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Hybrid Attention-Infused Ensemble Learning Model for EEG-Based Workload Assessment

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***Abstract*— Accurate and real-time assessment of cognitive workload is vital for enhancing human performance and safety in complex task environments such as aviation, driving, and human-computer interaction. Electroencephalogram (EEG) signals, due to their high temporal resolution and direct link to brain activity, have emerged as a promising modality for non-invasive workload monitoring. However, the non-stationary, nonlinear, and multi-dimensional nature of EEG signals poses significant challenges for conventional machine learning approaches. Therefore, this paper proposes the analysis of EEG-based workload assessment using a hybrid attention-infused ensemble learning model. An EEG dataset is first pre-processed using a Finite Impulse Response (FIR) filter to remove the high-frequency noises. The feature extraction using Hilbert-Huang Transform (HHT) is used to extract the relevant features and patterns. After that, the classification method of the attention-infused ensemble learning model is employed to detect the EEG-based workload assessment. This classification integrates attention mechanisms and an infused ensemble of classifiers for enhancing feature relevance, accuracy, and interpretability. Additionally, the classification algorithm has achieved high performance and accuracy. With a classification accuracy of 97% and a precision of 99%, are demonstrated by simulations using Python software. This system framework provides strong potential for real-world applications in adaptive interfaces, fatigue monitoring, and neuroergonomic systems.**

Keywords—Workload Assessment, EEG, Preprocessing, Finite Impulse Response, Hilbert-Huang Transform, Attention-Infused Ensemble Learning Model.

I. INTRODUCTION

In recent years, assessing mental workload through EEG signals has become a crucial component in the development of intelligent human-computer interaction systems, particularly in safety-critical domains such as aviation, driving, e-learning, and healthcare [1-2]. Cognitive workload represents the mental effort expended to perform a task and varies significantly based on task complexity, individual cognitive capacity, and fatigue [3]. Accurate and real-time assessment of mental workload using EEG led to adaptive systems that enhance user performance, reduce errors, and improve safety and usability. EEG signals are inherently nonlinear, non-stationary, and highly sensitive to noise and inter-subject variability [4-5]. Traditional Machine Learning (ML) models often struggle to capture these complex temporal and spatial dynamics, especially when the features are extracted from high-dimensional, multi-channel EEG data [6]. In ML, Support Vector Machine (SVM), Multilayer Perceptron (MLP) and K-Nearest Neighbors (KNN) classifications are used to detect behaviors workload assessment [7-8]. To the detriment of already overloaded system capacity, it necessitates updating the detecting algorithms. Furthermore, it is not handled by current ML techniques, necessitating future research into DL architectures [9-10]. In recent developments, Deep Learning (DL) models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown improved performance by learning abstract representations [11]. However, it often acts as black boxes and do not effectively highlight the most informative features or time segments contributing to workload changes. The Artificial Neural Networks (ANNs), Graph Neural Networks (GNNs), and EfficientNetB7 common neural network types in DL models, demonstrate encouraging results when handling graph or network data [12-13]. EfficientNetB7 it still performs poorly, though, when confronted with sparse or unbalanced training data, and it is also accessible to malicious assaults [14]. This hybrid architecture leverages the complementary strengths of attention and ensemble learning to effectively model the temporal, spectral, and spatial patterns of EEG signals, providing a robust and interpretable solution for real-world cognitive workload assessment. Classification is essential for ensuring the effectiveness, efficiency, and reliability of classification models, especially in complex or high-stakes scenarios [15]. To address these challenges, this study introduces a hybrid attention-infused ensemble learning

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model for EEG-based workload assessment. Consequently, the following are the objectives of the proposed system:

- To remove the high-frequency noises of EEG datasets, the FIR filter is used.
- To extract the relevant instantaneous frequency and amplitude information, HHT is employed.
- To classify the workload assessment and detect the final prediction with high accuracy, an attention-infused ensemble learning model is utilized.
- To calculate the precision, recall, and F1-score values, a performance matrix is used.

This paper's general format consists of four sections, including an introduction. Section II describes the structure of the proposed work and the modelling of components. Section III discusses the simulation results of the proposed system. Section IV concludes the entire proposed work.

II. PROPOSED METHODOLOGY

A hybrid attention-infused ensemble learning model is proposed in the analysis of EEG-based workload assessment. Fig. 1, shows processing block diagram.

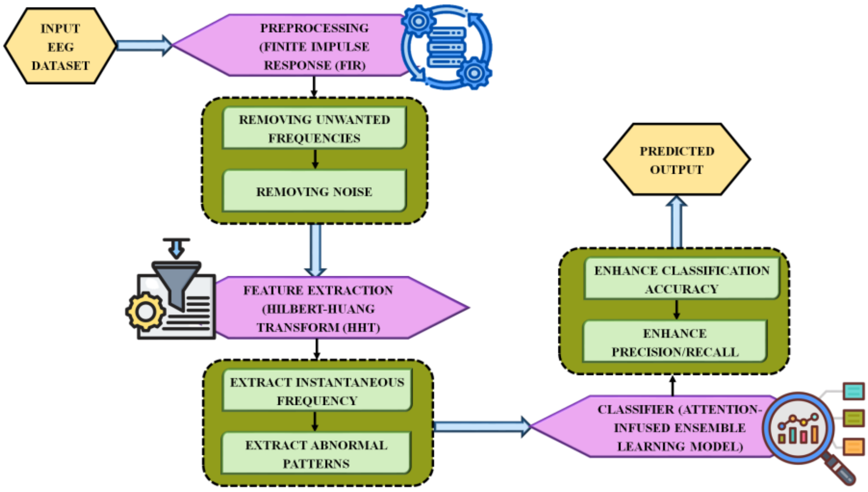

Fig. 1. Block diagram for the proposed work

This input data is allowed by data preprocessing method of the FIR filter. This filter used to remove high-frequency noises and any differences and to handle missing data. Following these preprocessing procedures, the data is allowed to feature extraction of HHT for the purpose of analyzing and extracting the data for the prediction model. Next, a classifier of attention-infused ensemble learning techniques is used to classify the output data based on workload assessment with the highest accuracy.

A. Data preprocessing

Data preprocessing in EEG refers to the set of techniques and steps applied to raw EEG signals to clean, transform, and prepare the data for further analysis. The goal is to reduce noise, remove artifacts, and standardize the data to accurately reflect brain activity. The procedure consists of a number of processes meant to enhance the data's relevance, quality, and usefulness.

a) Finite Impulse Response

The FIR filter, shown in Fig. 2, processes a limited number of input samples, ensuring stability and predictability. It is commonly used in EEG preprocessing to eliminate unwanted frequency noise.

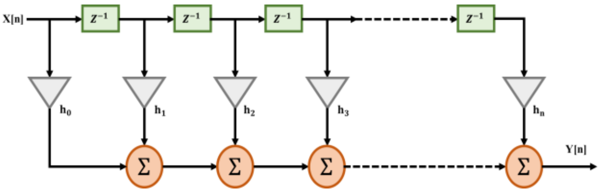

Fig. 2. The FIR Filter

It works by computing a weighted sum of current and previous input samples,

$$y[n] = b_0x[n] + b_1x[n-1] + \cdots + b_Nx[n-N] \quad (1)$$

Where, $y[n]$ filtered signal at time, $x[n]$ input signal at time, $b_0, b_1, \ldots b_N$ filter coefficients and N order of the filter. After the data preprocessing stage, the feature extraction process is applied to extract the datasets for purpose of classification.

B. Feature Extraction

It is the process of turning unprocessed data into a collection of quantifiable and illuminating values known as features that highlight the most pertinent aspects of the data for a specific task like classification, detection, or interpretation. Further, it reduces dimensionality while retaining key information, highlights the meaningful patterns in the data, and makes data more interpretable for DL or statistical analysis.

a) Hilbert-Huang Transform

The Hilbert Transform is used in the HHT, a two-step signal processing method, to retrieve instantaneous frequency and amplitude information after a signal has been broken down into Intrinsic Mode Functions (IMFs). Fig. 3 depicts the phases of HHT.

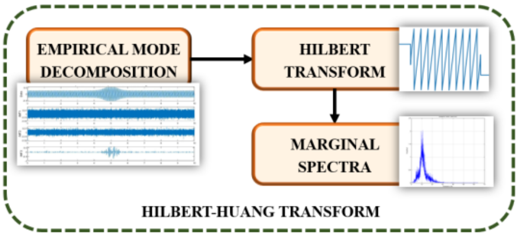

Fig. 3. Phases of HHT

Applied to each IMF to get instantaneous frequency and amplitude, forming a time frequency energy map or Hilbert Spectrum.

If $s(t)$ is the original signal, after EMD,

$$s(t) = \sum_{i=1}^{n} IMF_i(t) + r(t) \tag{2}$$

Where, $IMF_i(t)$ intrinsic mode function and $r(t)$ residual.

Apply the Hilbert Transform HHT to each IMF to get the analytic signal,

$$z_i(t) = IMF_i(t) + j.H[IMF_i(t)] \tag{3}$$

It derives instantaneous amplitude and instantaneous frequency. Analyze and extract meaningful frequency and amplitude information from nonlinear and nonstationary signals, such as EEG, in a highly adaptive and accurate way. Additionally, it detects brain rhythms that change over time and understands the dynamic brain activity with high time-frequency resolution. Following the feature extraction method, the classification technique is used to detect the anomalies and improve the model accuracy.

C. Classification

a) Attention-Infused Ensemble Learning Technique

The attention-infused ensemble learning technique is a relatively advanced concept that blends two powerful machine learning techniques: Ensemble learning and Attention mechanisms. Ensemble learning provides diversity and helps the model generalize better by training multiple models. Fig. 4 shows the architecture of an attention-infused ensemble learning model.

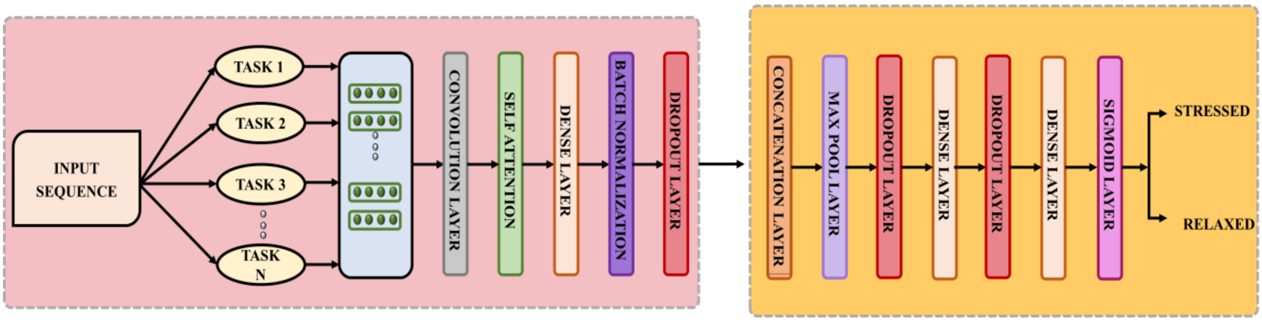

Fig.4. Architecture of an Attention-Infused Ensemble Learning

It is a concept from DL, particularly in neural networks like transformers. It allows model to focus on specific parts of input data that are most important for making a prediction, instead of treating all data points equally. This combination helps improve the performance, interpretability, and robustness of DL models, particularly when dealing with complex datasets, like EEG, images, or time-series data. After the base models are trained, their predictions are weighted by the attention mechanism, which decides which model or features are more relevant at each step. Further, it reduces overfitting, improve accuracy, and increase the stability of the model.

D. Performance of Evaluation

It is a crucial step in assessing the effectiveness of DL models, including those used in attention-infused ensemble learning techniques or any other models, such as those used for EEG classification or image classification.

a) Accuracy

The percentage of accurate forecasts among all forecasts.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Samples} \tag{4}$$

b) Precision

The percentage of all expected positives that are really positive.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{5}$$

c) Recall

The percentage of real positives arising from true positive forecasts.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{6}$$

d) F1-Score

The harmonic methods of recall and accuracy. It offers equilibrium between both.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

It helps to assess, compare, and validate DL models to ensure which are accurate, reliable, fair, and suitable for real-world applications.

III. RESULTS AND DISCUSSION

This paper proposes a hybrid attention-infused ensemble learning model for the analysis of EEG-based workload assessment. It simulates using a Python software tool, and the results are presented here.

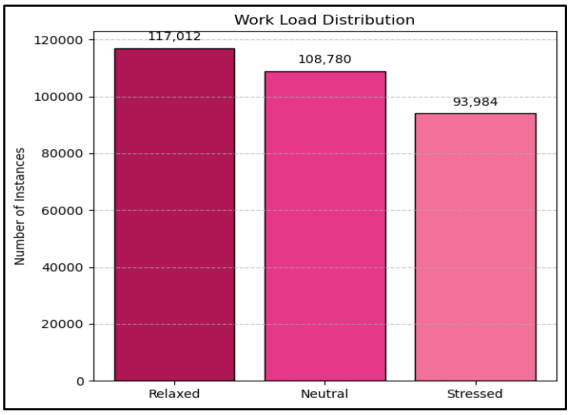

Fig. 5. Distributions of dataset

Fig. 5 represents the distribution of the dataset. This suggests that relaxed, neutral, and stressed datasets significantly affect workload assessment of types in the dataset.

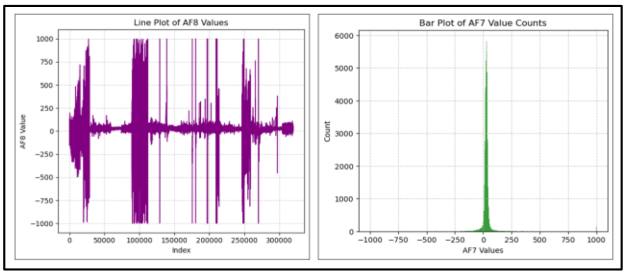

Fig. 6. Bar and Line Plots of AF7 and AF8 values

Fig. 6 shows the bar and line plots of AF7 and AF8 values. The line plot is achieved with a 1000 range of AF8 values, and the bar plot illustrates that the AF7 of 5800 values is attained.

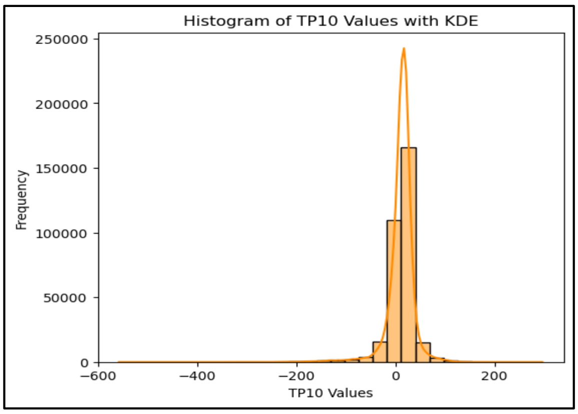

Fig.7. Histogram of TP10 Values

Fig. 7 displays the histogram of TP10 values, showing that TP10 has reached the highest count between TP10 and frequency. It indicates that the dataset under analysis has a significant preference for incoming data.

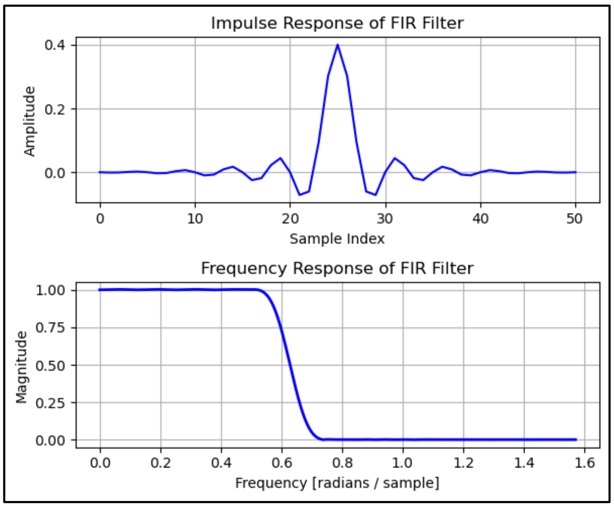

Fig. 8. Impulse and Frequency Response of FIR

Fig. 8 presents impulse and frequency response of FIR. In impulse response waveform, 0.4 is achieved when it is plotted between amplitude and sample index. Further, the frequency response of 1.00 is attained between magnitude and sample index.

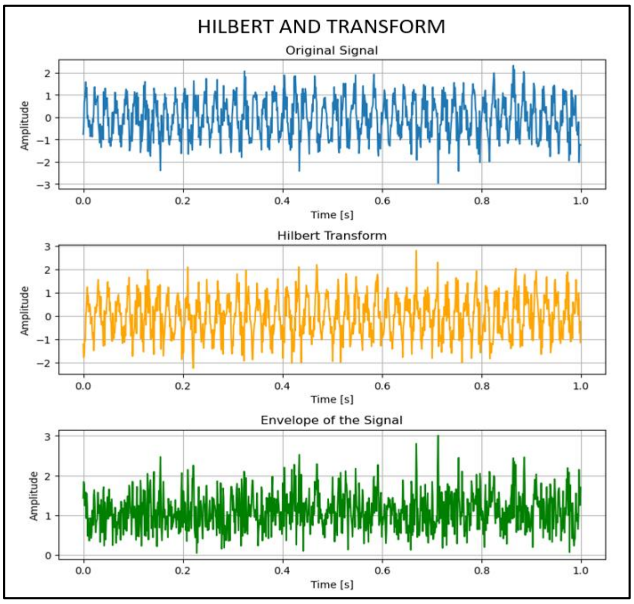

Fig. 9. Waveforms of Hilbert and Transform

Fig. 9 represents the waveforms of Hilbert and Transform. In the original signal, the signal range between -2 and 2 MHz is achieved with some oscillations. After that, the Hilbert transform is applied to achieve the signal range between -3 and 3 MHz. In the final stage, the enveloped signal is attained in a range between 0 and 3 MHz with a clear signal and noise removed.

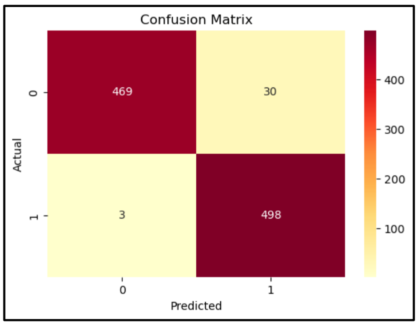

Fig. 10. Confusion Matrix Graph

Fig. 10 displays the confusion matrix, determining the predicted and actual classifications, with the relaxed, neutral, and stressed datasets reaching the highest levels in the matrix.

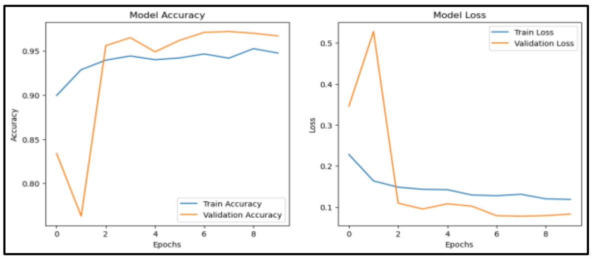

Fig. 11 Model Accuracy and and Model Loss

Fig. 11 displays the graph of model accuracy and model loss of training and validation. The first Figure illustrates that the epochs increase the high accuracy level of 0.97%. Similarly, the second Figure shows loss decreased from the level of 0.7 and reached the level after 8 epochs.

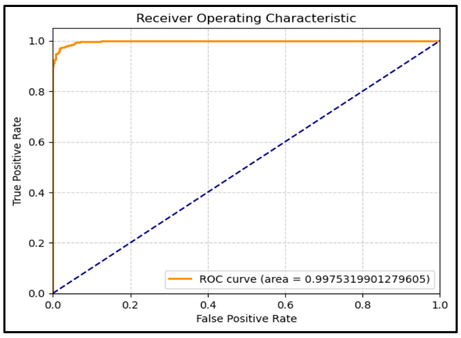

Fig. 12. ROC Curve

The ROC curve for the attention-infused ensemble learning classification is displayed in Fig. 12. The graph's Y-axis represents genuine positive rate, while X-axis represents false positive rate. With the use of attention-infused ensemble learning, 99% accuracy is attained.

TABLE I. PERFORMANCE OF COMPARATIVE ANALYSIS

Classifications	**Accuracy %**	**Precision %**	**Recall%**
KNN [9]	88.3	79	91.3
AdaBoost [10]	88	82.39	72.78
CNN [12]	91	89	90
EfficientNetB7 [13]	95.3	94.5	96.12
Proposed Hybrid Attention-Infused Ensemble Learning	97	99	97

The results of the comparative analysis of the previous classifications and the proposed classification are shown in Table I. When compared to previous algorithms, the proposed hybrid attention-infused ensemble learning method performs well in terms of classification.

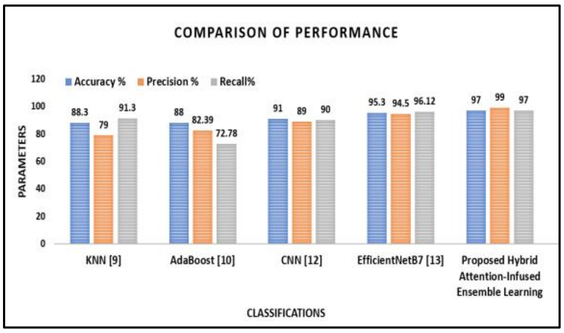

Fig. 13. Comparison of Performance

Fig. 13 demonstrates a comparison of different classifications of accuracy, precision, and recall values. It indicates that the hybrid attention-infused ensemble learning achieved the highest accuracy of 97%, whereas other classifications attained the lowest values. Similarly, the proposed hybrid attention-infused ensemble learning has the highest values of precision of 99% and recall of 99%.

IV. CONCLUSION

This paper proposes and implements a hybrid attention-infused ensemble learning classification for the successful analysis of EEG-based workload assessment. The goal of a hybrid attention-infused ensemble learning framework is to improve prediction skills and extract complicated features from datasets. By combining the strengths of ensemble learning with the attention mechanism, this approach leverages both model diversity and the ability to focus on the most informative EEG features and channels. Furthermore, it improves the accuracy of anomaly detection and classification. The proposed system provides the highest accuracy of 97% and precision of 99%, respectively. Moreover, the attention mechanism enhances interpretability, offering valuable insights into which brain regions and time segments are most relevant during different workload levels. Overall, this system provides significant implications for real-time mental workload monitoring, Brain-Computer Interfaces (BCIs), and adaptive human-machine interaction systems.

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