Deep CNN for Improved EEG Authentication Accuracy

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Problem Statement & Motivation

EEG-based biometric authentication offers strong security potential but still struggles with inconsistent accuracy (60% to nearly 100%) [7] and limited generalization across users, sessions, and devices. While deep learning has improved EEG signal feature extraction, most models perform well only under controlled lab environments or with small datasets. Accuracy often drops when tested on heterogeneous data, revealing poor robustness and transferability.
Moreover, there is a lack of standardized, large-scale EEG datasets. This hinders fair evaluation and reproducibility of results. This analytical research addresses these challenges by merging EEG open-source EEG datasets to train deep CNN architectures and consequently enhance classification accuracy and reliability in real-life applications.

Goals:

1. **Merge multiple open EEG datasets** to increase data diversity and improve generalization across subjects, sessions, and devices.
2. **Train optimized deep CNN architectures** (1D and 2D variants) for automatic spatiotemporal feature extraction.
3. **Evaluate cross-dataset performance** to assess transferability and real-world viability.

Background & Related Work

Due to the inimitable nature of brainwave patterns, EEG-based authentication offers a secure alternative to traditional biometrics. Recent deep learning advances have enhanced EEG feature extraction, yet generalizing across datasets, sessions, and devices remains challenging.

Robust datasets are an important research gap in previous EEG-based authentication research using CNN models. Many researchers record high classification accuracy results in controlled lab environments using small datasets. For example, Yu et al. (2019) achieved 97% accuracy results on data from 8 subjects [6]. However, Zhang et al. (2021) literature review revealed that it is difficult to replicate these results with larger datasets and account for session variability [7]. Consequently, the first research goal of this project to merge open-source EEG datasets fills this research gap by providing a larger dataset for cross-validation of research results.

Secondly, the success of a hybrid DE-CNN (Differential Entropy + CNN) proposed by Wang et al. (2020) conveys how integrating statistical and learned features enhances robustness for generalization testing [5]. This aligns with the feature-fusion strategy of deep CNN, validating the research goal of using deep CNN to improve the classification accuracy of EEG-based biometric authentication.

Furthermore, results from personalized EEG authentication research by Stergiadis et al. (2022) highlight the importance of intra-user variability when training a machine learning model [3]. Similarly, limited robustness across diverse datasets is a major limitation in Yap et al. (2023) research which evaluated transfer learning with pretrained CNNs (ResNet-50, DenseNet-201, EfficientNet-B0) on spectrogram EEG inputs [4]. Since user-specific fine-tuning is possible within deep CNN pipelines with extracted features, this research project addresses the issue of intra-user variability while producing a standardized dataset to help replicate classification results across diverse datasets.

Finally, Alsumari et al. (2023) achieved 99% accuracy and 0.187% EER using 2 channels and 5-second windows in a proposed lightweight 1D pyramidal CNN for raw EEG [1]. While the authors use small datasets in a controlled lab environment to achieve these results, the experiment shows the effectiveness of parameter-efficient models. The results validate the use of 5-second fixed windows in the feature extraction phase of this research project.

These studies show that CNNs provide the best accuracy results in EEG-based authentication but still face challenges with limited dataset variety, small participant numbers, and generalizing across different conditions. Building on this, this project combines several open EEG datasets and trains tailored 1D and 2D CNN models to improve accuracy and reliability across users, sessions, and recording setups.

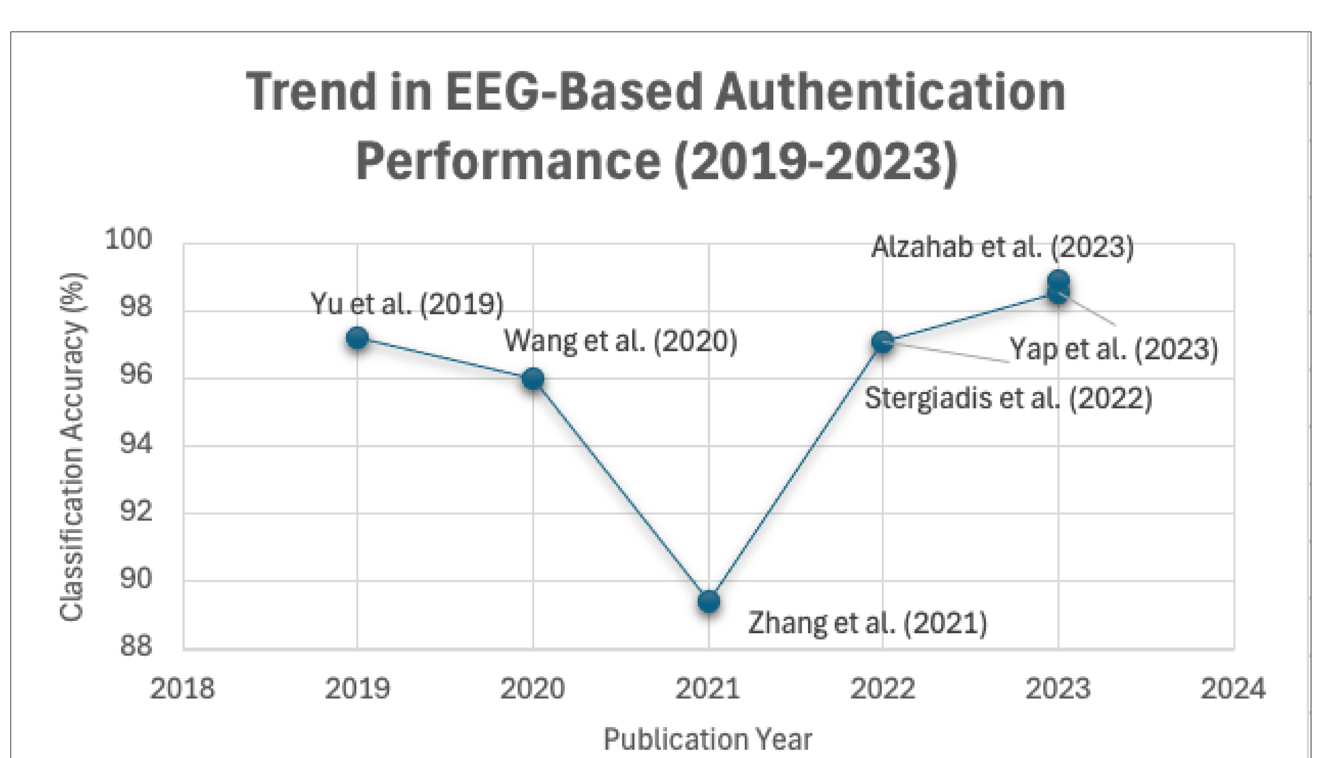

Figure 1. EEG-Based Authentication Research Trend

Data Description & Methodology

Deep CNNs work for feature extraction in biometric authentication by automatically learning hierarchical representations of biometric data through stacked convolutional & pooling layers. These features help distinguish unique characteristics for high accuracy in identity verification tasks.

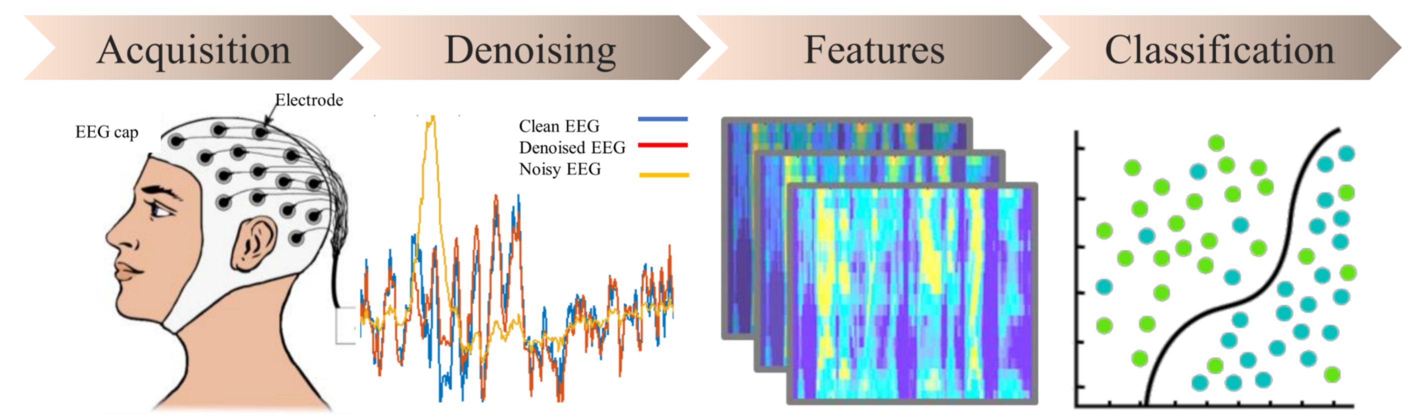

Figure 2. Feature Extraction of EEG Signals [2]

EEG signals capture brainwave activity through voltage fluctuations and provide unique neural signatures useful for biometric authentication. Using the **MNE** and **NumPy** Python libraries in **Google Colab**, I merge EEG signals from 5 open datasets in European Data Format (.edf) and BrainVision (.vhdr/.eeg/.vmrk) formats for preprocessing. MNE for signal loading and NumPy for normalization and array manipulation. Then, I apply a deep CNN in **PyTorch** to automate feature extraction for enhanced EEG-based authentication accuracy. The 5 EEG datasets (EEGMMIDB, BNCI Horizon, DEAP, MIID, OpenBCI) were selected for diversity, accessibility, and compatibility. They support cross-dataset validation and are compatible with CNN input formats. These characteristics are vital for robust, generalizable, and publishable EEG biometrics research.

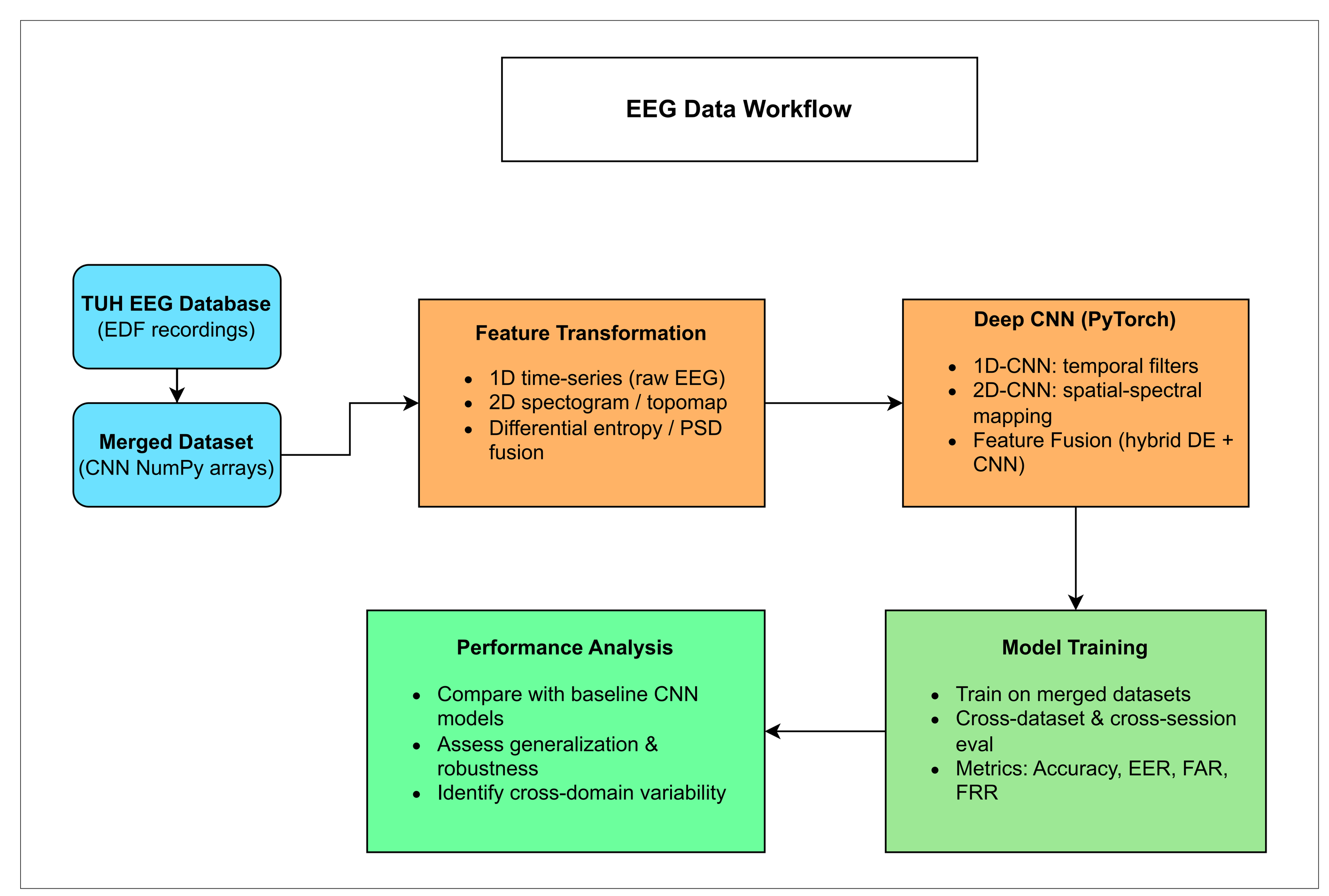

Figure 3. EEG Dataset Workflow

This experiment involves using real data (open-source EEG datasets) and an existing algorithm (deep CNN) to automate biometric feature extraction and measure classification accuracy. Comparison of the deep CNN's accuracy performance against the existing detection ability of other EEG-based authentication classifiers validate its effectiveness for improved verification accuracy in biometric authentication. The use of deep learning and quantitative methodology aligns this project with the Intelligent Systems & Data-Driven Computing subfield.

Feature Extraction

I focused on 1D time-series and 2D spectrogram feature extraction. The 1D time-series works to captures temporal dependencies in time-series EEG features and the 2D excels at extracting spatial/time-frequency patterns from spectrogram images. Recent studies show hybrids outperform 1D CNN or 2D CNN models alone on EEG tasks like motor imagery classification, seizure detection, and emotion recognition, reaching accuracies above 90% [4]. EEGNet is one of the best PyTorch deep CNN models for 1D time-series feature extraction due to its compact architecture and strong performance on EEG datasets. For 2D spectrogram features, I applied the pretrained ResNet18 deep CNN architecture to the dataset and saved the output PNG images. I chose ResNet because it is effective in capturing spatial-temporal EEG patterns applied to spectrogram images. Furthermore, Yap et al. (2023) demonstrated 97]% classification accuracy after using a ResNet model for 2D spectrogram feature extraction [5].
I performed these steps:

1. Extract and save 1D CNN tensor features for each file using EEGNet.
2. Extract and save 2D CNN features from spectrogram images using ResNet18.
3. Combine both datasets and normalize feature vectors
4. Feed this combined representation into a classifier or further layers for joint learning.

Experiment & Results

I created a 12 GB subset of the TUAB Abnormal dataset after gaining access to the Temple University Hospital (TUH) EEG Corpora. The full TUH EEG Corpora is a larger dataset that requires high storage and processing capabilities. Thus, I focused on the TUEG Abnormal dataset (63GB) within the TUH EEG Corpora to save time and use my resources effiecently. This dataset has balanced normal and abnormal labels for each EEG signal and many recordings. Moreover, it is easier to train and evaluate compared to the raw TUH base corpus. Therefore, I extracted biometric features locally, then uploaded the feature-extracted files to a Google Colab environment for model training and testing.
Next, I performed feature extraction with EEGNet and ResNet18 models for 1D time-series and 2D spectrogram respectfully. I derived two datasets, Output-1D and Output-2D. I used z-score normalization per feature and session-wise normalization to standardize both datasets. To concatenate both datasets for deep model training, I specified input size (748), batch number (32), number of channels (dynamically set), and the number of classes (4) for my final dataset of extracted features.
I chose a **Hybrid Deep CNN-LSTM** architecture to attempt to improve classification accuracy compared to results from other machine learning approaches. I fed the final concatenated dataset to the **Hybrid Deep CNN-LSTM** model to train it. The code snippet below shows the basic model setup:

```
# === Model setup with dynamic num_classes ===
input_size = 768  # 2D feature size you have
num_classes = train_dataset.num_classes  # detected automatically

model = HybridCNNLSTM(input_size=input_size, num_classes=num_classes).to(device)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=1e-3)
```

Figure 4. Hybrid Deep CNN-LSTM Model Setup

After training the CNN-LSTM model, I loaded a new evaluation dataset folder that is separate from the training folder for an unbiased measure of generalization. The evaluation dataset used in this project can be found here on the TUH EEG corpora:
`/projects/nedc/data/tuh_eeg/tuh_eeg_abnormal/v3.0.1/edf/eval/normal/01_tcp_ar`.

The image below shows the validation loss and accuracy metrics of the Hybrid CNN-LSTM model after 5 rounds of testing:

```
results_log.txt

1
2 Batch 1/5: Loss = 0.0071
3 Batch 2/5: Loss = 0.0073
4 Batch 3/5: Loss = 0.0104
5 Batch 4/5: Loss = 0.0093
6 Batch 5/5: Loss = 0.0110
7 Validation Loss: 0.0089, Accuracy: 1.0000
8
```

Figure 5. Experiment Results Showing Validation Error and Accuracy Scores

Discussion & Future Work

This project involves analytical modeling of deep CNN performance in EEG feature extraction. Due to time constraints, I do not train the model on the full TUH TUAB Abnormal dataset. However, I achieved 100% accuracy and 89% validation loss using a training dataset size of 700 EEG signal files and an evaluation dataset size of 300 EEG signal files using 10 epochs and 4 classes.

These results demonstrate that the combination of 1D time-series feature extraction, 2D spectogram feature extraction, and a hybrid deep CNN model such as CNN-LSTM further strengthens the classification accuracy of EEG-Based authentication. Future research involving larger training datasets and deep learning training based on this project's findings would help validate classification accuracy performance in real-world applications, replicating the success found in lab-controlled settings.

References

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