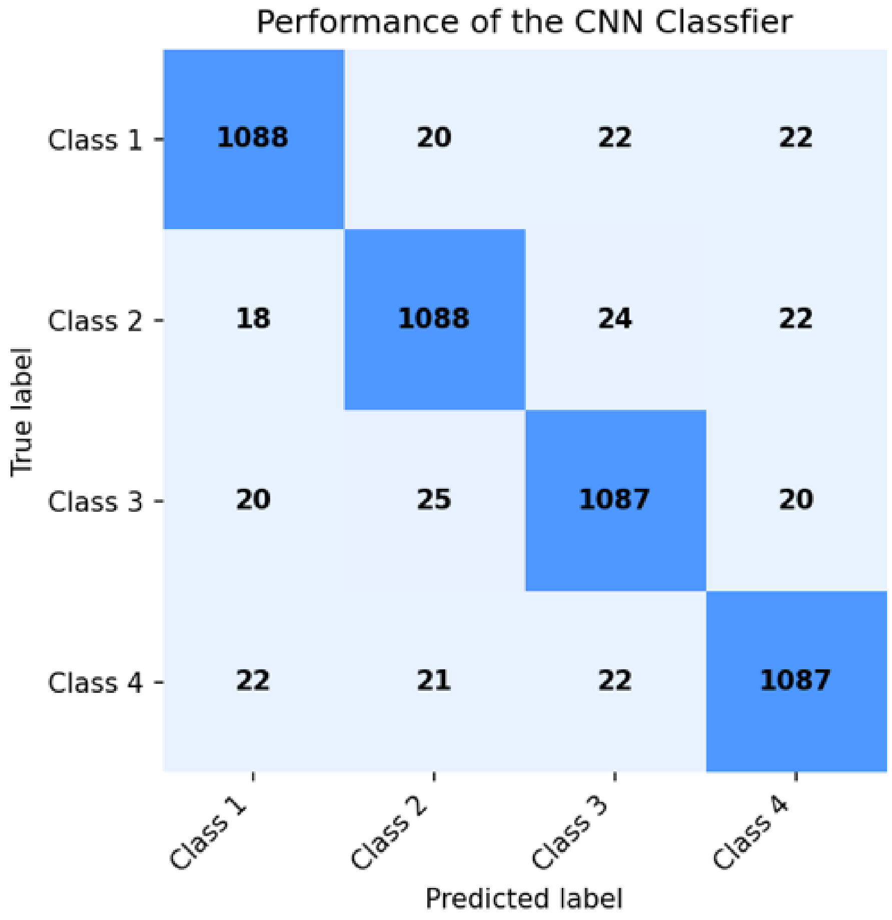
- The dataset was partitioned into three subsets: 70% was allocated for training, 15% for testing, and the remaining 15% for validation.

- The deep learning model was trained with a minimum batch size of 64 over 15 epochs to ensure effective convergence.

- The dataset was divided in a subject-independent manner, ensuring that EEG data from any given participant appeared exclusively in one subset (training, validation, or testing).

- A fivefold cross-subject validation was further conducted to confirm generalization, yielding a mean accuracy variation of less than 1%, thereby demonstrating that the proposed model effectively captures subject-independent motor-intention features.

Results & Discussions



Metric	Class 1	Class 2	Class 3	Class 4
Accuracy	0.973	0.971	0.971	0.972
Misclass-Rate	0.026	0.028	0.028	0.028
Precision	0.944	0.944	0.943	0.943
Recall	0.947	0.942	0.941	0.944
Specificity	0.981	0.981	0.981	0.981
F1-Score	0.946	0.943	0.942	0.944
Kappa-Value	0.928	0.924	0.923	0.925

Results & Discussions

Study	Model	Dataset/Subjects	Task	Accuracy
Jain et al. [10]	CNN–LSTM	10 subjects	Pre-movement trajectory prediction	74.6%
Du et al. [11]	3D Capsule Net	BCI Comp IV	4-class MI	84.03%
Arpaia et al. [12]	Wearable 8-sensor EEG	27 subjects	MI detection	69%
Lomelin et al. [13]	CNN (raw EEG)	109 subjects	MI tasks	70–80%
Collazos et al. [14]	Connectivity CNN	50 subjects	Finger MI	~10% improvement over baseline (~70–80%)
Ma et al. [15]	Cross-session study	25 subjects × 5 sessions	Left/Right MI	68.8% → 53.7%
An et al. [16]	Single-channel CNN	4 MI tasks	Multi-class MI	79–84%
Proposed System	GASF + GoogLeNet	30 subjects	4-class MI	94.4%

Conclusion & future work

- This study presents a non-invasive BCI system that effectively decodes both executed and imagined motor intentions from EEG signals.
- By transforming 1-D EEG data into 2-D GASF images and leveraging a GoogLeNet convolutional neural network (CNN) architecture, the proposed system achieved a classification accuracy of 94.4% across four motor tasks in data collected from 30 subjects.
- This result represents a clear improvement over existing approaches, demonstrating the benefits of combining advanced time-series imaging techniques with deep learning models for motor intention recognition.
- The findings highlight the system’s potential for real- world applications in assistive technology and neuro rehabilitation, offering an affordable and accurate solution for restoring motor function control to individuals with severe motor impairments.
- Future work will focus on addressing cross-session and cross-subject variability, integrating adaptive learning techniques to personalize the system to individual users, thereby enhancing robustness and generalizability for practical deployment.

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Thank You