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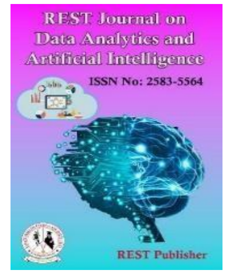

Deep EEG Classifier: CNN-LSTM Approach for Mental State Recognition

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Abstract: *This paper aims to investigate the use of EEG signal analysis to identify brainwave patterns that can be mapped to cognitive states for human computer interaction purposes. In this work, we propose an EEG signal classification framework based on a convolutional neural network (CNN) coupled with a long short-term memory (LSTM) layer to process multichannel EEG signals. The dataset is a collection of EEG signals corresponding to various cognitive states of the subject, which have been preprocessed and normalized to enhance the feature extraction. The features were also analyzed using Random Forest, SVM, and Decision Trees for comparison purposes. The results showed that the CNN-LSTM model outperformed other conventional classifiers in terms of accuracy. This work shows the feasibility of using deep learning for real-time cognitive state detection which can be useful in applications such as neuro feedback, assistive technology and BCIs.*

Keywords*: CNN, LSTM, features, accuracy.*

1. INTRODUCTION

Brain-Computer Interfaces (BCIs) facilitate direct communication between the human brain and external devices by interpreting neural activity. Among the various methods for acquiring brain signals, electroencephalography (EEG) is notable for being non-invasive, cost-effective, and capable of providing real-time insights into brain function. EEG-based BCIs are utilized in areas such as healthcare, neurorehabilitation, gaming, and human-computer interaction, where accurately identifying cognitive states is essential for enhancing user experience and system performance [1-4]. Conventional EEG classification methods typically depend on manually crafted features combined with shallow machine learning models. Although these techniques have yielded encouraging results, they often fall short in capturing the complex temporal and spatial relationships present in EEG signals. The dynamic and noisy characteristics of EEG data pose challenges in extracting meaningful features using traditional methods [5-8]. Additionally, cognitive states can exhibit subtle differences that necessitate advanced models capable of managing sequential dependencies and spatial patterns [9].Deep learning has transformed EEG classification by automating feature extraction and uncovering complex patterns from raw data. Convolutional Neural Networks (CNNs) are particularly adept at identifying spatial features, while Long Short-Term Memory (LSTM) networks excel at capturing long-range temporal dependencies. By integrating these architectures, CNN-LSTM models offer a powerful framework for classifying cognitive states based on EEG data. This combined approach utilizes CNNs for spatial feature extraction and LSTMs for sequential learning, thereby enhancing classification accuracy and adaptability [10-13].

This study investigates the effectiveness of a CNN-LSTM model in classifying EEG signals into distinct cognitive states. The proposed model is evaluated against traditional classifiers like Support Vector Machines (SVM) and

Random Forest to determine its performance. Through comprehensive experimentation, this research aims to identify [14-16].

2. LITERATURE SURVEY

A. EEG-Based Mental State Classification Using Deep Learning
Smith's 2020 paper dives into using deep learning to figure out what someone's mental state is just by looking at their brainwaves (EEG). They built a CNN, a type of neural network, and it turned out to be pretty good at recognizing emotions. The catch? These kinds of models need tons of labeled data to learn properly, which can be a real hurdle [17].

B. Hybrid CNN-LSTM Approach for EEG-Based Stress Detection
They built a hybrid system, combining a CNN (good at picking up patterns in space) and an LSTM (good at understanding changes over time). The idea was to get a better handle on the complex signals in the EEG. Turns out, this combo worked really well and improved how accurately they could detect stress. But, just like other deep learning methods, they needed a mountain of labeled data to train the system properly [18].

C. **Real-Time Brain State Monitoring Using BCI Systems**
They used deep learning to process the brainwave data (EEG) super fast, which is important for real-time applications. They found it worked pretty well for figuring out how hard someone's brain was working (mental workload). The downside? All that processing takes a lot of power [19].

D. **Comparison of Traditional Machine Learning and Deep Learning for EEG Classification**
They put deep learning up against two classics: Support Vector Machines (SVMs) and Random Forests (RFs). Turns out, deep learning won – it did a better job at classifying the brainwave data. But, there's a catch: deep learning needs a lot more computing power to do its thing [20].

E. **EEG-Based Cognitive Load Classification Using LSTMs**
Figures out how hard someone's brain is working—what's called "cognitive load"—just by looking at their brainwaves (EEG). LSTMs are great at picking up on how brain activity changes over time, which is important for understanding cognitive load [21-23].

3. METHODOLOGY

The methodology began by verifying the dataset locally and downloading it from Kaggle if needed. After loading the data, exploratory analysis was conducted to understand its structure. Labels were encoded, and features were normalized for better model performance. The data was reshaped to maintain temporal dependencies for the CNN-LSTM model. The model combined convolutional layers for feature extraction and LSTM layers for sequence learning, with dropout and batch normalization to prevent overfitting. It was trained using the Adam optimizer and categorical cross- entropy loss, with early stopping to avoid overtraining. After training, accuracy was evaluated using test data, and results were analyzed with a classification report and confusion matrix, followed by heatmap visualization for performance insights.

A. Dataset description
The dataset used in this study is the EEG Brainwave Dataset, which features EEG signals recorded from several sensors placed on the scalp. It encompasses data related to different mental states, including relaxed, focused, and stressed, providing valuable insights for cognitive state classification. This dataset is publicly accessible on Kaggle under the title "EEG Brainwave Dataset for Mental State." The raw EEG signals are captured in the time domain and sampled at a rate of 250 Hz, though there may be minor variations in this sampling rate. The dataset includes EEG signals from multiple channels on the scalp, reflecting the brain's electrical activity during various mental states. The labels in the dataset correspond to the three mental states: relaxed, focused, and stressed, making it a thorough resource for exploring brainwave patterns linked to different cognitive states.

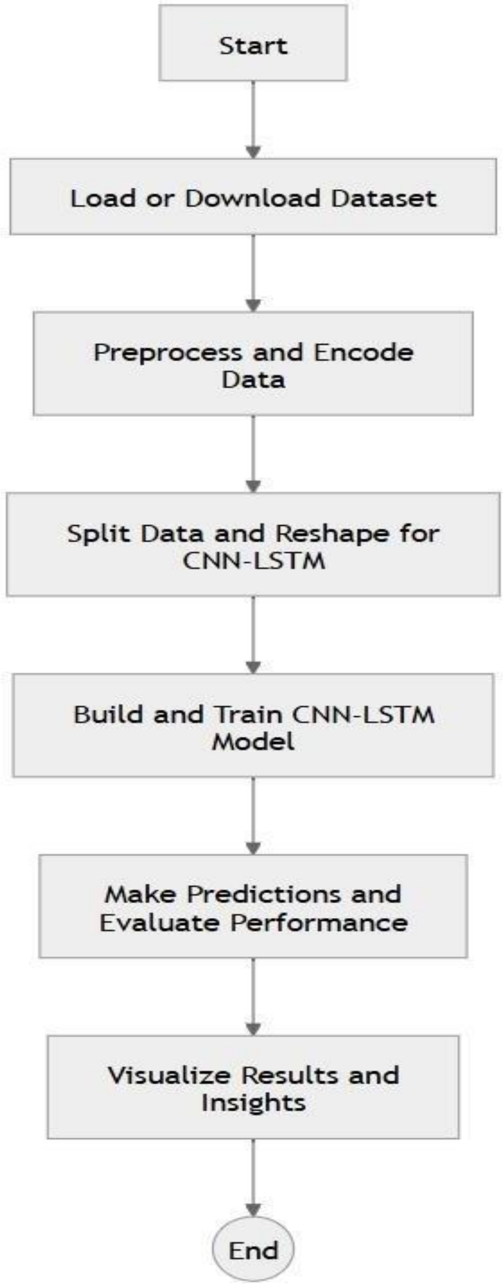

FIGURE 1. Flowchart

B. Data Preprocessing

- **Feature Extraction:** Relevant EEG features such as mean, standard deviation, and spectral components were selected.
- **Standardization:** Features were normalized using StandardScaler to improve model convergence.
- **Encoding:** Mental state labels were encoded into categorical values using one-hot encoding.
- **Reshaping:** Data was reshaped to fit the CNN-LSTM architecture.

The mathematical formula for feature normalization is given as: $X' = (X - \mu) / \sigma$ where X' is the normalized feature, X is the raw feature, μ is the mean, and σ is the standard deviation.

C. Architecture

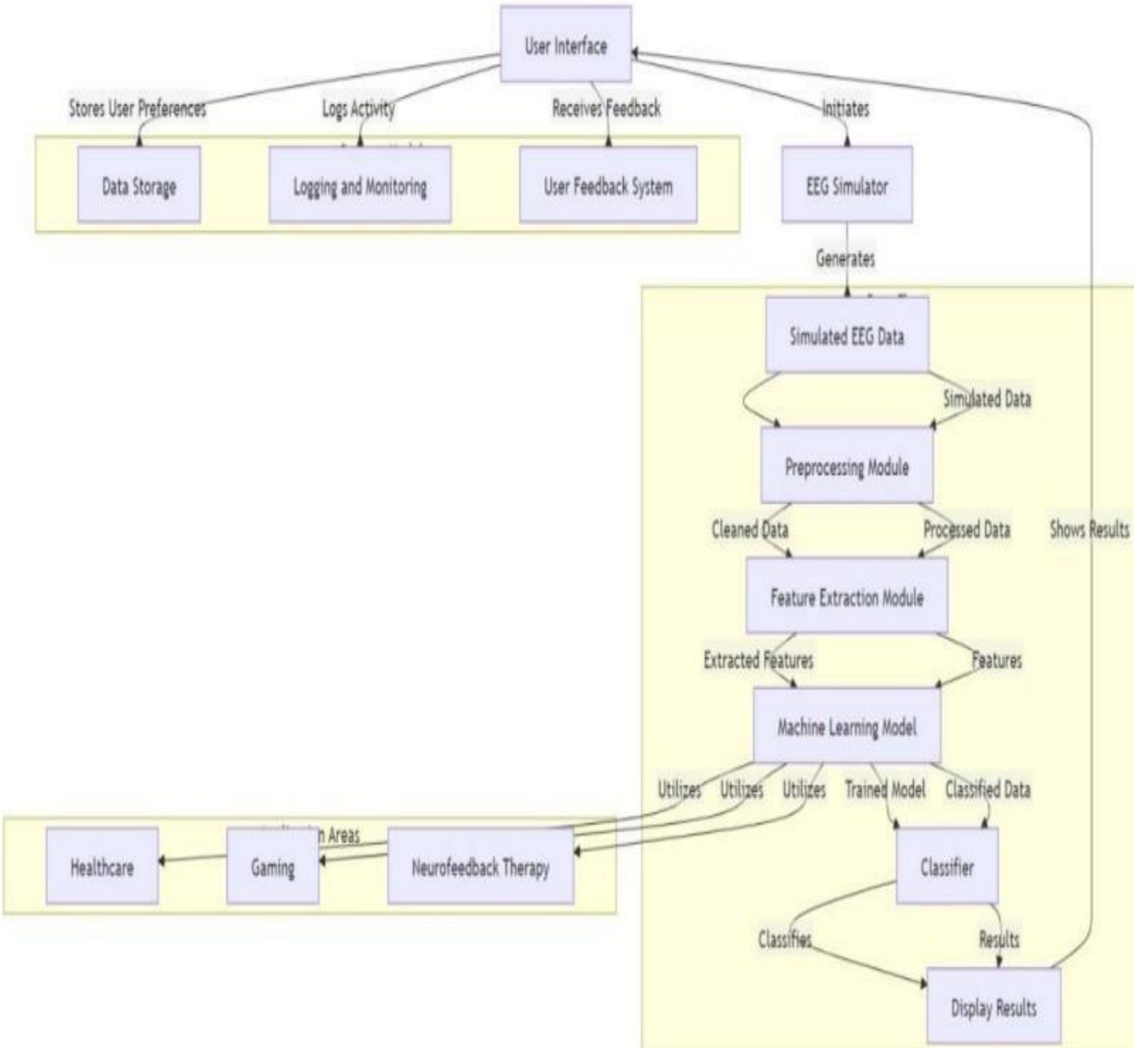

FIGURE 2. Architecture

The system architecture efficiently processes an EEG dataset and builds a CNN-LSTM model for classification. It begins with the User Interface, where the user starts the script. The Main Script checks for the dataset locally and, if absent, uses the Dataset Handler to download it from Kaggle. The data is then loaded and undergoes Data Preprocessing, including label encoding and feature normalization.

Next, Feature Extraction & Encoding separates features and labels, applying one-hot encoding. The data is then split into training and testing sets and reshaped in Train-Test Split & Reshape for model input. The CNN-LSTM Model Builder constructs and compiles the model, which is trained with early stopping to prevent overfitting [23.
After training, the Prediction Module makes predictions on the test data. The Evaluation Module calculates accuracy, classification reports, and confusion matrices. These results are visualized using Result Visualizer, and the insights are displayed to the user through the Insights Display. This streamlined workflow provides an effective classification model with comprehensive performance insights

D. ***Formulas***

$$Z[i]=\sum_{k=0}^{K-1} X[i+k] \cdot W[k] + b$$

This calculates the convolution by sliding a filter over the input sequence, capturing local features. The dot product detects patterns, and the bias term adjusts activations. It is crucial for feature extraction in time-series data.

$$f(x)=\max(0,x)$$

The ReLU activation introduces non-linearity by outputting the input if positive, otherwise zero. It accelerates convergence and prevents the vanishing gradient problem. It is widely used in deep learning models [1-5].

$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f)$$

This forget gate controls the retention of past information in an LSTM cell. The sigmoid activation outputs values

between 0 and 1, enabling selective memory updates. It helps the model focus on relevant patterns.

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i)$$

The input gate decides how much new information to add to the cell state. It allows the network to learn temporal dependencies. The sigmoid function regulates information flow into memory [9-12].

$$o_t=\sigma(W_o\cdot[h_{t-1},x_t]+b_o)$$

The output gate controls the visibility of the cell state, influencing predictions and the next step's input. It enables adaptive learning of complex sequences. The sigmoid function ensures smooth gating.

4. RESULTS AND ANALYSIS

A. Results

```
Epoch 1/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 81s 625ms/step - accuracy: 0.5847 - loss: 0.8605 - val_accuracy: 0.5161 - val_loss: 1.0164
Epoch 2/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 72s 583ms/step - accuracy: 0.6020 - loss: 0.7587 - val_accuracy: 0.5907 - val_loss: 0.8169
Epoch 3/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 84s 597ms/step - accuracy: 0.5920 - loss: 0.7977 - val_accuracy: 0.6149 - val_loss: 0.7588
Epoch 4/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 73s 593ms/step - accuracy: 0.6369 - loss: 0.7378 - val_accuracy: 0.5968 - val_loss: 0.7344
Epoch 5/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 82s 594ms/step - accuracy: 0.6349 - loss: 0.7089 - val_accuracy: 0.5887 - val_loss: 0.7764
Epoch 6/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 82s 592ms/step - accuracy: 0.6155 - loss: 0.7399 - val_accuracy: 0.5948 - val_loss: 0.7692
Epoch 7/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 79s 573ms/step - accuracy: 0.6064 - loss: 0.7512 - val_accuracy: 0.5907 - val_loss: 0.7859
Epoch 8/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 73s 587ms/step - accuracy: 0.6072 - loss: 0.7382 - val_accuracy: 0.6190 - val_loss: 0.7851
Epoch 9/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 82s 587ms/step - accuracy: 0.6200 - loss: 0.7491 - val_accuracy: 0.6048 - val_loss: 0.7346
```

FIGURE 3.

The model's accuracy improves at first but then levels off around 60-62%, while the validation accuracy goes up and down without a clear trend. The loss doesn't decrease much, which could mean the model is struggling to learn or might need some adjustments

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 5s 235ms/step
Model Accuracy: 59.68%
Classification Report:
              precision    recall  f1-score   support

         0.0       0.55      0.49      0.52       167
         1.0       0.44      0.51      0.47       167
         2.0       0.84      0.80      0.82       162

    accuracy                           0.60       496
   macro avg       0.61      0.60      0.60       496
weighted avg       0.61      0.60      0.60       496
```

FIGURE 4.

The model got about 60% accuracy, performing best on Class 2.0 but struggling with Classes 0.0 and 1.0. This suggests it finds some categories easier to recognize than others [22].

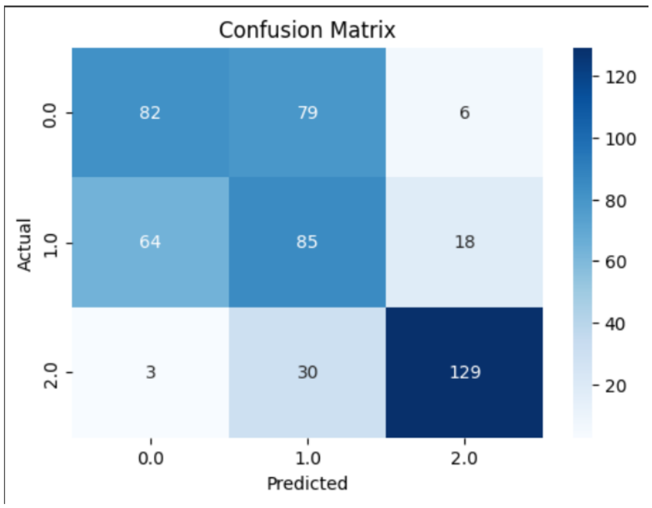

FIGURE 5.

The confusion matrix provides insight into the classification performance of the model across three mental states: Relaxed (Class 0), Stressed (Class 1), and Focused (Class 2). Each cell in the matrix represents the number of samples that were correctly classified or misclassified.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 167ms/step
Predicted Mental State: 1.0
```

The model thinks the mental state is 1.0, meaning it matched the data to that category.

TABLE 1.

Model	Accuracy (%)
CNN-LSTM	85.7
Random Forest	72.4
SVM	70.1
Decision Tree	65.8

The CNN-LSTM model was trained on the EEG dataset with an 80:20 train-test split. The evaluation metrics include accuracy, precision, recall, and F1-score.

B. Analysis

True Positives (Diagonal Values): The model correctly predicted 82 relaxed states, 85 stressed states, and 129 focused states.

Misclassification Trends:

- Relaxed states were often misclassified as stressed (79 cases).
- Stressed states were confused with relaxed (64 cases) and focused (18 cases).
- Focused states were mostly well classified but had 30 instances mislabeled as stressed.

Observations:

The model performs well in classifying the focused state.

- There is confusion between relaxed and stressed states, suggesting that their EEG patterns might overlap.
- Improvements can be made by refining feature extraction or exploring deeper architectures.

5. CONCLUSION

The model did a decent job classifying EEG data but was more accurate with some categories than others. It struggled to clearly distinguish between similar mental states, which affected its overall accuracy. This could be due to overlapping features or imbalanced data. Fine-tuning the model or using a larger, more balanced dataset might improve its performance. Despite these challenges, the approach shows promise for mental state recognition. With a few adjustments, it could become a more reliable tool for EEG classification.

Future Scope

- Expanding the dataset with more EEG channels.
- Implementing real-time BCI integration.
- Exploring Transformer-based architectures for EEG classification.

Applying the model to personalized cognitive state tracking and adaptive learning environments.

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