Application of EEG-based Machine Learning in Stock Trading-related Emotion Recognition

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Abstract—This paper develops a stock emotion recognition system based on a valence/arousal model using electroencephalogram (EEG) signals. The dataset is collected from participants who engage in paper trading using real stock market data, virtual currencies, and emotional outputs. The dataset contains five frequency bands, features such as differential entropy (DE), differential asymmetry (DASM), and rational asymmetry (RASM). Feature selection is performed using mutual information-based filtering combined with chi-square statistics and embedded algorithms in deep learning classifiers. Stock sentiment classification uses established machine learning models, stochastic gradient descent (SGD), linear discriminant analysis (LDA), K nearest neighbor (KNN) and naive Bayes (NB) algorithms. Subsequently, a comprehensive performance analysis and comparative evaluation of each classification algorithm are conducted. Notably, the K-nearest neighbor (KNN) method achieves remarkable accuracy rates of 89.2% for arousal and 94.59% for valence. These results highlight its exceptional performance when compared to pre-existing algorithms applied to stock emotion datasets.

Keywords: Emotion Recognition, Machine Learning, Stock, Valence-arousal, EEG, DWT, SGD, NB, LDA, KNN.

1. INTRODUCTION

Emotional computing is a field of computer science that focuses on enhancing human-computer interaction [1], including emotion recognition. Emotional recognition is crucial for improving interpersonal relationships and interactions. Emotions can significantly affect behavior, making their research valuable for improving emotional intelligence [2], especially in work and social environments [3].

A field of emotion recognition, namely Emotional Brain Computer Interface (aBCI), utilizes electroencephalogram (EEG) signals obtained through non-invasive brain computer interface devices [4]. These devices have become easier to use, including user-friendly headbands to analyze brain activity related to emotions.

Emotional recognition typically involves creating datasets through various heuristic methods [5], such as music, movies, or interactive experiences. Public databases [6] such as DEAP, IAPS, and IADS are commonly used for emotional research [7], providing labeled emotional stimuli for research.

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The Stock Emotion dataset simulates stock trading emotions without real money, mirroring real market activity. To analyze these emotions, we used machine learning [8] algorithms for EEG signals from OpenBCI headbands. Their dataset combines real and simulated stock trading [9] emotions, including fear, sadness, hope, and calmness. We use machine learning algorithms [10] to construct an emotion recognition system to solve the problem of stock emotion dataset classification [11].

Our research aims to use innovative machine learning classification algorithms [12] to compare their effectiveness in arousing key emotional states [13] related to trading activities in the stock motion dataset. We introduced the dataset and methods, described system implementation, and presented conclusions.

2. METHODOLOGY

2.1Dataset Acquisition

The Stock Emotion dataset, sourced from the National Institute of Technology in Ecuador, systematically records the electroencephalogram (EEG) signals of ten participants, consisting of five males and five females between the ages of 25 and 60. These participants engage in a simulated trading scenario within the US stock market. The EEG data is captured through Ultraportex MarkIV EEG headsets equipped with 8-channel dry electrodes. A Brain-Computer Interface (BCI) device is utilized, which incorporates a Cyton Bio-sensor board for wireless communication with a computer.

The recording procedure commences with a two-minute "relax state" reference phase, during which participants are instructed to achieve a state of relaxation before commencing their trading activities. Participants are well-versed in standardized trading methodologies, including the use of various trading indicators. A reward system is in place to incentivize high-performing participants based on their trading profits. This structured approach is designed to evoke and explore the diverse emotional states [14] associated with stock trading.

Participants assigned self-reported emotions to the data using the self-assessment manikin within the Valence-Arousal (VA) space, aligning with Russell's circumplex model. EEG readings were classified into four distinct emotional states: LVLA, LVHA, HVLA, and HVHA. The Valence-Arousal plane represents stock trading emotions, including fear, hope, and regret, with a notable inclusion of a relaxed state[15]. It is recognized that a calm emotional condition is considered ideal for traders to facilitate objective decision-making.

The Stock Emotion dataset employs an interactive emotional stimulation method that simulates real work scenarios to trigger emotions recognizable by machine learning systems. It's designed for broader sentiment recognition applications. The study involved 10 participants in 24-minute sessions, with emotions self-labeled every 2 minutes. EEG data was collected at 128 Hz [16], resulting in over 14 million data entries. Notably, the dataset lacks entries for a "relaxed state" (HVLA), which is typical for novice traders. Compared to other datasets, participant emotions were labeled every two minutes, considered sufficient for detection. EEG data processing focused on 30-second segments within each two-minute window, following a prior study's approach to assess classification accuracy for potential improvements.

2.2Preprocessing

In conjunction with the inherent preprocessing procedures conducted within the Cyton Open-BCI device, the dataset is subjected to artifact removal through the judicious application of two zero-phase Butterworth filters. These filters are meticulously designed to retain frequencies exclusively within the 1 Hz to 80 Hz spectrum, thereby guaranteeing the comprehensive eradication of noise artifacts originating from ocular movements and cardiac pulsations. Furthermore, a highly precise 60 Hz notch filter is strategically employed to entirely eliminate any vestiges of electrical noise contamination.

2.3FEATURE EXTRACTION

The adept construction of an emotion recognition model is profoundly contingent upon the pivotal feature extraction process. These extracted features are mandated to inherently encompass distinctive attributes, affording them the capability to efficaciously and precisely discriminate among signals.

The feature extraction procedure involves acquiring information concerning the electrode locations and their attributes within the frequency domain. The EEG data is spatially referenced to digitally linked ears (DLE) [17], providing spatial insights into the source locations for each electrode.

Initially, the data is transformed into the frequency domain, with distinct frequency bands delineated utilizing Python's frequency filters. These bands encompass Delta, Theta, Alpha, Beta, and Gamma frequencies.

Given the complexity and non-linearity inherent in EEG signals, spectral entropy serves as a metric to quantify non-linearity, randomness, and information content [18]. Various features, including Differential Entropy (DE), Differential Asymmetry (DASM), and Rational Asymmetry (RASM), are computed for each frequency band. These computations account for variations in DE between electrodes exhibiting hemispheric asymmetry.The process of feature selection involves mutual information-based filtering.

2.4 Classification

1) *SGDC classifier*: The stochastic gradient descent (SGD) is a straightforward yet highly effective approach for optimizing classifiers employing convex loss functions such as SVM or logistic regression. Despite its longstanding existence in the machine learning community, SGD has garnered substantial acceptance only in recent years. SGD has demonstrated considerable success in addressing large-scale sparse machine learning challenges, particularly in domains like text classification and natural language processing. When confronted with sparse data, the classifier in this module adeptly handles the training of datasets exceeding 10^5 samples and features exceeding 10^5.

2) *LDA classifier*: Linear Discriminant Analysis (LDA) distinguishes features based on Fisher distance [19]. Its fundamental principle involves the projection of data into lower dimensions. In this projection, the goal is to make the projected points of each data category as close as possible while maximizing the separation distance [20] between the category centers of different data categories. The primary objective of LDA is to minimize the ratio of intra-class variance and, concurrently, maximize the inter-class discrimination. Masood et al.

introduced an emotion analysis method that combines Common Spatial Patterns (CSP) and LDA. In their experiment, data was collected using Emotion Epochs, with the first part of the data originating from EEG signals generated as subjects self-imagined terrifying images, and the second part from EEG signals produced when subjects were exposed to terrifying video stimuli. The research employed the CSP algorithm for feature extraction and LDA for emotion classification, resulting in commendable classification outcomes.

3) KNN classifier: The K-Nearest Neighbor (KNN) algorithm, originally introduced by Cover and Hart in 1968, stands as one of the simplest and most comprehensible machine learning techniques. Over the years, KNN has undergone significant refinements and found extensive application in domains such as facial recognition, text analysis, and medical image processing. The fundamental principle underpinning KNN is that if a majority of the k closest samples in the feature space belong to a specific category, the sample in question is assigned to that category and shares the characteristics of these neighboring samples. The KNN method relies on an established training sample set where the categories of all included samples are known. When classifying new samples, it assesses the similarity between these samples and those in the training set. Subsequently, it selects the k samples exhibiting the highest similarity, and the category of the new samples is determined based on the categories of these k nearest neighbors. KNN falls under the category of instance-based learning or lazy learning methods, signifying that the dataset is pre-classified and processed directly upon receiving new samples. It is worth noting that the computational complexity of KNN scales with the dataset's size, making it more suitable for datasets with limited sample sizes.

4) NB classifier: The Naive Bayesian classifier is a pragmatic classification method grounded in Bayesian theorem, exhibiting efficiency comparable to other classifiers within specific domains. Its fundamental concept involves computing the probability of each category's occurrence based on the attributes of a given project and subsequently assigning the project to the category with the highest computed probability. The "naive" aspect of the Bayesian algorithm assumes that samples are mutually independent. Notably, when applied to high-dimensional data, the Naive Bayesian classifier [21] stands out for its rapid execution, computational efficiency, and straightforward algorithmic structure. Furthermore, researchers have introduced various enhanced algorithms, such as the tree-enhanced Naive Bayes and network-enhanced Naive Bayes algorithms, aimed at advancing algorithm performance and bolstering classification accuracy.

3. RESULTS

The classification process is characterized by two discrete phases: the training and testing stages, which are conducted within the framework of a specific methodology known as "n-folds," where the value of n is predetermined to be 10. Within the context of the n-folds approach, the dataset is systematically partitioned into ten subsets of equal size, and the entire experimental protocol is iterated over ten consecutive rounds. In each such round, nine of these subsets are exclusively allocated for the purpose of model training, while the remaining one subset is reserved exclusively for model testing. Consequently, each of these ten subsets assumes the role of a dedicated testing set during one of the ten rounds, thus ensuring a comprehensive and meticulous evaluation of the entire dataset. The final results are presented as a culmination of the outcomes derived from all ten rounds, offering a comprehensive and in-depth assessment of the model's performance.

Within the domain of emotion classification, the primary focal points encompass valence and arousal. The comparative evaluation of classifiers rests upon critical variables, such as the magnitude of the training and testing datasets, the computational execution time, and the performance characteristics exhibited by each classifier. Ultimately, the results of this model are subject to benchmarking against the research outcomes of other scholars and experts in the field.

Tables I and II present the outcomes of three data partitioning scenarios employed for training and testing the stock emotion dataset and its associated classifiers. Subsequent sections provide a summary and in-depth discussion of these results, highlighting a notable accuracy of 70% in training and 30% in testing the signals. Particularly noteworthy is the outstanding accuracy exhibited by the K-nearest neighbor (KNN) algorithm [22] in both Valence and Arousal. This distinction is further elucidated through visual representations in Figure 1 and Figure 2, which portray the confusion matrices delineating the classification outcomes achieved by the KNN algorithm for Valence and Arousal.

TABLE1 Classification Outcomes for Valence with 70% Training and 30% Testing of EEG feature data

Classifier	Accuracy	Precision	Recall	F1
SGDC	54.87	99.99	9.77	17.81
LDA	88.62	79.08	64.86	65.76
KNN	94.59	91.08	98.87	94.81
NB	82.28	83.45	80.55	81.97

TABLE 2 Classification Outcomes for Arousal with 70% Training and 30% Testing of EEG feature data

Classifier	Accuracy	Precision	Recall	F1
SGDC	62.03	57.24	95.05	71.45
LDA	88.91	71.31	78.23	73.92
KNN	89.2	91.93	88.41	83.28
NB	82.25	78.71	88.41	83.28

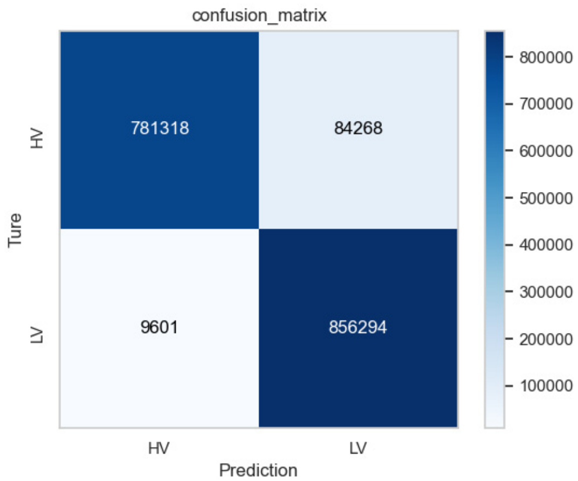

Figure 1 Confusion Matrix Generated by the K-Nearest Neighbor (KNN) Algorithm for Valence

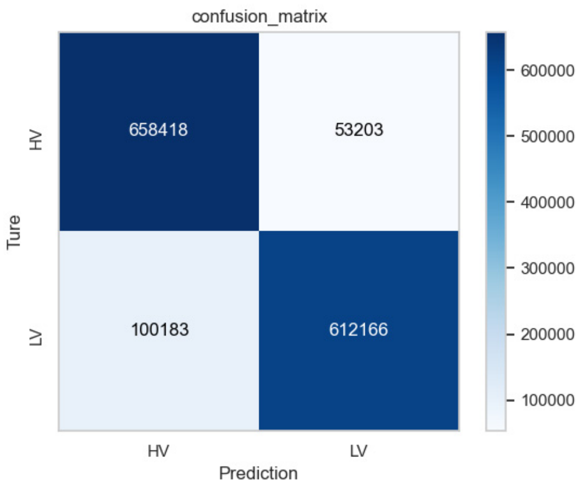

Figure 2 Confusion Matrix Generated by the K-Nearest Neighbor (KNN) Algorithm for Arousal

4. DISCUSSION AND CONCLUSION

Contemporary advancements in sensor technology and signal processing have provided the means to leverage human organ signals, including those emanating from the cerebral and cardiac systems, for the precise identification and differentiation of psychological and pathological conditions. Consequently, the application of sophisticated signal classification methodologies, as expounded in reference [23], becomes imperative to augment the efficacy of case-based diagnostic and therapeutic interventions.

Classifying emotions using EEG signals is complex but vital for understanding emotional states. In this study, machine learning, including SGDC, LDA, Naive Bayes, and KNN classifiers, was used to classify emotions. The study found KNN classifiers performed best in model performance [24].

Differences are discernible in classifier performance metrics, with K-Nearest Neighbors (KNN) exhibiting exceptional proficiency in both accuracy and F1 measurement [25]. In a comprehensive evaluation, it is evident that KNN [26]consistently outperforms alternative methods in the domain of EEG signal classification.

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