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EEG BASED MENTAL STABILITY ANALYSIS FOR CORPORATE EMPLOYEES USING TRANSFORMER NEURAL NETWORK

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Abstract: This project explores the novel use of transformer neural networks to assess the mental stability of corporate workers based on electroencephalogram (EEG) data. With rising stress levels and mental health issues among corporate workers, there is a pressing need for sophisticated tools that can track and sustain employee well-being.

Transformers, with their better capacity to handle sequential data, offer a promising method for EEG signal analysis, which is sequential and complex in nature. The research proposes to develop a strong and interpretable model that can detect patterns in EEG data reflecting mental well-being or distress. Transformers have the potential to provide more accurate and detailed insights by extracting long-range dependencies in the temporal dynamics of brain signals compared to conventional models.

The workflow of the project involves a number of key steps. First, raw EEG data preprocessing to eliminate noise and artifacts so that the data is reliable and of good quality. Then the cleaned data from which features related to the aspects most representative of mental health are extracted. The backbone of the project is to train a transformer neural network on this feature-rich dataset so that the model can learn and recognize complex patterns that could reflect different mental states.

The long-term aim is to create a tool that can be fully integrated into corporate wellness initiatives. This tool has the potential to offer actionable insights, enabling businesses to act preemptively on mental health concerns and promote employees' overall well-being. Through the use of state-of-the-art technology, this study not only seeks to improve individual health but also to foster a healthier, more productive workplace. The project underscores the vital importance of innovative technologies in encouraging mental health consciousness and intervention within the business community.

Keywords: Electroencephalogram (EEG), Mental stability, Transformer neural network, Feature extraction, Temporal dynamics, Corporate wellness, Employee support

INTRODUCTION

In today's fast-changing corporate environment, the well-being of employees has become paramount. EEG signals offer a distinctive window into brain function and thus are great biomarkers to assess mental well-being and screen for possible disorders. Conventional EEG analysis can be based on manual interpretation or straightforward algorithms, which are both time-consuming and subjective. To transcend these shortcomings, scientists are increasingly relying on deep learning methods, which have proven phenomenal in numerous domains. Of these,
Transformer neural networks are notably powerful tools for identifying intricate patterns within sequential data. This project is centered on EEG-based mental stability analysis and leverages the transformational capabilities of neural networks to enhance the accuracy and depth of evaluations.

ACADEMIC SURVEY

A Convolutional Neural Network (CNN) model was utilized to assess mental states with EEG signal data as illustrated in [1]. Different emotions were detected by analyzing and classifying the EEG data, with an aim to group these emotions

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into four categories as per the DEAP dataset's valence and arousal features. The accuracy obtained by the suggested method on various CNN architectures was as follows:
33.44% on AlexNet,34.31% on SqueezeNet,34.06% on GoogLeNet, 34.31% on ShuffleNet, 34.31% on ResNet50, and 32.53% on MoveNetV3. These results show that the accuracy and results are not best possible, which may be because of some shortcomings in the dataset.

In [2].deed, a proposal has been put forward to employ EEG data in AI-driven diagnosis of many mental diseases. Precisely, the research focuses on correctly classifying mental disorders in an ecological setting. In order to solve this problem, a transformer-based architecture has been designed and optimized, using class weight balancing and focal loss to handle class imbalance. Following preprocessing, the transformer network classifies EEG signals from the TDBRAIN dataset into three and five classes. It was able to attain a classification accuracy of 65.8% for closed eye conditions and 63.2% for open eye conditions. Considering both open and closed eye situations, the windowlevel classification accuracy was 75.1% and 69.9%,respectively.
The research is centered on precise categ orizing of mental disorders, with specific limitation to the three main categories: ADHD, SMC, and MDD.

EEG is an excellent tool to detect mental fatigue and monitor cognitive load build-up among workers in real-time [3]. Construction workers experience high cognitive workload in dynamic and compl ex contexts, resulting in mental fatigue. This exhaustion affects their movement and cognitive function, requiring supervision to ensure safety. The aim is to determine mental exhaustion levels without manual feature extraction. A continuous wavelet transform and a convolutional neural network were used to analyze the EEG time-frequency-energy data.

The proposed framework achieved an accuracy of 88.85% in classifying cognitive exhaustion levels ,which corresponds to self-reported fatigue states. Therefore, this method may help in real time fatigue recognition and ongoing updates to improve safety management on construction sites.

A Convolutional Neural Network with Domain Discriminator (CADD-DCCNN) has been proposed in [4] for emotion detection based on multi-view EEG. Its purpose is to automatically train the model to identify more emotion-related features and minimize individual differences. CADD-DCCNN extracts nonlinear interactions among multiple channels through a multi-view cross-attention approach, allowing multiple emotionrelated details to be extracted. Information received from a number of electrodes is the input signal for the CADD-DCCNN algorithm, and it produces an emotion label on the basis of this data. The above method was tested on the SEED and DEAP public datasets.

A research has used Graph Neural Networks (GNN) and EEG data to examine the classification of PNES and ES [5]. The model effectively distinguishes between PNES and ES with a 92.9% accuracy rate using a GNN structure. In addition, the model surpasses the state-of-the-art by recording 94.4% accuracy and an even higher accuracy of 97.58% using Leave One Group Out cross-validation. Besides that, by extending the categorization into healthy patients, the model also outperforms stateof-the-art with 85.7% accuracy and obtains the accuracy of 91.12%.

It has been established through a study [6] that a mobile EEG-based system can detect considerable stress levels in construction workers based on their risky work environments. A stress recognition framework based on EEG was designed in the study by utilizing two Deep Learning Neural Network architectures to enhance the accuracy of existing algorithms for detecting stress. By comparing the results of the optimal DNN configuration with previous manual feature-based stress detection methods, the research attained a highest accuracy of 86.62% in detecting worker stress from EEG signals. This is at least a 6% improvement in accuracy.

In [7], a deep learning model was designed and implemented to measure human stress levels by utilizing pulse rate and electroencephalogram (EEG). In this study, the EEG signals and pulse rates of healthy participants were monitored while they answered four sets of progressively more difficult questions. It is believed that the subjects experienced four different levels of stress: "no stress," "low stress," "medium stress," and "high stress" while answering these questions. A CNN-TLSTM model, based on the mechanism of attention, was proposed to gauge an individual's level of mental stress. The suggested CNN-TLSTM model achieved an average accuracy of 97.86%.

It has been demonstrated in [8] that a transformer-based EEG analysis model, named EEG former, can reliably capture EEG characteristics. A one-dimensional convolution neural network (1DCNN) was employed to extract features automatically from the EEG channel. The three parts of EEG former—regional, synchronous, and temporal transformers—are sequentially used in the building process. The result of this process was input into the model.

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For the BETA dataset, the sensitivity, specificity, and accuracy are 69.86%, 75.86%, and 70.15%, respectively. For the SEED dataset, the average sensitivity, specificity, and accuracy are 89.14%, 92.75%, and 91.58%, respectively. For the Dep EEG dataset, the sensitivity, specificity, and accuracy are 72.19%, 70.95%, and 77.83%, respectively.

The results confirm that a machine learning method can consistently extract EEG characteristics for brain activity analysis tasks. While comparing the three EEG datasets with previous works, the comparison models do well but the proposed EEG former performs better.

The strategy presented in [9] proposes a method for using multi-channel EEG signals to improve the recognition accuracy of emotional stress. This technique introduces a novel architecture that combines a three-dimensional convolutional neural network with an attention mechanism, known as the 3D convolutional gated self-attention neural network. The technique begins by splitting the EEG signals into four frequency bands to capture both the temporal and spatial components of the data. Each frequency band is then processed through a separate 3D convolutional block. Subsequently, a gated self-attention mechanism block is used to extract significant features from each frequency band, allowing the model to understand global information and longrange connections crucial for stress recognition. Moreover, the technique of frequency band mapping is used to combine feature vectors of different frequency bands so that the model can learn complementary features. The integration produces a holistic attentional representation needed for stress recognition. In summary, this technique provides a promising method to exploit EEG signals to improve the detection of emotional stress. The newly suggested 3DCGSA method had the highest recognition rates on all the datasets with the accuracies of 91.68%, 95.64%, 91.52%, and 90.12% for DEAP, VRE, and two-level EDESC, respectively.

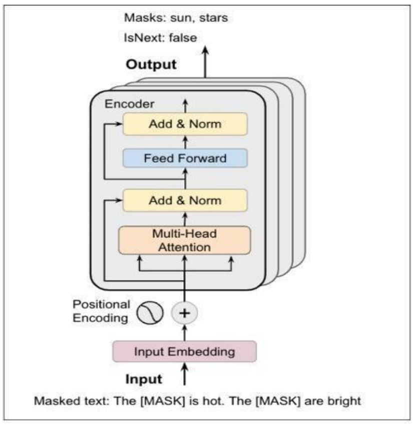
The research entailed the classification of long-term stress based on EEG signals in a resting state with the assistance of machine learning methods. Expert ratings and perceived stress scale score were used to identify the stress and control groups. Alpha asymmetry was calculated from data from four channels and utilized as a feature, with meaningful attributes identified by a t-test. It was discovered that the best method to classify long-term stress was through the utilization of alpha asymmetry as a feature in a support vector machine. The expert evaluationbased labeling method enhanced classification accuracy by as much as 85.20 percent. The results indicate that alpha asymmetry, when labeled using expert judgment, can be a viable biomarker for stress classification.

Deep learning promises a lot for risk assessment and mental health diagnosis. Deep learning algorithms like CNN and RNN can forecast the mental health of an individual. But these algorithms have a few challenges like small datasets, skewed class distribution, low accuracy, and inapplicability in real-time usage. Thus, there is a need to devise more sophisticated approaches to counter these challenges and achieve accurate, high-quality mental stability predictions for employees in corporations.

HYPOTHETICAL METHOD

BERT: Bidirectional Encoder Representations from Transformers, also referred to as BERT, is a model that takes both the left and right context of a word into account when it encodes it into a vector representation. In this way, it is able to comprehend the meaning and context of words and sentences. BERT is first pretrained on a large dataset, which enables it to learn language nuances. Then it is refined by fine-tuning through training another layer with special training data for the target downstream task.

BERT ARCHITECTURE



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Embedding

An input token is processed by a Transformer model, which can be a word, subword, or character. Tokens are most often represented as pre-trained word embeddings or one-hot vectors. For expressing information regarding the ordering of tokens within a sequence, positional encodings are added on top of the token embeddings.

Positional encoding:

To give information regarding the position of tokens within a sequence, positional encodings are incorporated into the input embeddings. These are fixed and calculated by employing varying frequency sine and cosine functions.

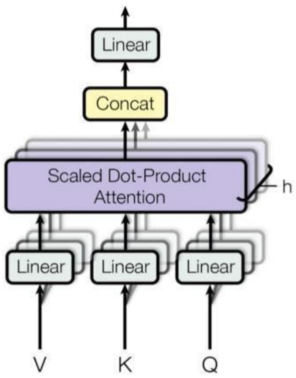
Concentration:

The Encoder block has one multihead attention mechanism, while the Decoder block consists of two multi-head attention mechanisms, one being masked. Self-attention is the key building block of the transformer architecture.

Self-Attention:

The model employs the selfattention mechanism to identify and evaluate the relative significance of different segments in the input sequence. It initially transforms the input sequence into vectors using a linear transformation. The attention mechanism then calculates a weighted sum of the transformed vectors based on the similarity between the query and key vectors. Lastly, the original input and weighted sum are added together and passed through a feed-forward neural network to generate the ultimate output.

Multi- head attention:



Multi-head attention is a technique in neural networks where attention is computed at the same time from different viewpoints or "heads." Each head learns distinct features of the input data independently, allowing the model to attend to different regions of the input at the same time. These separate attention heads assist the model in finding intricate patterns and relationships in the data better, improving its performance. By employing multiple attention heads, the model can naturally focus on different parts of a sequence, e.g., being able to capture both short and longrange dependencies.

Encoder unit:

In a TNN, the encoder is tasked with examining and encoding the input data. Every encoder layer has two sub-layers, repeated across the layer, both augmented by residual connections and layer normalization. As indicated in the encoder blocks on the left of Figure 3.1, the architecture consists of a feed-forward layer, two Add & Norm layers, and a multihead attention layer.

Decoding module:

The decoder, in turn, is made up of a stack of the same layers. It has one more third sub-layer, and it makes use of the encoded input as well as its internal state to produce the output sequence. The decoder of the transformer, as shown on the righthand side of Figure 3.1, wraps every sublayer in a residual connection, followed by layer normalization. The output of the last decoder layer is fed into a linear layer and a soft-max layer.

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Complete connectivity layer:
The last element of the TNN architecture is a standard, fully connected neural network that projects the decoder output to a sequence of predicted output tokens. It normalizes the raw scores (logits) into probabilities via the soft-max function. In inference or decoding, the most probable token is usually chosen as the next predicted token. This approach is particularly important in applications where coherent and contextually relevant sequences need to be generated.

Softmax layer:
In the output layer of a neural network, the softmax function is frequently employed to transform raw output scores to probabilities. In the architecture of a TNN, the output layer can be composed of multiple neurons, each representing a distinct class. Through the application of the softmax function, the outputs of the neurons are normalized to the form of probabilities, representing the probability of each class. This aids the interpretation of predictions made by the model by giving a probabilistic measure of confidence in each class or potential outcome.

DATASET:
Raw EEG signals are obtained by placing electrodes at four channels (f3, f4, f6, f7) in both working and normal states. Spectral analysis is utilized to break down the signals into their frequency components so that power distribution over different frequency bands can be understood. The analysis aids in determining patterns and power values in these bands, which provide information on mental states, stress levels, and cognitive processes. EEG signals are now transformed into the CSV format with Python. The output CSV file has five input columns—Delta, Theta, Alpha, Beta, and Gamma—which show whether the power in these bands increased or remained steady when compared against the two states. There is also a "Result" column in binary form: a 1 confirms stress, and a 0 shows no stress. Stress is detected if Theta and Alpha have an increase, but Beta has a drop.

RESULTS ANALYSIS

1. Accuracy:
Accuracy determines the effectiveness of a model by evaluating the proportion of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN).

2.Classification Metrics:
Specificity:
The reliability of a model's positive prediction.
Recollection:
Among all the actual positives in the data, it determines the proportion of true positive predictions. Its emphasis is on reducing false negatives.
F1-score:
It is the harmonic mean of precision and recall, balancing both memory and accuracy effectively.
Foundation:
Support refers to the count of examples from each class that the model accurately classifies. Essentially, it represents the number of real-world instances of a class that the model correctly identifies.
Confusion Matrix:
In deep learning, a confusion matrix serves as a report card, illustrating how effectively your model classifies various categories. It highlights both the areas where your model excels and the instances where it struggles with misclassification.
ROC Curve:
A Receiver Operating Characteristic (ROC) curve is a graph that illustrates the performance of a binary classification model across various threshold levels. It plots the false positive rate (1 - specificity) against the true positive rate (sensitivity) to evaluate the model's predictive capabilities.

CONCLUSION

In short, using EEG-based mental stability analysis in corporate employees through a transformer neural network presents an effective way to enhance workplace wellness. The application of new neural network architectures, such as transformers, presents immense potential in determining mental stress correctly. This could allow proactive intervention in mental health, leading to a healthier and more productive workplace.

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