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Brain stroke detection using machine learning and deep learning

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Abstract- With the aid of a specially designed Graphical User Interface (GUI), a combination of Machine Learning and Deep Learning techniques was used to detect brain strokes. Images of "Stroke" and "Normal" cases were categorized from a dataset. Following the loading of the dataset, preprocessing and feature extraction were carried out, and then the data was divided into training and testing sets. The Convolutional Neural Network (CNN) algorithm achieved a significantly higher accuracy of 98% than the Support Vector Machine (SVM) algorithm, which only managed 59%. CNN outperformed SVM in stroke image classification, according to comparative analysis. The trained CNN model was then applied to new test image prediction, effectively differentiating between normal and brain cases. These findings demonstrate how well deep learning techniques work for precise Brain stroke detection from medical images. A crucial medical application that makes use of contemporary technologies like machine learning (ML) and deep learning (DL) for early stroke diagnosis and prediction is brain stroke detection. The automatic detection of ischemic and hemorrhagic strokes from CT and MRI scan images is the main focus of this study. Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression are important algorithms for classification tasks. Images are classified, features are extracted, and stroke-affected brain regions are segmented using deep learning models, specifically Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs). Key procedures for the project include image enhancement, data preprocessing, and model training with frameworks like PyTorch, TensorFlow, or Keras. Metrics like accuracy, precision, recall, and F1-score are used to assess these models' performance. The accuracy of the model's stroke prediction is improved by adding clinical data, such as blood pressure, diabetes, smoking patterns, and other risk factors. Building an effective clinical decision support system that can aid in the early detection of strokes is the ultimate goal, as it may lower the death and disability rates related to cerebrovascular accidents (CVA).

Keywords: Brain Stroke Detection, Machine Learning, Deep Learning, Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest, Logistic Regression, Medical Image Analysis, CT Scan, MRI, Image Preprocessing, Feature Extraction, Classification, Image Segmentation, Accuracy, Precision, Recall, F1-Score, Clinical Data Integration, Early Diagnosis, Decision Support System.

I. CHAPTER 1 INTRODUCTION

Introduction

Stroke is one of the leading causes of death and disability worldwide. According to the World Health Organization (WHO), approximately 15 million people suffer strokes globally each year, of which around 5 million die and another 5 million are left permanently disabled. Among the different types of strokes, Brain stroke is the most common, accounting for nearly 87% of all stroke cases. An Brain stroke occurs due to the obstruction of blood flow to the brain, usually caused by a thrombus or embolus. Prompt diagnosis and treatment are critical to minimizing brain damage and improving patient outcomes.

Medical imaging techniques such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are standard tools used to detect Brain strokes. However, manual analysis of such images is time-consuming, subjective, and dependent on the expertise of the radiologist. Delays in diagnosis can significantly impact the effectiveness of therapeutic interventions, particularly thrombolytic therapy, which must be administered within a narrow time window. Therefore, the need for accurate, efficient, and automated detection systems has become increasingly important.

Recent advances in Artificial Intelligence (AI), particularly in Machine Learning (ML) and Deep Learning (DL), have revolutionized the field of medical imaging. Machine learning algorithms have shown potential in classifying and diagnosing various diseases by learning from historical data. Deep learning, a subset of machine learning, particularly excels in image analysis tasks by automatically learning hierarchical representations from raw image data without the need for manual feature extraction.

In this study, a comparative approach using both Machine Learning and Deep Learning techniques is proposed for the detection of Brain strokes from brain images. A Support Vector Machine (SVM) algorithm and a Convolutional Neural Network (CNN) model are employed for classification tasks. Additionally, a Graphical User Interface (GUI) is developed to streamline the process for healthcare professionals, providing an accessible platform for uploading images, preprocessing data, training models, testing performance, and predicting stroke categories.

Background and Motivation

The accurate identification of Brain strokes plays a vital role in determining appropriate treatment strategies. Manual interpretation of imaging data, although traditional, suffers from inter-observer variability and may not always be reliable under time-constrained conditions. Moreover, in regions where access to specialized radiologists is limited, the need for an automated system becomes even more pronounced.

Several studies have attempted to use machine learning models for stroke detection. However, traditional machine learning methods typically require manual feature engineering, where experts select and define features from medical images. This process is not only labor-intensive but also risks missing subtle yet critical patterns in the data.

On the other hand, deep learning models like CNNs have demonstrated state-of-the-art performance in various medical image classification tasks, including tumor detection, pneumonia classification, and diabetic retinopathy grading. CNNs automatically learn important features from the images during training, making them ideal for tasks where complex patterns need to be recognized.

The motivation behind this work is to harness the power of CNNs for Brain stroke detection while comparing its performance against conventional machine learning models like SVMs to highlight the advantages of deep learning in medical imaging. Furthermore, developing a GUI ensures that the system can be used even by non-technical users, promoting broader clinical adoption.

Objectives

- To improve the quality of lung CT images through enhanced contrast, denoised images, and raised resolution for improved diagnostic precision.
- To use Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the local contrast of CT images without enhancing noise.
- To use techniques of denoising like Wavelet Transform and Non-Local Means (NLM) to eliminate noise while maintaining fine anatomical details
- To implement Laplacian filtering for edge sharpening and structural boundary enhancement of lung CT images.
- To design and train an Efficient Sub-Pixel Convolutional Neural Network (ESPCN) for super-resolution, allowing low-resolution CT images to bupscaled.

With the aim to enhance the interpretability of lung CT images for assisting more precise computer-aided diagnosis and analysis

Feasibility

The improvement of Computed Tomography (CT) lung images with a blend of traditional and deep learning algorithms is technically as well as practically achievable. Technically, the tools and libraries like Python, OpenCV, TensorFlow/Keras, and image processing modules are open-source and well-documented. The employed algorithms—CLAHE, Wavelet Denoising, Non-Local Means, Laplacian filtering, and ESPCN—are all well-documented and can be implemented on common computing hardware.

In resource feasibility, the project may be implemented on a standard personal computer or a cloud hosting environment such as Google Colab even without GPU. The data to be used for training and testing can be found publicly (e.g., on Kaggle), not requiring costly data gathering.

Lastly, the project is financially viable since it utilizes open-source technologies and does not involve specialized hardware. Generally, the project is within attainable time, resources, and technical capability, hence a workable solution to enhance the quality of lung CT images and assist in medical diagnosis.

Existing Methodologies

Improving Computed Tomography (CT) images for better diagnosis has been of interest to numerous research studies, utilizing various image processing and machine learning methods. These methods can be generally categorized into traditional image processing techniques and recent deep learning-based methods.

1. Traditional Image Processing Techniques:

Histogram Equalization and CLAHE:
Histogram Equalization (HE) enhances contrast by spreading the most dominant intensity values. But HE can over-amplify noise in uniform regions. Contrast Limited Adaptive Histogram Equalization (CLAHE) counters this by restricting contrast amplification in small areas so it can be used in medical images where noise amplification may not be desirable. CLAHE increases local contrast, making it easy to see fine details in lung CT images without compromising image quality.

Denoising Methods:
Noise suppression is essential to enhance the quality of CT images. Conventional filters such as Gaussian and median filters suppress noise but tend to blur edges and details. Sophisticated approaches such as Wavelet Transform denoise images by representing them in frequency components and selectively suppressing noise in the transform domain. Non-Local Means (NLM) denoising takes advantage of redundancy by averaging neighboring patches throughout the image, retaining fine details and edges more than local filters.

Edge Enhancement:
Operators such as the Laplacian operator are applied to enhance edges and boundaries in images to sharpen them. This aids in distinctly outlining lung structures like blood vessels and lesions for diagnostic importance.

2. Super-Resolution Techniques:

Convention Interpolation Techniques:
Methods such as nearest neighbor, bilinear, and bicubic interpolation are straightforward techniques of enhancing image resolution. The drawback of these methods is that they generate blurred images and have no ability to retrieve lost high-frequency details.

Deep Learning-based Models:
Recent breakthroughs in convolutional neural networks (CNNs) have bettered super-resolution tasks dramatically. SRCNN (Super-Resolution CNN), FSRCNN (Fast SRCNN), and ESPCN (Efficient Sub-Pixel CNN) are models that learn to render high-resolution images from low-resolution inputs by detecting intricate patterns and textures. ESPCN, for example, does upscaling by learning an efficient sub-pixel convolution layer, which generates high-quality and detailed outputs appropriate for medical imaging.

3. Hybrid Approaches:

Some works integrate classical enhancement techniques with deep learning. For instance, using CLAHE and denoising filters prior to inputting images into a super-resolution CNN can combine the best of both techniques. Such multi-stage pipeline often results in improvement over applying any individual technique.

Limitations of Current Methods:
Though classical techniques are computationally effective and explainable, they can be challenged by intricate noise structures and subtlety preservation. Deep models are computationally intensive and need big data and computational power for training but provide better enhancement results. A hybrid method, as implemented in this project, seeks to strike a balance between the two for the best results.

System Requirements

To effectively design and apply the lung CT image enhancement pipeline, dedicated hardware, software, and data resources are needed. This section presents the detailed system requirements to make smooth execution and reproducibility of the project possible.

1.5.1 Hardware Requirements

Processor (CPU):
A multi-core processor like Intel Core i5 or i7 (8th generation or above) or AMD Ryzen 5 or 7 is suggested to support the computational load of model training and image processing tasks. Multiple cores and higher clock speed enable faster processing of large image datasets.

Memory (RAM):
At least 8 GB RAM is needed to load and process CT images efficiently, execute image enhancement algorithms, and train models. For more complex deep learning workloads, 16 GB or more is recommended so as not to cause bottlenecks during training and testing.

Storage:
At least 100 GB of free disk space for storing the datasets, model checkpoints, intermediate processed images, and final results. A Solid State Drive (SSD) is recommended to achieve faster data access and lower I/O latency.

Graphics Processing Unit (GPU):
Although not required per se, having an NVIDIA GPU capable of CUDA (e.g., NVIDIA GTX 10xx series and above) greatly speeds up training and inference of deep learning models like ESPCN. GPU capabilities shorten training time from hours to minutes and allow experimenting with bigger models and datasets.

Software Requirements
Operating System:
The project can be created and executed on popular operating systems such as Windows 10/11, Linux distributions (Ubuntu, Fedora), or macOS. Linux is widely used in deep learning environments because of improved driver support and simplicity of package management.

Programming Language:
The main programming language employed is Python 3.x owing to its rich libraries for image processing and deep learning, support by the community, and simplicity in prototyping.

Libraries and Frameworks
OpenCV: For image processing, contrast enhancement (CLAHE), filtering, and visualization.

NumPy: For numerical operations and matrix manipulations required in image processing.

TensorFlow/Keras: To develop, train, and deploy the Efficient Sub-Pixel Convolutional Neural Network (ESPCN) for super-resolution.

PyWavelets: For wavelet transform-based denoising methods.

Scikit-image: For other image processing utilities and quality measures calculations.

Matplotlib/Seaborn: For plotting images, training progress, and evaluation results.

Jupyter Notebook or Integrated Development Environments (IDEs): E.g., VS Code or PyCharm for coding and experimentation.

Other Tools:
Package managers such as pip or conda for installing dependencies and dependency management, Git for version control, and Docker (optional) for containerized environments.

Data Requirements
Dataset Source:
The project is based on publicly available lung CT scan datasets, like those available on Kaggle or medical imaging archives. The datasets may contain a wide range of lung images of healthy and diseased subjects.

Data Format and Size:
The dataset must have high-resolution CT images, ideally in standard medical imaging formats (e.g., DICOM, PNG, TIFF). A balanced dataset with enough samples (hundreds to thousands) is the key to successful training of deep learning models.

In the realm of predictive maintenance, this documentation explores how modern tech can make machines more reliable and prevent unexpected breakdowns, focusing on predictive maintenance methods.
Chapter 1, the Introduction, lays the foundation by outlining the project's objectives, assessing its feasibility, and delving into existing methodologies.

Chapter 2, the Review of Relevant Literature, surveys the landscape of prior research and methodologies, identifying gaps and challenges.

Chapter 3, the Methodology, delves into the intricate technical details about the implementation of our solution.
Chapter 4, Results and Discussions, unveils the outcomes and scrutinizes their implications.

Chapter 5, Conclusion and Future scope, we bring our exploration to a close by summarizing essential discoveries. Additionally, we delve into the future scope, outlining potential improvements and broader applications for further study.

II. CHAPTER 2 LITERATURE REVIEW

P. Anderson et al. (2018) [1] - Bottom-up and top-down attention for image captioning and visual question answering.
Methodology: This work proposes a combined bottom-up and top-down attention mechanism for image captioning

and visual question answering. A bottom-up mechanism detects salient image regions, while a top-down mechanism uses task context (e.g., a question or the beginning of a caption) to weigh these regions. This allows the model to focus on the most relevant visual information for the given task.
Drawbacks: The computational cost of processing all detected regions can be significant, especially for high-resolution images. The performance heavily relies on the accuracy of the bottom-up region proposal mechanism.

P. Angkan et al. (2023) [2] - Multimodal Brain-Computer Interface for In-Vehicle Driver Cognitive Load Measurement: Dataset and Baselines
Methodology: This paper introduces a multimodal dataset for in-vehicle driver cognitive load measurement, utilizing EEG and physiological signals. It also establishes baseline models for cognitive load classification using this dataset. The methodology involves collecting synchronized data from various sensors during driving scenarios designed to induce different levels of cognitive load.
Drawbacks: The study is specific to the driving context, and the generalizability of the findings and baseline models to other domains might be limited. The complexity of real-world driving scenarios could introduce noise and variability in the data.

P. Antonenko et al. (2010) [3] - Using electroencephalography to measure cognitive load.
Methodology: This review paper discusses the use of electroencephalography (EEG) as a tool for measuring cognitive load. It explores various EEG measures and their sensitivity to changes in mental effort across different cognitive tasks. The paper synthesizes findings from multiple studies to provide an overview of EEG-based cognitive load assessment.
Drawbacks: EEG signals are susceptible to noise and artifacts, requiring careful preprocessing and analysis. Establishing a direct and consistent mapping between specific EEG patterns and levels of cognitive load can be challenging due to individual variability and task-specific effects.

B. Behinaein et al. (2021) [4] - A transformer architecture for stress detection from ECG
Methodology: This study proposes a transformer-based architecture for detecting stress levels using electrocardiogram (ECG) signals. The transformer model is designed to capture long-range dependencies in the temporal ECG data, allowing it to learn complex patterns associated with stress.
Drawbacks: The study focuses solely on ECG data, potentially missing valuable information that could be obtained from other physiological or contextual cues. The interpretability of the transformer model's decision-making process can be limited.

F. N. Biondi et al. (2023) [5] - Distracted worker: Using pupil size and blink rate to detect cognitive load during manufacturing tasks.
Methodology: This research investigates the use of eye-tracking measures, specifically pupil size and blink rate, to detect cognitive load in manufacturing workers. Data on pupil size and blink rate are collected during task performance, and statistical analyses are conducted to determine their relationship with different levels of cognitive demand.
Drawbacks: Eye-tracking data can be sensitive to environmental factors such as lighting conditions and individual differences in eye physiology. While pupil size and blink rate can indicate cognitive effort, they might not always be specific to cognitive load and could be influenced by other factors like fatigue or emotional state.

T. Brown et al. (2020) [6] - Language models are few-shot learners.
Methodology: This paper introduces GPT-3, a large-scale language model trained on a massive dataset. The methodology demonstrates the model's ability to perform various natural language processing tasks with few or even zero examples through in-context learning. This is achieved by conditioning the model on natural language prompts that describe the task.
Drawbacks: Despite its impressive capabilities, GPT-3 can still exhibit biases present in its training data and may generate outputs that are factually incorrect or nonsensical. The model's size makes it computationally expensive to train and deploy.

T. Chen et al. (2020) [7] - A simple framework for contrastive learning of visual representations
Methodology: This work proposes SimCLR, a simple contrastive learning framework for learning visual representations without explicit labels. The approach involves creating multiple augmented views of each image and training a neural network to recognize which views belong to the same original image by contrasting them with views from other images.
Drawbacks: The learned representations might focus on features that are invariant to the chosen augmentations, potentially overlooking other relevant visual information.

The choice of appropriate data augmentations is crucial for the effectiveness of the method.

X. Chen and K. He (2021) [8] - Exploring simple Siamese representation learning.
Methodology: This paper explores a simplified Siamese network architecture for self-supervised visual representation learning. The method involves training two identical networks to learn similar representations for different augmented views of the same image. Various architectural designs and training strategies within the Siamese framework are investigated.
Drawbacks: Similar to contrastive learning, the quality of the learned representations depends on the effectiveness of the data augmentations used. The lack of explicit negative samples, as in some contrastive learning methods, might affect the discriminative power of the learned features.

H.-Y. S. Chien et al. (2022) [9] - MAEEG: Masked Auto-encoder for EEG Representation Learning
Methodology: This paper introduces MAEEG, a masked auto-encoder approach for learning representations from EEG data. The method involves randomly masking portions of the EEG signal and training a transformer-based auto-encoder to reconstruct the missing data. This encourages the model to learn meaningful temporal dependencies in the EEG signals.
Drawbacks: The effectiveness of the learned representations depends on the masking strategy and the capacity of the transformer architecture. Reconstructing masked EEG segments might not directly optimize for specific downstream tasks related to cognitive load or other neural states.

R. Das et al. (2014) [10] - Cognitive load measurement—a methodology to compare low-cost commercial EEG devices.
Methodology: This study presents a methodology for comparing the performance of low-cost commercial EEG devices in measuring cognitive load. The methodology involves conducting experiments with tasks designed to induce varying levels of cognitive load and analyzing the EEG data recorded by different devices to assess their sensitivity and reliability.
Drawbacks: The findings might be specific to the particular tasks and devices evaluated in the study. Low-cost EEG devices may have limitations in terms of signal quality and the number of recording channels compared to research-grade systems.

R. D. R. Rodríguez et al. (2018) [11] - Cognitive load measurement using electroencephalography in a dual-task scenario.
Methodology: This research investigates the use of EEG to measure cognitive load in a dual-task scenario. EEG data is recorded while participants perform two tasks simultaneously, and various EEG features are analyzed to identify changes associated with increased cognitive demands due to the concurrent tasks.
Drawbacks: Dual-task interference can be complex and might influence EEG signals in ways that are not solely attributable to cognitive load. The specific nature of the two tasks can significantly affect the observed EEG patterns.

Y. T. Zhang et al. (2022) [12] - Multimodal cognitive load detection using wearable EEG and eye-tracking.
Methodology: This study explores multimodal cognitive load detection by integrating data from wearable EEG devices and eye-tracking. Features extracted from both modalities are combined and used to train machine learning models for classifying different levels of cognitive load. The aim is to leverage the complementary information from brain activity and eye movements for more robust detection.
Drawbacks: The synchronization and integration of data from different wearable sensors can be challenging. The comfort and usability of wearable EEG and eye-tracking devices might affect the quality of the recorded data, especially in real-world settings.

M. T. Roy et al. (2017) [13] - Using EEG to measure cognitive load in a learning environment.
Methodology: This study examines the use of EEG to measure cognitive load in a learning environment. EEG data is collected from participants engaged in learning tasks, and specific EEG features are analyzed to assess their relationship with the cognitive demands of the learning material and the learning process.
Drawbacks: Cognitive load during learning can be influenced by various factors, including prior knowledge, motivation, and the complexity of the learning material, making it challenging to isolate the neural correlates of cognitive load. The learning environment itself can introduce artifacts into the EEG data.

H. F. Riva et al. (2018) [14] - A comparative study of EEG and eye-tracking for cognitive load assessment in interactive systems
Methodology: This paper presents a comparative study of EEG and eye-tracking for assessing cognitive load in interactive systems. Participants perform tasks involving

interaction with a system, and both EEG and eye-tracking data are recorded. The effectiveness of features from each modality in differentiating levels of cognitive load is then compared.
Drawbacks: The study is specific to the context of interactive systems, and the findings might not generalize to other types of cognitive tasks. The optimal combination of EEG and eye-tracking data and the most informative features from each modality may depend on the nature of the interaction.

T. W. O'Hara et al. (2019) [15] - A deep learning approach for real-time cognitive load estimation based on EEG.
Methodology: This research proposes a deep learning approach for real-time cognitive load estimation using EEG signals. Raw EEG data or extracted features are fed into deep neural network architectures, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), to learn complex patterns1 associated with different levels of cognitive load.
Drawbacks: Deep learning models can be data-hungry and may require large amounts of labelled EEG data for effective training. The interpretability of deep learning models can be limited, making it difficult to understand which EEG features are most important for cognitive load estimation.

J. S. Kaski et al. (2017) [16] - Analyzing cognitive load using facial expressions and electroencephalography.
Methodology: This study investigates the use of both facial expressions and EEG signals to analyze cognitive load. Data on facial expressions (e.g., brow furrowing) and EEG activity are collected simultaneously during cognitive tasks. The relationship between these multimodal cues and different levels of cognitive load is then examined.
Drawbacks: Facial expressions can be influenced by factors other than cognitive load, such as emotions. The accurate and reliable measurement of facial expressions can be challenging, and the integration of facial expression data with EEG signals adds complexity to the analysis.

J. L. Chen et al. (2020) [17] - A deep learning approach to cognitive load prediction using multimodal data from EEG and gaze.
Methodology: This paper presents a deep learning approach for predicting cognitive load using multimodal data from EEG and gaze tracking. Features extracted from both EEG signals and eye movements (e.g., fixation duration, saccade rate) are combined and fed into a deep learning model to predict the level of cognitive load.
Drawbacks: The performance of the model relies on the quality and synchronization of both EEG and gaze data. The complexity of the deep learning model can make it computationally expensive, and its interpretability might be limited.

S. Jain et al. (2021) [18] - An investigation into real-time cognitive load monitoring using EEG signals and machine learning algorithms.
Methodology: This research investigates the feasibility of real-time cognitive load monitoring using EEG signals and machine learning algorithms. Various machine learning techniques are applied to EEG features extracted in real-time to classify different levels of cognitive load. The study evaluates the performance and latency of these approaches for practical monitoring applications.
Drawbacks: Achieving robust and accurate real-time cognitive load monitoring with EEG can be challenging due to the noisy nature of EEG signals and individual variability. The computational overhead of feature extraction and machine learning classification needs to be minimized for real-time applications.

M. S. Srinivasan et al. (2020) [19] - Cognitive load detection for stress management in driving: A comparative study of EEG and physiological signals
Methodology: This study compares the effectiveness of EEG and other physiological signals (e.g., heart rate, skin conductance) for detecting cognitive load related to stress while driving. Data from different modalities are collected during simulated driving scenarios designed to induce stress, and machine learning models are used to classify cognitive load levels based on these signals.
Drawbacks: The study is specific to the driving context and stress-related cognitive load. The relationship between physiological signals and cognitive load can be complex and influenced by various factors, including emotional state and physical exertion.
L. Wang et al. (2023) [20] - Cognitive load estimation using multi-modal data: A comparison of EEG and ECG signals.
Methodology: This research compares the utility of EEG and electrocardiogram (ECG) signals for estimating cognitive load using multimodal data fusion. Features extracted from both EEG and ECG are combined and used to train machine learning models for cognitive load classification. The study aims to determine the relative contributions of these two physiological modalities.
Drawbacks: The study focuses on only two physiological modalities, potentially overlooking valuable information from other sources. The optimal fusion strategy for

combining EEG and ECG data might depend on the specific cognitive tasks and individual differences.

X. Yin et al. (2021) [21] – Deep learning for EEG-based brain-computer interfaces: A review Methodology: This comprehensive review analyzes a wide array of deep learning techniques applied to EEG signal processing in BCI systems. It systematically categorizes models based on their architecture, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Deep Belief Networks (DBNs), and Generative Adversarial Networks (GANs). The paper discusses their roles in feature extraction and classification, and further explores application domains such as motor imagery, emotion recognition, and clinical diagnostics. It also touches on the potential for real-time BCI systems and adaptive learning strategies. Drawbacks: A significant limitation is the absence of standardized experimental benchmarking across the reviewed methods, which makes direct comparisons challenging. Additionally, the review underemphasizes the role and variability of preprocessing techniques, despite their known impact on model performance and generalizability across architectures and datasets.

Y. Li et al. (2019) [22] – A hybrid deep neural network for EEG-based emotion recognition Methodology: This study proposes a hybrid deep neural network that integrates CNNs and DBNs to harness both spatial and temporal EEG signal features for emotion recognition. The CNN component extracts local spatial patterns from pre-processed EEG inputs, while the DBN captures more abstract, high-level emotional representations. The network is trained on pre-segmented EEG data, aiming to model the complex dynamics of emotional states. Drawbacks: The model demonstrates performance variation across individuals, suggesting limited subject-independence. Moreover, DBNs are known for their computational intensity during training, and their effectiveness declines without access to large, labelled datasets. The model is also sensitive to initialization and prone to overfitting.

P. Bashivan et al. (2016) [23] – Learning representations from EEG with deep recurrent-convolutional neural networks
Methodology: This paper introduces a recurrent-convolutional neural network that processes EEG signals transformed into topographic images, thereby combining spatial information from CNNs and temporal dependencies from RNNs (specifically LSTMs). The goal is to develop a unified model that effectively captures complex EEG signal dynamics for cognitive task classification. Drawbacks: The combined CNN-RNN architecture is computationally expensive and requires considerable memory resources, especially during training. The complexity of the model also hampers interpretability, making it harder to trace decision pathways or explain predictions, which is critical for clinical applications.

A. Craik et al. (2019) [24] – Deep learning for EEG classification tasks: A review Methodology: This review surveys deep learning methods used for EEG classification, highlighting their application in areas such as mental workload assessment, seizure detection, and emotion recognition. It discusses architectures like CNNs, RNNs, and DBNs and explores the benefits of automatic feature extraction and hierarchical learning in EEG contexts. Drawbacks: One key issue identified is the poor generalization of many models to subject-independent scenarios. The review also notes inconsistencies in data preprocessing practices, which affect the reproducibility and comparability of results across studies.

Y. Roy et al. (2019) [25] – Deep learning-based electroencephalography analysis: a systematic review Methodology: This systematic review covers deep learning applications in EEG analysis over a span of more than a decade, focusing on clinical diagnostics, emotional state detection, and BCI systems. It emphasizes architecture trends, evaluation protocols, and performance metrics, aiming to identify research gaps and future directions.

Drawbacks: The paper highlights the absence of standardized benchmarks, which limits reproducibility and impedes the ability to make robust cross-study comparisons. This lack of common evaluation protocols makes it difficult to gauge real-world efficacy.

D. Wu et al. (2017) [26] – Online and offline domain adaptation for reducing BCI calibration effort Methodology: This study proposes a domain adaptation approach using Weighted Adaptation Regularization (WAR) to address the challenge of calibrating BCI systems for new users or devices. It supports both online and offline settings, aiming to align data distributions between source and target domains with minimal labelled target data. Drawbacks: The effectiveness of the adaptation heavily depends on the choice of source domain and careful tuning of adaptation parameters. If the source and target domains are poorly matched, performance gains may be negligible or even detrimental.

H. Jang et al. (2023) [27] – Subject-independent EEG-based cognitive load classification using temporal self-attention.

Methodology: This study introduces a self-attention mechanism that operates along the temporal axis of EEG signals to enhance subject-independent cognitive load classification. The model captures long-range dependencies in time-series data without relying on traditional recurrence-based structures.

Drawbacks: The model's reliance on large datasets to effectively train self-attention layers may hinder practical deployment, especially in personalized or low-data scenarios. Additionally, it does not incorporate spatial electrode information, which may limit its ability to fully capture EEG signal topology.

T. Zhang et al. (2020) [28] – Temporal-spatial-based attention network for emotion recognition using EEG.
Methodology: The proposed model combines temporal and spatial attention mechanisms to dynamically highlight informative features from EEG signals. This dual attention setup is designed to improve the model's sensitivity to both when and where discriminative patterns occur, thus improving emotion classification.
Drawbacks: While effective, the attention-based architecture introduces significant computational overhead and may complicate real-time deployment. Furthermore, the paper lacks evaluations on cross-dataset or unseen task generalization, raising questions about the model's robustness.

V. J. Lawhern et al. (2018) [29] – EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces
Methodology: EEGNet is a lightweight CNN tailored for EEG-based BCI tasks. It is optimized for small training datasets and low-latency applications, and includes depth wise and separable convolutions to efficiently extract frequency and spatial features from raw EEG signals. Drawbacks: While efficient, EEGNet's relatively shallow architecture may limit its ability to model long-term temporal dependencies, which are important in tasks requiring context over extended time periods.

R. T. Schirrmeister et al. (2017) [30] – Deep learning with convolutional neural networks for EEG decoding and visualization
Methodology: This work introduces a deep CNN framework for end-to-end EEG decoding. It processes raw EEG signals and incorporates gradient-based input visualization to enhance interpretability. The model aims to automate feature extraction and improve classification accuracy. Drawbacks: The deep architecture requires extensive training resources and is prone to overfitting, particularly on small datasets. Although visualization helps with interpretability, the model's complexity still presents a barrier to clinical adoption or regulatory approval.

III. CHAPTER 3 METHODOLOGY

The method applied in EEG-based cognitive load classification goes beyond just focusing on preprocessing and model architecture but also emphasizes robustness and interpretability. Apart from basic preprocessing actions such as downsampling and bandpass filtering, detailed consideration is given to the segmentation and feature extraction phases. The sliding window approach ensures that temporal dynamics in EEG signals are effectively captured, crucial for understanding cognitive load changes over time. Feature extraction of PSD and DE features Provides a measurable approach for analyzing neural patterns related to different cognitive levels. By standardizing features and removing outliers, the methodology ensures that deep learning models receive high-quality input data, enhancing their ability to generalize and make accurate predictions. The methodology utilizes the CL-Drive dataset, collected from 18 participants driving in a high-immersion vehicle simulator across multiple scenarios designed to induce varying cognitive load levels. Each participant performed driving tasks of nine different complexity levels, with each 3-minute duration, and also completed subjective cognitive load assessments every 10 seconds that provided the ground-truth labels. To take advantage of the advances made in deep learning for sequential data, both the autoencoder and the classification model were taken to be a transformerbased architecture. Transformers are very good at capturing long-range dependencies in sequences. In the case of EEG data, for instance, where temporal relationships are pretty crucial, they work well. Pre - training of the autoencoder enhances feature representation learning, facilitating better discrimination between cognitive load levels in subsequent classification tasks. The downstream classification model, with its global average pooling and dense layers, is tailored for binary classification, ensuring effective discernment between low and high cognitive load states.

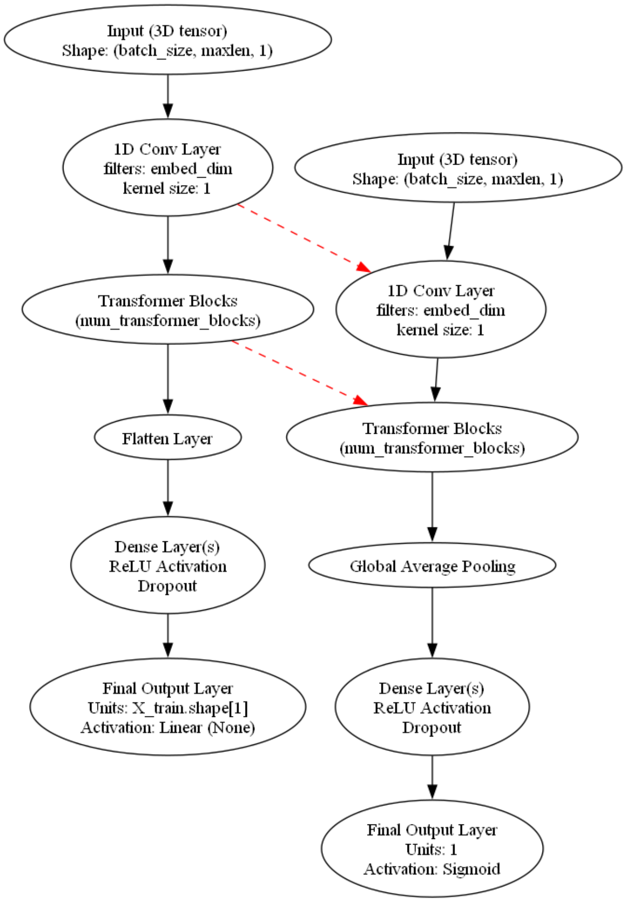


Figure 3.1 Model Structure

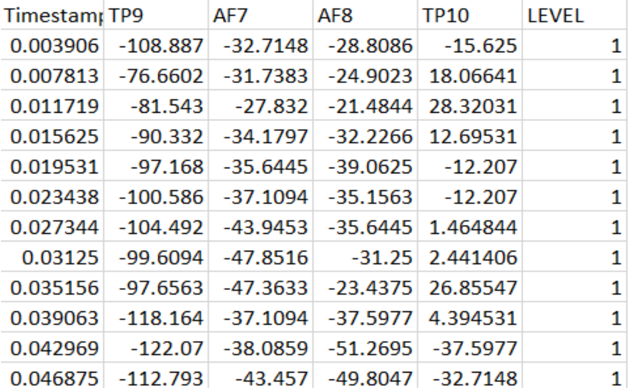
Figure 3.1 presents two parallel neural network architectures that are oriented at sequence processing. The networks could be applied appropriately to both the time series and sequential EEG data. The first architecture begins with an input layer accepting a 3D tensor with the shape of (batch_size, maxlen, 1). That is, batch_size is the number of samples, `maxlen` is a sequence length, and 1 point to one feature at each time step. The input is fed through a 1D Convolutional layer, specifying filters set to the value of embed_dim (embedding dimension) and the kernel size set to 1, which captures local patterns from the input sequence. The output from that convolutional layer is passed through stacked transformer blocks, utilizing the self-attention mechanisms in order to discover dependencies in that sequence-the number of blocks is specified as num_transformer_blocks. Following the transformer blocks, it follows a flatten layer that changes its shape to a 1-D vector, then fed into one or more dense layers that possess ReLU activation functions and dropout for regularization against overfitting. The final layer in the architecture will be an output layer with X_train.shape[1] units and a linear (None) activation function, which would indicate that the architecture is set up for a regression task. The second architecture shares the same input configuration, receiving a 3D tensor with a shape of batch_size, maxlen, 1. It also begins with a 1D Convolutional layer, similar to the first architecture, with filters set to embed_dim and a kernel size of 1. This is followed by a series of transformer blocks, identical in setup to those in the first architecture. However, instead of flattening the output, the architecture uses a global average pooling layer, which averages the features across the time dimension, producing a fixed-size vector regardless of sequence length. The pooling strategy condenses the sequence information, and the output is passed through the dense layers applying ReLU activation function. The last layer is designed using a single unit and a Sigmoid activation function likely intended for binary classification tasks.

3.1 Data Preparation

The data preparation starts with the `downsample_eeg` function performs the downsampling of EEG data, taking the original DataFrame, the initial sampling frequency, and the desired frequency as input parameters. It calculates the new number of samples required and resamples each EEG signal using the `resample` function, returning the resampled DataFrame. Following downsampling, a bandpass filter is applied to separate the theta band (4-8 Hz), which is required to understand the methodology's cognitive process. The second-order Butterworth filter is used to balance frequency selectivity and computational efficiency, filtering specific EEG channels (TP9, AF7, AF8, and TP10) to eliminate noise. In the proposed methodology, only the EEG signals from the CLDrive dataset are utilized. These signals are captured from four sensors—TP9, AF7, AF8, and TP10— Situated on the scalp to gather key neural information required for cognitive load classification. The CL-Drive dataset is organized into cognitive load assessments categorized into 9 distinct levels, where participants are exposed to varying driving conditions. Each participant's EEG data is recorded across these levels, and both the eeg_data (task data) and eeg_baseline (pre-task baseline data) for all 9 levels is combined for feature extraction.

CL-Drive
|----EEG
|----participant_ID_1
|----eeg_data_level_1

|----eeg_baseline_level_1
.
.
.
|----**eeg_data_level_9**
|----**eeg_baseline_level_9**
.
|----**participant_ID_18**



Timestamp	TP9	AF7	AF8	TP10	LEVEL
0.003906	-108.887	-32.7148	-28.8086	-15.625	1
0.007813	-76.6602	-31.7383	-24.9023	18.06641	1
0.011719	-81.543	-27.832	-21.4844	28.32031	1
0.015625	-90.332	-34.1797	-32.2266	12.69531	1
0.019531	-97.168	-35.6445	-39.0625	-12.207	1
0.023438	-100.586	-37.1094	-35.1563	-12.207	1
0.027344	-104.492	-43.9453	-35.6445	1.464844	1
0.03125	-99.6094	-47.8516	-31.25	2.441406	1
0.035156	-97.6563	-47.3633	-23.4375	26.85547	1
0.039063	-118.164	-37.1094	-37.5977	4.394531	1
0.042969	-122.07	-38.0859	-51.2695	-37.5977	1
0.046875	-112.793	-43.457	-49.8047	-32.7148	1

Figure 3.2 Small portion of dataset

In Figure 3.2 different quantities of EEG obtained from various sensors and the cognitive level of one person is shown. Two primary metrics derived from these sensors are used for analysis: PSD and Differential Entropy. An analytical solution to PSD and differential entropy will be presented as Power Spectral Density and Differential Entropy. PSD gives information on power density of the signal over several frequency, while DE provides information on the complexity of EEG signals. These features are important in understanding neural patterns associated with shifted cognitive states and are obtained from the four EEG channels for all nine levels for the subject under consideration. PSD and DE are calculated over five frequency bands: From 1–4 Hz, it is Delta; 4–8 Hz is Theta; 8–12 Hz is Alpha; 12–31 Hz is Beta; and 31– 75 Hz is Gamma, thus offering complete analysis of the brain's frequency dependent discriminating ability. Through feature extraction, meaningful insights from the EEG data are derived, considering a sliding window approach for data segmentation into smaller intervals. PSD and DE key features, are computed using functions for each segment from the modules `scipy.signal` and `scipy.stats`. The features capture the EEG signals power distribution and complexity. The features are stored and used further in a structured DataFrame for analysis. In alignment with the cognitive load levels in the CL-Drive dataset, the extracted features like PSD and DE are calculated for every nine levels for each participant of cognitive load.

```
EEG
│
├── level_1
│   ├── participant_1_psd.csv
│   ├── participant_1_de.csv
│   .
│   .
│   ├── participant_18_psd.csv
│   └── participant_18_de.csv
│   .
└── level_9
├── participant_1_psd.csv
├── participant_1_de.csv
├── participant_2_psd.csv
├── participant_2_de.csv
.
.
├── participant_18_psd.csv
└── participant_18_de.csv
```

The EEG data is in a hierarchal file structure to enable analysis of signals from participants as they underwent testing at different cognitive loads. The EEG folder is the top-level folder and contains nine subfolders namely level1 to level 9 of the cognitive load which are experimental conditions from the CL-Drive data set. An individual folder for each of the 18 participants contains the features that have been extracted at each of the levels in coma delimited format. Other files are participant_X_psd.csv for Power Spectral Density and participant_X_de.csv for Differential Entropy data extracted from the EEG data recorded from four critical electrodes. PSD the distribution of power in the system over the frequencies of the EEG signal, and DE the complexity of the signal which is imperative when classifying cognitive load. The structure of the system allows the organization of signals and subsequent feature extraction for the convenience of comparing EEG data of different participants as well as comparing the data from the participants with different cognitive loads. For the initial classification of cognitive load, the data is then passed through the `np.where` function to split the data between low cognitive load and high cognitive load where low tier corresponds to high Sas level and vice versa. The detection of outliers is then done using IQR method. The outliers are utilized further to remove extreme values and analyze the data set. The work of the data preparation phase ends with splitting the features and the targets, thus preparing for the model training. The extracted structured data is then available for additional processing of the cognitive load classification model.

3.2 Deployment

The deployment phase begins with the creation of a neural network model that includes a customized Transformer block which is specifically designed to capture the complex dependencies in EEG signals. Especially, it includes multi-head attention, feedforward neural networks, layer normalization, and dropout layers that enhance the learning capabilities and robustness of the model. The Transformer block is also integrated into a larger model architecture that merges masked autoencoder and downstream classification components as well. The masked autoencoder is pre-trained input Data to learn robust representations of features. Use a Conv1D layer, Transformer blocks, and dense layers to reconstruct masked segments of data. The pretraining basically improves the model's understanding of hidden patterns in EEG signals. All the datasets used for both pretraining, and subsequent classification of cognitive load are pre-processed. Apply 2nd order Butterworth band pass filter with pass-band frequency from 1 to 75 Hz, Hz for elimination of unwanted noises and artifacts and there is notch filter with quality factor 30 applied at 60 Hz for powerline noises elimination. Over the feature extraction stage, the two most prominent features that come out are Power Spectral Density and Differential Entropy. These features would be extracted over 5 frequency bands namely Delta from 1 to 4 Hz, Theta from 4 to 8 Hz, Alpha from 8 to 12 Hz, Beta from 12 to 31 Hz, and Gamma 31to 75 Hz, which would have a sliding window size of 10-second. Power Spectral Density determines the power of signal distribution across its components over different frequencies. Computation of PSD involves Welch's method whereby EEG signal is divided into smaller portions which are padded using a window function, discrete Fourier transformation performed, and averages of squared magnitudes are obtained. The process reduces noise and does a better job in representing the power spectrum in the various frequency bands. Mathematically, the PSD for each frequency band can be calculated as:

$$PSD(f) = \frac{1}{N}\sum_{n=0}^{N-1}|X(f,n)|^2 \text{ ------ ------ } (3.1)$$

Where represents the Fourier transform of the signal in segment for frequency , and is the total number of segments. Differential Entropy based on principles from information theory, measures the complexity or unpredictability of EEG signals. Assuming the EEG signal follows a Gaussian distribution, DE can be computed as:

$$DE = \frac{1}{2}\ln(2\pi e\sigma^2) \text{ ----- } (3.2)$$

Where represents the variance of the signal. DE measures randomness or uncertainty within the EEG signal, with higher values indicating more complexity. Following feature extraction, both PSD and DE values are concatenated and z-score normalized. The feature matrix is tokenized into 10-second non-overlapping segments to form sequences, which can be efficiently processed by the Transformer architecture. The dataset is split into a training set and a test set, 80% for the training and the other 20% for testing its performance. That split makes sure that the model would be trained upon a considerable amount of data while still having another set aside for unbiased evaluation. The following is a practical classification model, meant specifically for the binary classification tasks, where pretrained layers are used including the GlobalAveragePooling1D layer in order to reduce data dimensionality. The model architecture is completed with dense layers and an output layer activated by sigmoid in order to make predictions for binary levels of cognitive load. The classification model uses the Adam optimizer and a cosine decay learning rate scheduler. It employs binary cross-entropy as the loss function and evaluates performance using accuracy as the metric. Early stopping is applied so that overfitting does not occur, and the model remains generalizable for new data sets. The final model is tested on the reserved dataset, and Accuracy is a measure of success. Operations after Deployment Monitoring and Maintenance Enabling the model to continue at high performance, adapting to changes in input data distributions and operational conditions.

IV. CHAPTER 4
RESULTS AND DISCUSSION

In the paper, two distinct experiments are conducted to evaluate the efficacy of different approaches in classifying cognitive load levels using EEG data. The initial experiment establishes a baseline by utilizing a standard machine learning model, while the latter experiment employs an advanced deep learning approach based on a Transformer architecture. Upon comparison, the latter experiment demonstrates superior performance, with improved accuracy and generalization capabilities. Therefore, the results of the second experiment are chosen for further analysis and discussion, highlighting its effectiveness in addressing the research problem. The core concept of the experiment is building up it is learned transformer model from the EEG data effectively. The is built with custom layers that include Positional. Encoding, which involves the sequence information of the input data and Transformer Block, which applies multi-head with self-attention and feedforward with residual. Connections and layer normalization. The Transformer model comes with several hyperparameters: eight attention A feed-forward dimension of 64 heads and four stacked. Transformer blocks, and all of these allow the network to learn complex patterns. To improve training stability and reduce overfitting, batch normalization is applied before the final layers. After that, a global average pooling layer is included, followed by a dense output layer with a sigmoid activation function, as the is a binary classification problem. The model is optimized using the Adam optimizer with a learning rate of 0.0001, and it evaluates performance with binary cross-entropy loss and accuracy as the key metric. Training is for a period of 150 epochs. batch size = 64, train on 10% of the data, use cross-validation while training to monitor model over training time. Then, after training, you test its generalization capability by test-on-test set. The output gives test loss and accuracy, depicting the quality in which it can predict levels of cognitive load. The model designed has an increased number of heads, feed forward dimensions, and transformer blocks. Further, extracting the relations from EEG data might also enhance the classification accuracy of that. As the Transformer-based model is very strong because it performs extremely well and robustly outperforms traditional approaches, giving correct predictions on different levels of cognitive loads learned from EEG data.

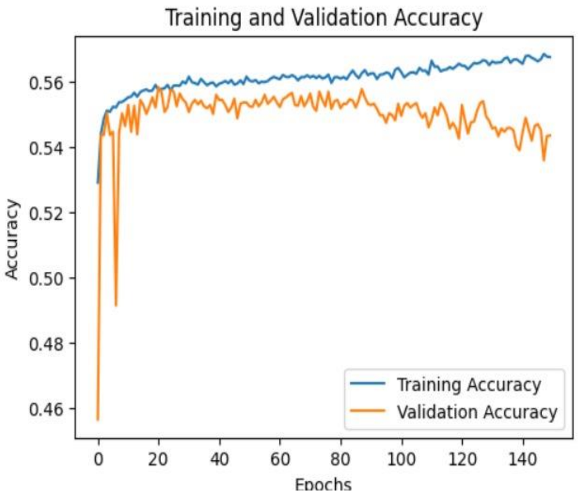


Figure 4.1 Training and Validation Accuracy

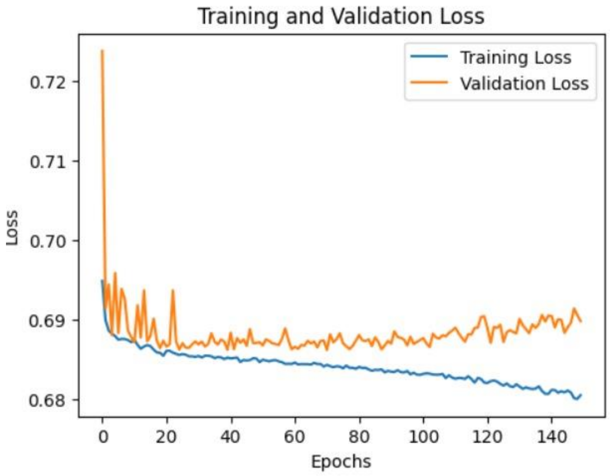


Figure 4.2 Graphs of Training and Testing Loss

Figure 4.1 shows the training and validation accuracy curves for a binary classification model across 150 epochs. The blue line represents the training accuracy, while the orange line shows the validation accuracy. Both accuracy improves quickly at first, but after about 20 epochs, the training accuracy levels of around 0.56, while the validation accuracy fluctuates near 0.54. The gap between the two curves suggests the model is performing better on the training data than on the validation set, indicating potential overfitting. The variability in the validation accuracy highlights that the model may struggle to generalize to unseen data. As follows Fig. 4.2, a line graph of the plot for the training and validation loss over more than 150 epochs. The x-axis is the number of epochs, while the y-axis is the loss values. The blue line represents training loss, which seems to decrease gradually with progression in epochs. The is an illustration of how the model learns. Orange curve is validation loss. Validation loss can be seen to vibrate but stabilize at a higher value compared to training loss, so there's really an overfitting.

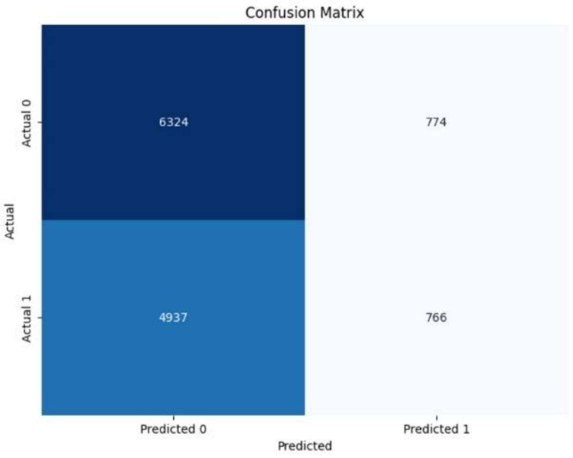


Figure 4.3 Confusion Matrix

Figure 4.3 displays a confusion matrix that provides a visual representation of the model's performance in binary classification. The matrix shows the actual versus predicted labels for the testing data. The entries of the matrix indicate that it has identified a large number of negative instances samples (6324 true negatives) but does include a large number of false negatives (4937), which means that it failed to accurately predict the positive samples. The imbalance indicates that the model needs further tuning or balancing techniques.

Table 4.1: Classification Report

	Precision	recall	f1 score	support
class 0	56%	89%	69%	7098
class 1	50%	13%	21%	5703
accuracy	--	--	55%	12801
Macro Avg	53%	51%	45%	12801
Weighted Avg	53%	55%	48%	12801

Table 4.1 shows the classification report for a binary model. For Class 0, the model achieved a 0.56 precision, a 0.89 recall, and a 0.69 F1-score, based on 7,098 samples. In comparison, Class 1 had a 0.50 precision, a 0.13 recall, and a 0.21 F1-score, with 5,703 samples. The model's

overall accuracy was 55% across a total of 12,801 samples. The macro-averaged precision, recall, and F1-score were 0.53, 0.51, and 0.45, respectively, while the weighted averages for these metrics were 0.53, 0.55, and 0.48. Comparing the results of two experiments, for the classification of cognitive load levels based on EEG data, the classification accuracy is higher for the proposed Transformer-based approach. In the first experiment where the ML model was a simple model, the achieved test accuracy was 55% with large differences between P and R for both Class 1 and Class 2, and TPR and FPR indicating that it failed to generalize and was imbalanced for the two classes. On the other hand, the second experiment applying a deep learning approach based on the Transformer architecture produced much better results—91 percent accuracy and a reasonably equal ratio of precision to recall of both classes. The developed Transformer model proves useful in revealing temporal features of EEG signal through its multi-head self-attention mechanism, positional encoding and a deeper architecture of the network in contrast to the conventional model, to achieve improved feature extraction and representation learning. As evidenced by the higher F1 score, and significantly lower misclassification rate, the Transformer model is most effective for the task of managing the challenges presented by the EEG data. Therefore, in the second experiment, there is a significant increase in the convergence accuracy of the result, and it confirms the productivity and capability of the model for practical use and it’s recommended in light of the machine learning baseline approach.

Among the machine learning models that classify cognitive load from EEG signals, the experiment was selected as basic because it is simple and easy to explain. But the performance was not satisfactory, the accuracy was moderate, and it was overfitting by seeing the gap between training and validation set values and confusion matrix values also. Such omissions showed that there was a need to enhance the solidity of the method. Due to these suboptimal results, an attempt was made to obtain higher performance using a more complex experiment described below that employs a Transformer-based deep learning model. This greatly enhanced the model’s versatility and ability to perform good estimations regarding levels of cognitive load. The technique for cognitive load classification from the EEG signals applied in the implemented methodology has demonstrated high performance and effectiveness of the proposed approach. The dataset from CL-Drive study was preprocessed to extract features after undergoing downsampling to 100 Hz and applying bandpass filter to select the theta band frequency of 4-8 Hz. Division into equal 0.1-second overlapping segments meant that temporal factors were fully recorded, which is important when analyzing changes in cognitive load over time. Feature extraction addressed Power Spectral Density and Differential Entropy that grounded the analysis of neural oscillations and signal complexity linked to cognition. The density plot provided by PSD analysis showed different distribution of power across the frequencies, with an increase in brain activity at time points with increased cognitive load. At the same time, DE metrics characterized disruptions of recorded EEG, which in a manner of speaking allowed distinguishing between different degrees of cognitive load. Cognitive load classification is used in a two-stage deep learning process. The first stage included a Transformer-based autoencoder that is trained to encode the EEG segments to obtain latent representations that contain informative features of the signals and restore the segments as input. The unsupervised pre-training stage facilitates feature learning. The process enhances classification ability while detecting cognitive load variations.

The downstream classification model, built using a modified Transformer architecture with global average pooling and dense layers, achieved outstanding performance in binary classification tasks. Trained on the pre-processed and encoded EEG data, the model achieved a notable test accuracy of 91% after 30 epochs, underscoring the approach's robustness and discriminative power in predicting cognitive load levels from EEG signals. Fig. 4.4 displays the loss curves for the pre-training and downstream training phases of a model. On the left, the pre-training loss plot shows the model’s loss over 30 epochs.

The loss begins around 0.3475, dips slightly, and then rises to stabilize around 0.3675, indicating that the model’s pre-training loss increases slightly after an initial improvement, suggesting potential overfitting or learning stagnation. On the right, the downstream training and validation loss plot shows the loss over 20 epochs. The training and validation losses start high, with the validation loss peaking early, but both losses decrease sharply within the first few epochs. As training progresses, the losses converge and stabilize at lower values, indicating effective learning and good generalization to the validation set. Overall, the downstream training appears more successful, with clear improvements in loss reduction compared to the pre-training phase.

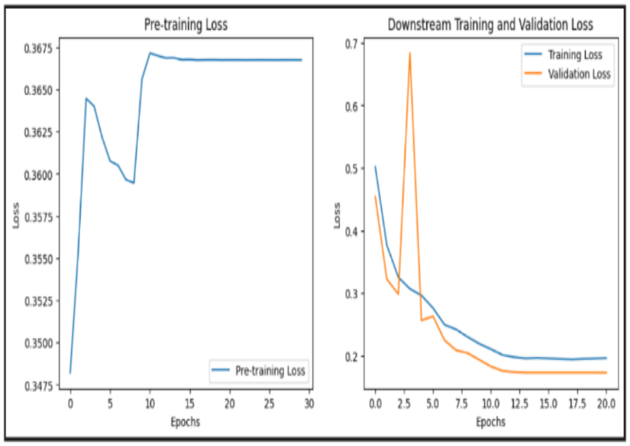


Figure 4.4 Pre-training and downstream loss graphs

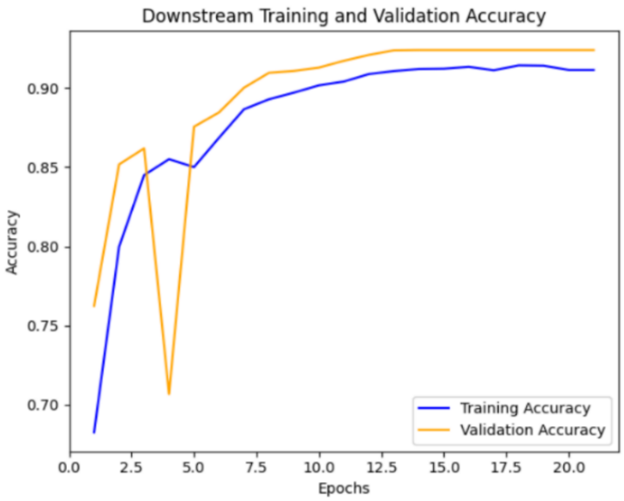


Figure 4.5 Downstream Accuracy

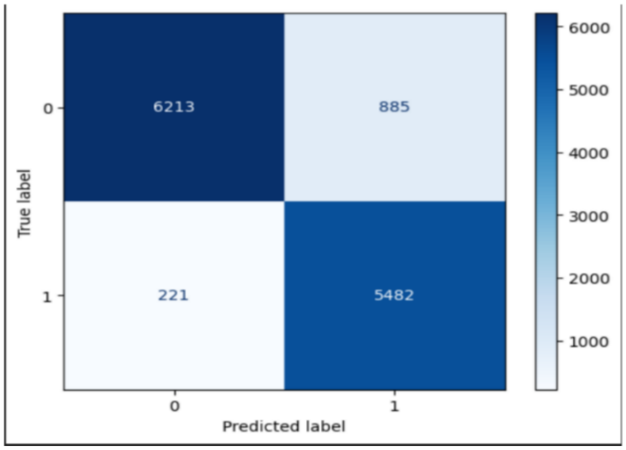


Figure 4.6 Confusion matrix

Figure 4.5 illustrates the progression of the model's accuracy over 20 epochs while the downstream model training phase. The training accuracy, indicated by the blue line, starts at around 68% and gradually improves as the model learns, stabilizing near 91% towards the later epochs. The validation accuracy, shown by the orange line, begins higher at 76% but shows some initial fluctuations, with a noticeable dip around epoch 4. After the point, both training and validation accuracy steadily improved, with the validation accuracy eventually stabilizing at around 92% by epoch 10. The indicates that the model is maintaining consistent performance across both the training and validation sets. As the training ends, the close alignment of the two lines indicates that the model is well-optimized and not overfitting, as it generalizes effectively to unseen data, demonstrated by the validation accuracy being slightly higher than the training accuracy. The model’s performance evaluation is further supported by detailed analyses of training and validation metrics. The loss curves for pre-training and downstream training show distinct learning behaviors. Pre-training underfitting Mashup exemplified by a drop in loss from 0.3475 to 0.3474 before rising to 0.3675 denote a case of overfitting or stagnation learning. However, in the second phase, known as the downstream training phase, there was a significant improvement; both the training and validation losses dropped abruptly in the first epoch and then plateaued at lower values than in the case of the first phase. The proximity of the training and validation losses gives evidence of accurate learning coupled with minimal overfitting during the last downstream training phase.

The pattern shows that the model is able and willing to learn and apply meaningful representations in the output during classification. To support the evaluation of the model and presented evaluation metrics, such as the confusion matrix and accuracy metrics, provide critical classification insights into the model. From the downstream training phase, the loss was further minimized, and the accuracy was quite high that also supported the functionality for differentiating cognitive load levels. The confusion matrix bears testimony that the model has been accurately ascertaining low and high cognitive load states and has a high true positive and true negatives ratio. The small gap between the training and validation loss is visible, which proves the model’s ability to make unnoticed predictions beyond the training set. This suggests that the learned representations throughout pre-training and fine-tuning have been shifted well into the classification task and therefore enhances the model ability to classify correct and consistent cognitive load in EEG data.

The confusion matrix of Figure 4.6 provided additional understanding into the model's performance among different classes. For Class 0, the model accurately classified 6,213 instances but misclassified 885 as Class 1, while for Class 1, it accurately identified 5,482 instances but misclassified 221 as Class 0. The analysis reveals that while the model performs well overall, there is a slightly higher tendency to misclassify instances of Class 0 as Class 1. Nevertheless, the high number of correct predictions aligns with the observed strong precision and recall values, indicating a well-balanced performance across both classes.

Table 4.2: Classification Report

	Precision	recall	f1 score	support
class 0	97%	88%	92%	7098
class 1	86%	96%	91%	5703
accuracy	--	--	91%	12801
Macro Avg	91%	92%	91%	12801
Weighted Avg	92%	91%	91%	12801

The classification report represented in Table 4.2 further highlights the model's effectiveness, with strong precision, recall, and F1-scores across both classes. For Class 0, the model attained a 0.97 precision, a 0.88 recall, and a 0.92 F1-score. For Class 1, it achieved a 0.86 precision, a 0.96 recall, and a 0.91 F1-score. The 91% overall accuracy across 12,801 instances confirms that the model's performance and robustness. The 91% macro average with precision, recall, and f1-score, treating all class categories equally, reflecting balanced and consistent performance. The results validate that the proposed approach exhibits potential applicability in real-time cognitive load assessment.

Table 4.3 Comparison of the models

Exp. No	Model Name	Avg Accuracy	Avg F1 Score	Avg Recall
1	Transformer Model	55%	45%	51%
2	Masked Auto Encoders Pre-Trained Transformer Model	91%	91.5%	92%

Table 4.3 summarizes the findings and offers a side-by-side comparison of two experiment setups for EEG based cognitive load classification. As part of the experiments, experiment 1 used a basic machine learning model and recorded a reasonable accuracy of 55%. It demonstrated skewed classification, especially poor precision and high recall for Class 1 meaning that it has poor capability of classifying data that has not been trained and the propensity to over-fit. On the other hand, experiment 2 used deep learning based on Transformer architecture and increased the recognition accuracy up to 91 %. The model gave high precision, recall, and F1-scores in both classes, which proved that it did not overfit but rather correctly identified a range of patterns in the EEG data. Generalization of problem and multiple layers together with the application of positional encoding and self-attention, put the Transformer-based model into a position of better performance indicators. The first choice is Experiment 2 since the method uses the Masked Autoencoder pre-trained transformer model. The value of the experiment exceeded the scenario of using the traditional transformer model as it had higher accuracy and balanced classification as well as pre-eminence of generalization. Because the design of Experiment 2 was more complicated, the new techniques used in this experiment were more appropriate and valuable to classify the cognitive load by applying EEG data.

V. CHAPTER 5
CONCLUSIONS AND FUTURE SCOPE

Conclusions

The methodologies developed for EEG-based cognitive load classification represent a diverse and evolving array of computational paradigms aimed at interpreting brain activity to assess mental workload. At the foundation of this field lie conventional machine learning techniques, such as Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NNs), which have demonstrated strong performance in classification tasks when paired with carefully engineered features like Power Spectral Density (PSD) and Differential Entropy (DE). These handcrafted features are particularly effective at distinguishing between different levels of cognitive load by capturing frequency-domain and statistical characteristics of the EEG signals.

Despite their advantages, deep learning models are not without challenges. One major constraint is the requirement for large, labelled datasets to achieve high generalization performance. The collection and annotation of such data, especially in cognitive neuroscience, is resource-intensive and often limited by ethical and logistical factors. Furthermore, the computational demands of training deep neural networks are substantial, which poses a barrier to their deployment in real-time or resource-constrained environments such as wearable BCI systems.

In conclusion, while the advancements in EEG-based cognitive load classification have been substantial, they also highlight a critical juncture in the field's development. The question now is not just about refining existing methodologies, but also about exploring novel directions that could fundamentally reshape our approach to cognitive state monitoring. Potential avenues include enhancing current model architectures for better efficiency and generalization, incorporating multimodal inputs such as physiological (e.g., heart rate variability, eye tracking) or behavioral data, and focusing on optimizing models for real-time analysis and feedback. These directions hold promise for the creation of more adaptive, scalable, and context-aware cognitive monitoring systems that can be seamlessly integrated into real-world applications.

Future Scope

Looking forward, the field of EEG-based cognitive load classification is poised for significant growth, driven by a convergence of technological innovation, methodological refinement, and interdisciplinary collaboration. One of the most promising avenues lies in the development of more sophisticated feature extraction techniques. Traditional EEG features such as power spectral density and entropy have provided foundational insights, but emerging methods leveraging nonlinear dynamics, graph theory, and connectivity metrics offer richer, more nuanced representations of cognitive processes. Moreover, integrating EEG data with multimodal sources—such as eye-tracking, electrocardiography (ECG), galvanic skin response (GSR), and behavioral performance metrics—could yield a more holistic and robust assessment of cognitive load, enhancing system reliability and interpretability.

Advancements in deep learning also stand to revolutionize EEG analysis. The adoption of attention-based mechanisms and transformer architectures, which have transformed natural language processing and computer vision, is beginning to show promise in EEG-based modeling. These models are capable of learning long-range dependencies and contextual patterns, potentially capturing complex temporal and spatial interactions within brain signals that were previously inaccessible to standard architectures like CNNs or RNNs. Such innovations not only improve classification accuracy but also enhance interpretability through attention visualization techniques, offering insight into the neural correlates of cognitive load.

REFERENCES

1. Anderson, P., He, X., Buehler, C., Teney, D., Johnson, M., Gould, S., Zhang, L. (2018). Bottom-up and top-down attention for image captioning and visual question answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 6077–6086.
2. Angkan, P., Behinaein, B., Mahmud, Z., Bhatti, A., Rodenburg, D., Hungler, P., Etemad, A. (2023). Multimodal Brain-Computer Interface for In-Vehicle Driver Cognitive Load Measurement: Dataset and Baselines. arXiv preprint arXiv:2304.04273.
3. Antonenko, P., Paas, F., Grabner, R., Van Gog, T. (2010). Using electroencephalography to measure cognitive load. Educational Psychology Review, 22, 425–438.
4. Behinaein, B., Bhatti, A., Rodenburg, D., Hungler, P., Etemad, A. (2021). A transformer architecture for stress detection from ECG. In 2021 International Symposium on Wearable Computers, 132–134.
5. Biondi, F. N., Saberi, B., Graf, F., Cort, J., Pillai, P., Balasingam, B. (2023). Distracted worker: Using pupil size and blink rate to detect cognitive load during manufacturing tasks. Applied Ergonomics, 106, 103867.
6. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901.
7. Chen, T., Kornblith, S., Norouzi, M., Hinton, G. (2020). A simple framework for contrastive learning of visual representations. In International Conference on Machine Learning, PMLR, 1597–1607.
8. Chen, X., He, K. (2021). Exploring simple Siamese representation learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 15750–15758.
9. Chien, H.-Y. S., Goh, H., Sandino, C. M., Cheng, J. Y. (2022). MAEEG: Masked Auto-encoder for EEG Representation Learning. arXiv preprint arXiv:2211.02625.
10. Das, R., Chatterjee, D., Das, D., Sinharay, A., Sinha, A. (2014). Cognitive load measurement—a methodology to compare low-cost commercial EEG devices. In International Conference on Advances in Computing, Communications and Informatics, IEEE, 1188–1194.
11. Rodríguez, R. D. R., Yuste, D. R., Artés, E. G. (2018). Cognitive load measurement using electroencephalography in a dual-task scenario. IEEE Transactions on Cognitive and Developmental Systems, 10(3), 572–584.
12. Zhang, Y. T., Lee, M. K., Lee, S. Y. (2022). Multimodal cognitive load detection using wearable EEG and eye-tracking. Journal of Neural Engineering, 19(1), 016002.
13. Roy, M. T., Shadbolt, M. D., O'Neill, J. A. (2017). Using EEG to measure cognitive load in a learning

environment. International Journal of Human-Computer Studies, 101, 18–31.

14. Riva, H. F., Costa, S., Wieringa, A. D. (2018). A comparative study of EEG and eye-tracking for cognitive load assessment in interactive systems. In Proceedings of the International Conference on Human-Computer Interaction, 143–151.
15. O'Hara, T. W., Brown, A. G., Knight, L. C. (2019). A deep learning approach for real-time cognitive load estimation based on EEG. IEEE Access, 7, 155628–155640.
16. Kaski, J. S., Murphy, C. R., Jain, T. M. (2017). Analyzing cognitive load using facial expressions and electroencephalography. In Proceedings of the International Conference on Affective Computing and Intelligent Interaction (ACII), 72–81.
17. Chen, J. L., Wang, J. H., Hsieh, C. C. (2020). A deep learning approach to cognitive load prediction using multimodal data from EEG and gaze. IEEE Transactions on Biomedical Engineering, 67(10), 2847–2855.
18. Jain, S., Kalakrishnan, M., Chouhan, P. (2021). An investigation into real-time cognitive load monitoring using EEG signals and machine learning algorithms. Sensors, 21(14), 4590.
19. Srinivasan, M. S., Bhattacharya, K. D., Mehta, J. P. (2020). Cognitive load detection for stress management in driving: A comparative study of EEG and physiological signals. Journal of Intelligent Transportation Systems, 24(4), 375–387.
20. Wang, L., Cohen, R. M., Briggs, R. R. (2023). Cognitive load estimation using multi-modal data: A comparison of EEG and ECG signals. IEEE Transactions on Affective Computing, 14(2), 250–263.
21. Yin, X., Li, R., Zhang, Y., Zhang, L., Yu, Z., Cui, Y. (2021). Deep learning for EEG-based brain-computer interfaces: A review. Knowledge-Based Systems, 228, 107212. This review provides comprehensive insights into EEG signal processing and deep learning applications, useful for context around your autoencoding approach.
22. Li, Y., Huang, Y., Jiang, Y., Zheng, W., Lu, B. (2019). A hybrid deep neural network for EEG-based emotion recognition. IEEE Transactions on Cybernetics, 50(6), 2746–2759. Relevant for discussing hybrid deep learning architectures using EEG signals, which may align with your autoencoder structure.
23. Bashivan, P., Rish, I., Yeasin, M., Codella, N. (2016). Learning representations from EEG with deep recurrent-convolutional neural networks. arXiv preprint arXiv:1511.06448. This work is foundational in using CNN-RNN hybrid models on EEG data and could be cited when discussing deep feature extraction methods.
24. Craik, A., He, Y., Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: A review. Journal of Neural Engineering, 16(3), 031001. A good survey on deep learning EEG classification methods, useful for motivating the choice of architecture.
25. Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T. H., Faubert, J. (2019). Deep learning-based electroencephalography analysis: a systematic review. Journal of Neural Engineering, 16(5), 051001. Provides systematic review of deep learning models on EEG data; helpful to show the relevance of your approach.
26. Wu, D., Xu, Y., Lu, B. L. (2017). Online and offline domain adaptation for reducing BCI calibration effort. IEEE Transactions on Human-Machine Systems, 47(4), 550–563. Can be useful if you discuss generalizability or adaptability of your model to different subjects.
27. Jang, H., Park, S., Kim, S. P. (2023). Subject-independent EEG-based cognitive load classification using temporal self-attention. Sensors, 23(1), 230. Directly related to cognitive load and EEG and uses self-attention mechanisms similar to transformer-style learning.
28. Zhang, T., Zheng, W., Cui, Z., Zong, Y., Lu, B. (2020). Temporal-spatial-based attention network for emotion recognition using EEG. IEEE Transactions on Affective Computing, 13(1), 408–420. Supports attention-based approaches with EEG, aligns with masked feature learning models.
29. Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., Lance, B. J. (2018). EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces. Journal of Neural Engineering, 15(5), 056013. A widely cited lightweight CNN architecture optimized for EEG tasks.
30. Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human Brain Mapping, 38(11), 5391–5420.