Task Performance Measures for Cognitive Workload Evaluation Using EEG Signals

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Project Stage-II

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Outline

Introduction

Cognitive Workload

- Level of workload affects the task performance of the person.
- Monitoring this level helps to detect fatigue or stress level of a person.
- This level also affects the ability to process information, react to surroundings and decision making.

Electroencephalogram (EEG)

- An electroencephalogram (EEG) is a test that detects electrical activity in your brain using small, metal discs (electrodes) attached to your scalp.
- The EEG may also be used to determine the overall electrical activity of the brain

EEG Analysis

- Analysis of EEG signals requires time and other resources as well.
- Proposing deep learning approach to modify the process and obtain better results.

- **Objectives**

1. To analyze and classify users' mental workload while performing cognitive tasks.
2. To apply deep learning techniques on EEG signals for classifying Cognitive Workload.

- **Scope**

Category	Application
Safety	Defence sector, Pilot stress, Driver fatigue
Performance	Student Performance during different tasks

Table 1 : Scope

Problem Statement

- To evaluate and classify the cognitive workload level of a person based on task performance from EEG signals using deep learning algorithms.
- To improve classification accuracy and propose a modified approach of EEG signal analysis for cognitive workload evaluation.

Literature Survey(1/3)

Title	Author, Publication, Year	Technique	Remark
Mental Workload Estimation using EEG	V. Pandey, D. K. Choudhary, V. Verma, G. Sharma, R. Singh, S. Chandra, Fifth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), May 2020	CNN-LSTM, LSTM, MLP Classifier, RF Classifier, KNN Classifier	Comparison between Deep Learning and Machine Learning Algorithms.
EEG-based mental workload estimation using deep BLSTM-LSTM network and revolutionary algorithm.	D. D. Chakladar, S. Dey, P. P. Roy, D. P. Dorga, Elsevier Publications, May 2020	Composite framework of GWO and deep neural network(BLSTM-LSTM)	Proposed deep learning approaches and comparison of same

Literature Survey(2/3)

Title	Author, Publication, Year	Technique	Remark
EEG based spatio-temporal Convolutional Neural Network for Driver Fatigue Evaluation	Z. Gao, X. Wang, Y. Yang, C. Mu, Q. Cai, W. Dang, S. Zuo, IEEE Transactions on Neural Networks and Learning Systems, January 2019	ESTCNN model	This model is employed using dense layers to get spatial features.
Detecting Fatigue Status of Pilots based on Deep Learning Network using EEG Signals	E. Q. Wu, P. Y. Deng, X. Y. Qu, W. M. Zang, L. M. Zhu, IEEE Transactions on Cognitive and Developmental Systems, January 2019	Deep Sparse Contractive Auto Encoder (DSCAEN) model.	DSCAEN model for obtaining mental status of pilots

Literature Survey(3/3)

Title	Author, Publication, Year	Technique	Remark
An Effective Hybrid Model for EEG-based Drowsiness Detection	U. Budak, V. Bajaj, Y. Akbulut, O. Atila, A. Sengur, IEEE Sensors Journal, September 2019	Building blocks LSTM	Each feature is considered in LSTM Model with three main building blocks
STEW: Simultaneous Task EEG Workload Dataset	W. L. Lim, O. Sourina, L. P. Wang, IEEE Transactions on Neural Systems and Rehabilitation Engineering, November 2018	Support Vector Regression Model with NCA Technique	Proposed an open source EEG dataset for mental workload evaluation.

Table 2 : Literature Survey

Architectural Diagram

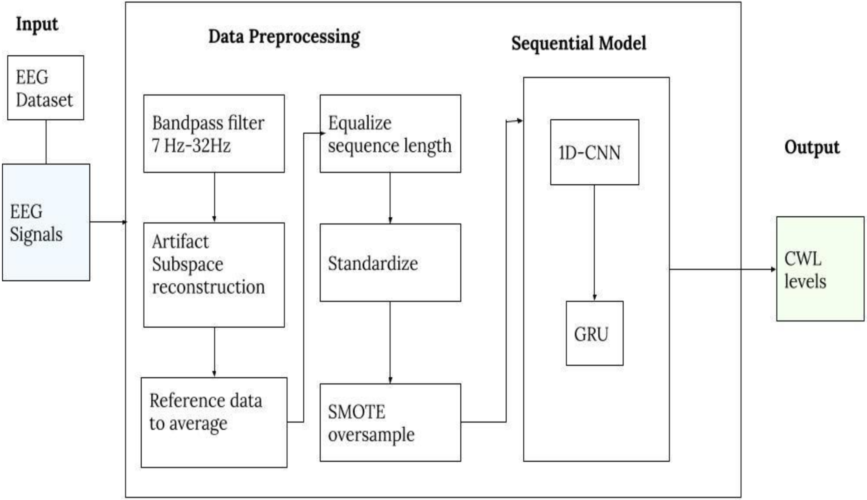

Figure 1 : System Architecture Diagram

Algorithmic Approach(1/3)

- Pre-processing raw EEG data:
  Artifact Subspace Reconstruction(ASR):
  It repeatedly computes a principal component analysis (PCA) on covariance matrices to detect artifacts based on their statistical properties in the component subspace.

- Feature Extraction:
  Convolutional Neural Network(CNN):
  To extract spatial and temporal features from pre-processed EEG data.

- Classification:
  Gated Recurrent Unit (GRU) algorithm:
  To classify the EEG data which is a sequential time series data.

➢ **CNN-GRU model architecture**

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 1, 128)	18432128
batch_normalization (BatchNo	(None, 1, 128)	512
max_pooling1d (MaxPooling1D)	(None, 1, 128)	0
conv1d_1 (Conv1D)	(None, 1, 64)	8256
batch_normalization_1 (Batch	(None, 1, 64)	256
max_pooling1d_1 (MaxPooling1	(None, 1, 64)	0

Algorithmic approach(3/3)

➢ **CNN-GRU model architecture (Continued)**

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_2 (Sequential)    (None, 1, 64)             18445568
_________________________________________________________________
gru_3 (GRU)                  (None, 1, 64)             24768
_________________________________________________________________
gru_4 (GRU)                  (None, 32)                9312
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 66
=================================================================
Total params: 18,479,714
Trainable params: 18,479,202
Non-trainable params: 512
```

System Specifications

Software Requirements

Sr.no	Software	Description
1	Operating System	Windows 8+
2	Language Used For Implementation	Python 3.7
3	Development Environment	EEGLAB(2020b), Visual Studio Code, Google Colaboratory

Table 3 : Software Requirements

Hardware Requirements

Sr.no	Hardware	Description
1	RAM	8GB and above
2	Processor	intel CORE i5 and above

Table 4 : Hardware Requirements

Input / Dataset

- **STEW**
  Simultaneous Task EEG Workload Dataset
- **Data collection**
  Emotiv EEG Device.
- **Electrode Positions**
  10-20 international system.
- **Description**
  14 EEG channels recorded over duration of 2.5 minutes.
- **Raw EEG recordings of 48 Subjects under**
  - Rest condition.
  - Performing Task.
- Subjective ratings (1 - 9) based on NASA-TLX standard scale.

Channel	Position
AF3, F7, F3, FC5, FC6, F4, F8, AF4	Frontal
T7,T8	Temporal
P7, P8	Parietal
O1, O2	Occipital

Table 5 : Channels and their Positions

Performance Metrics

Performance Parameters

- ➢ Classification Accuracy
- ➢ Precision
- ➢ Recall
- ➢ F1 Score
- ➢ Sensitivity

Output

- ➢ Cognitive Workload Levels
(Low, Moderate, High)

Result(1/4)

SIMKAP CNN-GRU Evaluation Report

```
SIMKAP - CNNGRU EVALUATION REPORT
              precision    recall  f1-score

      Class0       1.00      0.50      0.67
      Class1       0.71      1.00      0.83

    accuracy                           0.78
   macro avg       0.86      0.75      0.75
weighted avg       0.84      0.78      0.76


CONFUSION MATRIX
 [[2 2]
 [0 5]]

  Sensitivity    Specificity
-------------  -------------
          100             50
```

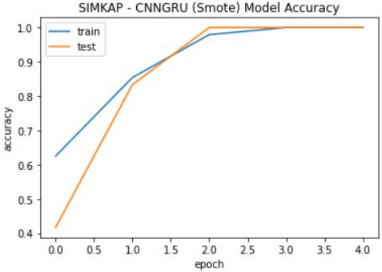

Figure 2 : SIMKAP Training Accuracy Plot

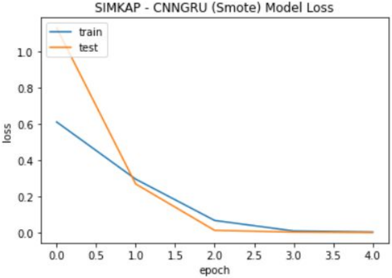

Figure 3 : SIMKAP Training Loss Plot

Result(2/4)

No Task CNN-GRU Evaluation Report

```
No Task -CNNGRU EVALUATION REPORT
              precision    recall  f1-score

      Class0       0.89      1.00      0.94
      Class1       0.00      0.00      0.00

    accuracy                           0.89
   macro avg       0.44      0.50      0.47
weighted avg       0.79      0.89      0.84


CONFUSION MATRIX
 [[8 0]
 [1 0]]

  Sensitivity    Specificity
 -------------  -------------
             0            100
```

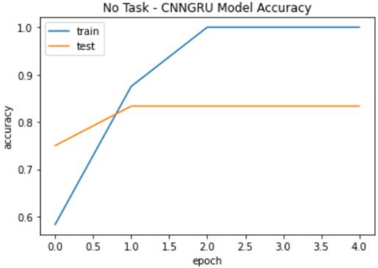

Figure 4 : No Task Training Accuracy Plot

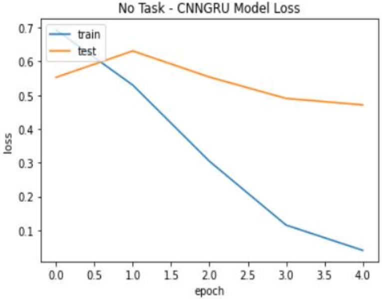

Figure 5 : No Task Training Loss Plot

Result(3/4)

SIMKAP Results

Classification	Deep Learning					
Models	CNN		GRU		CNN-GRU	
	Train	Test	Train	Test	Train	Test
Accuracy	96%	66%	99%	88%	97%	78%
Precision	67.5%		91.5%		85.5%	
Recall	67.5%		87.5%		75.5%	
Sensitivity	60%		99%		99%	
F1 Score	67%		88.5%		75%	

Table 6 : SIMKAP Classification Results

Result(4/4)

No Task Results

Classification	Deep Learning					
Models	CNN		GRU		CNN-GRU	
	Train	Test	Train	Test	Train	Test
Accuracy	100%	89%	100%	89%	100%	90%
Precision	89%		89%		89%	
Recall	99%		99%		99%	
Sensitivity	60%		70%		60%	
F1 Score	94%		94%		94%	

Table 7 : No Task Classification Results

Conclusion

- Proposed a composite sequential model CNN-GRU for predicting cognitive workload levels.
- Proposed model gives increased accuracy through oversampled data.
- The cognitive workload levels is classified as low, moderate and high for both resting as well as multitasking condition shown via web application.
- Proposed model has the ability to enhance the analysis process of EEG signals for any information extraction.

Papers Published and Participation in Project Competition

Title
Performance Comparison of Different EEG Analysis Techniques Based on Deep Learning Approaches

Conference
2021 IEEE International Conference on Emerging Smart Computing and Informatics (ESCI)

DOI
https://doi.org/10.1109/ESCI50559.2021.9396856

Published Paper
S. Belsare, M. Kale, P. Ghayal, A. Gogate and S. Itkar, "Performance Comparison of Different EEG Analysis Techniques Based on Deep Learning Approaches," 2021 *International Conference on Emerging Smart Computing and Informatics* (ESCI), 2021, *pp.* 490-493.

Project Competition:
Participated in Round 2 of CSI-inApp 2021 Competition

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Thank You