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Emotion Recognition Related to Stock Trading Using Machine Learning Algorithms With Feature Selection

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ABSTRACT This article proposes an emotion elicitation method to develop our Stock-Emotion dataset: a collection of the participants' electroencephalogram (EEG) signals who paper-traded using real stock market data, virtual money, and outcomes that emotionally affected them. A system for emotion recognition using this dataset was tested. The system extracted from the EEG signals the following features: five frequency bands, Differential Entropy (DE), Differential Asymmetry (DASM), and Rational Asymmetry (RASM), for each band. Our system then carried out feature selection using a filter method (Mutual Information Matrix), combined with a wrapper process (Chi-Square statistics) and alternatively using the embedded algorithms in a Deep Learning classifier. Finally, this work classified emotions in four quadrants of the circumplex model using Random Forest and Deep Learning algorithms. Our findings show that 1) the proposed emotion elicitation method is useful to provoke affective states associated with trading, 2) the proposed feature selection process improved the classification performance of our emotion recognition system, and 3) classifier performance of the system can recognize trading related emotions and has results comparable with the state of the art research corresponding to a similar number of output classes.

INDEX TERMS BCI, EEG, DE, DASM, RASM, random forest, deep learning, emotion recognition, stock market trading, emotion elicitation.

I. INTRODUCTION

Affective computing is a computer science field that expands human-computer interactions, including emotional communication and emotion recognition [1]. Emotion recognition is a field of affective computing that could improve human relationships and human-computer interactions. Emotions are affective states that influence behavior. Studying them might allow for self-managing emotions to increase emotional intelligence applied to work performance and other social situations.

Brain-Computer Interface (BCI) based electroencephalogram (EEG) emotion recognition is called affective BCI (aBCI). EEG signals can be acquired through BCI devices, which is a non-invasive method for capturing brain activity. Currently, different types of BCI devices are available on the market. Emotion recognition has benefited from the development of low-cost and easy to use BCIs in the form of headbands to analyze brain activity associated with emotions.

In emotion recognition, datasets are generated with several emotion elicitation methods. For instance, remembering emotionally-charged past experiences, watching music video clips, pieces of film, listening to sounds, music, viewing images, dyadic interactions, video games, flight simulators, and virtual reality immersion. Such approaches have different characteristics and merits.

There are publicly available databases [2]. For example, the DEAP database consists of EEG data from 32 subjects, with emotions motivated through music videos [3].

The most popular resources for emotion stimulation are the International Affective Picture System (IAPS) [4] and the International Affective Digitized Sound System (IADS) [5].

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IAPS and IADS stimuli are standard, and their information is labeled, which allows for the convenient construction of a ground-truth emotion assessment [6].

Other researchers use movie clips to provoke emotions. In [7], the authors state that emotions using visual or auditory stimuli are similar. A few studies used interactive stimuli where participants played games or are in a flight simulator to induce emotions [8], [9]. Finally, some authors successfully used auto-induced emotions through memory recall [10]. To the best of our knowledge, currently, none of the procedures for emotion elicitation are applied in an environment resembling everyday work activities in a competitive environment.

Consequently, our research proposes a type of elicitation of feelings that proved useful in provoking emotions. We generated a dataset with a group of people executing paper-trading in the stock market. Paper trading is virtually simulated trading (i.e., no real money is at stake) that uses live stock market data for recording paper trades (i.e., simulated transactions). Thus, paper trading is virtually the same as real stock market trading, but without actual money at risk. Paper trading is useful for our area of interest because it also triggers emotions (like real stock market trading). Naturally, financial decisions have consequences for individuals and society in general. Therefore, paper trading plays a crucial role in emotion detection in stock traders working in a competitive securities market.

Stock market trading consistently induces feelings in participants due to its money component. Simulated trading is as emotionally charged as real trading because money has a strong emotional connotation for most humans [11]. Money represents variables such as resources, lifestyle, survival odds, value, status, health, and even the likelihood of leaving offspring, to name a few [12]. Thus, participants have strong emotions tied to money, making real and even simulated trading a powerful emotional stimulus. In particular, paper trading is also emotionally charged because it evidences the participant's ability (or lack thereof) to be profitable with real money.

In summary, in this article, we used machine learning algorithms to process EEG signals detected using an OpenBCI headband with feature extraction and selection. We aimed to capture critical emotions related to trading activities such as fear, sorrow, hope, and a calm (relaxed state) [13]. To do so, we generated our dataset using an innovative type of emotion elicitation: trading in the stock market. To evaluate results, we obtained machine learning models tested in our dataset and a publicly available database. We handle the EEG feature vector high-dimensionality problem using feature selection algorithms in the developed emotion recognition system.

Our research objectives were to 1) generate a dataset for emotion recognition using a new emotion elicitation method, 2) investigate if the proposed emotion elicitation method was useful to provoke critical affective states associated with trading activities, 3) design a system to recognize these emotions, and 4) study the relationship between the application of feature extraction and selection processes and the performance of the system.

This article is organized as follows: the present section introduces the current situation where methods with active stimuli, resembling a specific work environment, could be welcomed to emotion recognition research. We propose an innovative approach to provoke emotions for EEG-based BCI emotion recognition, which utilizes trading in a competitive stock market as a method to motivate emotions. With this approach, we generated a dataset of EEG signals. This dataset was the input of an emotion recognition system.

In Section 2, we reviewed related work. In Section 3, we explain the materials and methods used in our research: emotion representation, frequency bands, and their relationship with feelings, emotion stimulation, and components of our EEG-based BCI system to recognize four trading related affective states. Section 4 shows details about the system's implementation, the acquisition of the EEG data, feature extraction and selection, training and testing classification, and performance evaluation. Section 5 presents conclusions and future work.

II. RELATED WORK

Many research papers have been published in emotion recognition using EEG-based BCI devices for data acquisition in recent years. They included different models and strategies that produce a wide range of frameworks. For context, a Google Scholar search (from 2015 to 2020) of the terms: BCI EEG emotion recognition yielded 15100 results. These copious search results demonstrate that the topic is "hot" and has many active contributions.

We found several articles that use a publicly available dataset for their systems; others develop their datasets with information gathering experiments. These datasets most commonly have from 8 to 32 participants. Most papers perform standard preprocessing by removing frequencies above 50 to 100 Hz that correspond to ranges outside the EEG characteristic bands. With this method, the body' signals, such as blinking or heartbeats, and external electrical noise, are removed [14].

For feature extraction, researchers have explored several procedures. In the time-domain, authors have used statistical features, Hjorth parameters [15], and Higuchi's Fractal Dimension [17]. Some works extracted features using Deep Belief Networks (DBN) or other deep learning algorithms [16]. In the frequency domain, characteristics extraction is obtained using the Short-Time Fourier Transform (STFT) and Discrete Fourier Transform (DFT) [18], [19]. Some researchers use Autoregressive spectral analysis (AR) as an alternative to Fourier Transform [26]. In the time-frequency domain, some papers applied the Wavelet Transform (WT) [27] and the Discrete Wavelet Transform (DWT) [27].

EEG signals may generate a high-dimension feature vector that could be inefficient in a classification process. Various algorithms are used to select characteristics to avoid

TABLE 1. Emotion elicitation methods, classified emotions, and accuracy.

Reference	Emotion elicitation method	# of Participants	Classes - emotions	Accuracy (%)
[15]/2016	Music videos (DEAP dataset)	32	Three classes for arousal, three classes for valence	Arousal/60.7 Valence/62.33
[16]/2015	Movie clips	15	Positive, neutral, negative	Avg. 85.04
[10]/2015	Self-induced emotions (recall)	10	Disgust	Avg. 90.2
[17]/2018	Video clips	10	Happy, calm, angry	Avg. 60
[18]/2017	Video clips	30	Three positive emotions: joy, amusement, tenderness. Four negative emotions: anger, disgust, fear, sadness. A neutral emotion: neutrality	Positive emotions/86.43 Negative emotions/65.09 Neutral/92.26
[19]/2020	Music videos (DEAP dataset)	32	Dislike	Avg. 76.36
[20]/2019	Music videos, and movie clips (DEAP and SEED datasets)	32/15	Four quadrants Valence – Arousal Space	Avg. 77.75
[21]/2016	Music tracks	30	Happy, Sad, Love, Anger	Avg. 75.5
[22]/2017	Movie clips (SEED)	15	Positive, neutral, negative	Avg. 78.9
[23]/2019	Video clips	16	Happy, sad, fear, relaxed	Avg. 90.41
[24]/2019	Flight simulator	8	Happy, sad, angry, surprised, scared	Avg. 53.18
[25]/2020	Video games	28	Boring, calm, horror, funny	Avg. 73.21
[15]/2016	Music video (DEAP dataset)	32	Three classes for arousal, three classes for valence	Arousal/60.7 Valence/62.33
[16]/2015	Movie clips	15	Positive, neutral, negative	Avg. 85.04
[10]/2015	Self-induced emotions (recall)	10	Disgust	Avg. 90.2

a high-dimensionality problem. Among these techniques, we found that researchers use Linear Discriminant Analysis (LDA) [18], MaxPooling [22], Principal Component Analysis (PCA) [10], and Minimum redundancy Maximum Relevance (mRMR) [15].

Among used classifiers are shallow methods as Support-Vector Machine (SVM) [10], [15] k-Nearest Neighbors (kNN) [19], ensemble techniques such as Classification and Regression Tree (CART) [19]. Also, neural networks like Radial Basis Function Neural Network (RBF NN) [19], Deep Belief Network (DBN) [19], NB [19], Extreme Machine Learning (ELM) [22], Multilayer Perceptron (MLP) [28] are used. The systems recognize a different number of classes with varied accuracy, as Table 1 shows.

In most cases, researchers used various types of stimuli to elicit emotions: music videos, film clips, music tracks, and memories to provoke a specific emotion. Active emotion elicitation is not as frequently implemented. Few works used video games, flight simulators, or in general, stimuli with which the participants interact. In our sample of analyzed papers, accuracy values go from 53.18 (for five classes) to 92.16 (for one neutral class).

It is worth noting that comparing approaches and results obtained by the different EEG-based BCI systems is difficult. Each experiment had its settings: other forms of emotion elicitation, protocols, data acquisition methods, feature extraction and selection, and various classification algorithms. Ideally, to enable comparisons, systems should be tested under similar conditions. Approaches that use public databases allow some comparability level, but without detailed information about their systems, the contrast level is limited even if the same characteristics are handled. However, these public databases may enable scenarios that could lead to conclusions if objective evaluations were made. We believe that more public databases, with labeled data and standardized settings, contribute to the field.

III. MATERIALS AND METHODS

This section presents elements that have to be considered to develop an aBCI system: emotion representations, the association between frequency bands and affective states, emotion elicitation methods, and components of an aBCI system.

A. EMOTION REPRESENTATION

Emotions can be differentiated through general models [29]. The most popular are the discrete and dimensional models. One discrete model identifies six basic emotions: happiness, sadness, anger, surprise, disgust, and fear [30]. Dimensional models are good at expressing complex emotions in a two-dimensional continuous space: Valence - Arousal (VA), or in three dimensions: Valence, Arousal, and Dominance (VAD) [31].

The dimensional model's axes are orthogonal to each other. Valence is used to rate positive and negative emotions. Arousal measures emotions from calm to stimulated.

The dominance axis evaluates affective states estimating emotion control from submissive to explosive.

B. FREQUENCY BANDS AND EMOTIONS

Some papers studying EEG-based functional brain connectivity have reported links between the location of brain activity and emotional states. For instance, in studies that take the at-single-electrode level analysis into account, it has been shown that asymmetric activity at the frontal site in the alpha band is associated with emotion [32]. The increased power of the theta band at the frontal midline is associated with mindfulness and meditation [33].

Many studies confirm an association of frequency bands with affective responses. However, emotions are complex processes. Authors in [33] assert that recognizing different emotional states may be more valid if EEG-based functional connectivity is examined rather than make analysis using a signal from a single electrode level. Correlation, coherence, and phase synchronization indices between each pair of EEG electrodes are used to estimate functional connectivity between different brain locations.

We believe that the growing consensus is that a simple mapping between emotions and specific brain structures is inconsistent with observations of different emotions activating the same structure, and one emotion triggering several structures [34]. Additionally, functional connectivity between brain regions or signal complexity measures may help to detect and describe emotional states [35].

C. EMOTION ELICITATION

Research suggests that emotions play a role in stock market trading because they may influence decisions. Traders often cannot ignore such emotions, which sometimes distracts them from their work process when real or even simulated money is at risk [11].

Emotional states also manifest through changes in confidence and risk tolerance [36]. If the trader has a constructive mindset, performance will likely increase. Likewise, if emotions are too intense, then trading performance can worsen because stock market trading requires continuous decision-making efforts while analyzing objectively potential risks and rewards.

Emotions allow humans to respond to stimuli quickly and without rational thought. Evolutionarily, this offers a cheap way to react to preprogrammed scenarios, such as fight or flight emotions. Likewise, emotions can generate biases that influence decision making, often unbeknownst to humans [37]. Likely, the brain's parts that create emotions evolved first and directly connected with the body, unlike the prefrontal cortex with several separation neuronal layers [38]. Thus, emotions are often harder to curtail through rational thought, but they can be managed through recognition.

Traders often report making decisions because they feel right at first but regrets them shortly after. Excellent examples of emotional choices like these are "panic selling" or "fear of missing out" [13]. These emotions cause traders to sell at market bottoms or buy market tops. These trading decisions occur due to emotions, expressed as the psychological pain avoidance of losing money. However, such decisions are often inadequate after logical scrutiny. For example, buying oversold and undervalued assets probably has a positive long-term expectancy. However, doing so is typically emotionally difficult for traders due to the previously explained dynamics.

Therefore, we believe that it is vital for traders to recognize how their emotions affect their trading process. This way, traders could use emotions to their advantage and not take over their systematic methods in their trading strategy. Thus, our approach aims to understand how traders can get the best of both worlds in trading through emotions and rational thought.

We see a similar dynamic in other peak performance activities, such as playing chess. For instance, chess grandmasters are reportedly capable of observing a chess position and instantly "feeling" who is winning or losing, without much need for calculating further moves. This example shows the need for intuition (emotion or feeling) through experience, combined with a disciplined, rational process (i.e., calculating chess moves).

In particular, stock market trading triggers three key emotions: 1) fear, 2) hope, and 3) regret [39]. These emotions directly affect the participant's trading, and these effects are detectable through EEG readings [40].

The application of the present research results may improve trading performance and profits because they are likely linked to emotional management and peak performance techniques. Finally, we believe that enhancing trading performance is supportive of a more efficient market, which is generally understood to be positive for society. The results of the present research can also be applied in other competitive workplace scenarios.

D. aBCI SYSTEM COMPONENTS

This project obtains models for emotion recognition using EEG-based BCI devices that acquire signals. Such signals are processed using algorithms for characteristic extraction, feature selection, and classification. We apply FFT to obtain bands in the frequency domain. Also, Differential Entropy (DE) and its variations on symmetrical electrodes: Differential asymmetry (DASM), and rational asymmetry (RASM) are computed, taking into account the spatial location of the electrodes. Feature selection algorithms are used to decrease the dimensionality of the feature vector. Finally, Random Forest and Neural Networks classifiers are used. Performance evaluation is carried out with 10-fold cross-validation. The present work carries out the process shown in Figure 1.

IV. IMPLEMENTATION AND RESULTS

In this section, we present information about the implementation of the aBCI system and its results. EEG data acquisition, training and test data used, feature extraction and selection, and classification are explained.

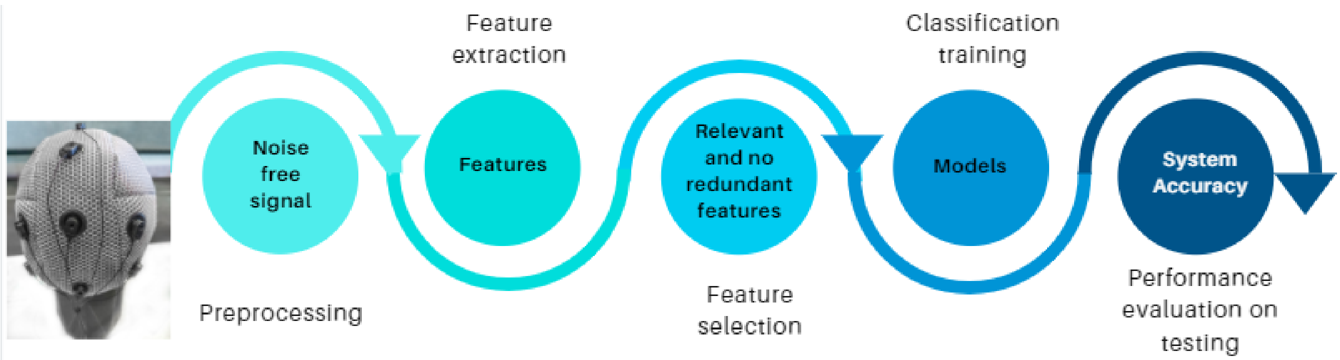

FIGURE 1. Components of an EEG-Based BCI for emotion recognition (aBCI) – training and testing.

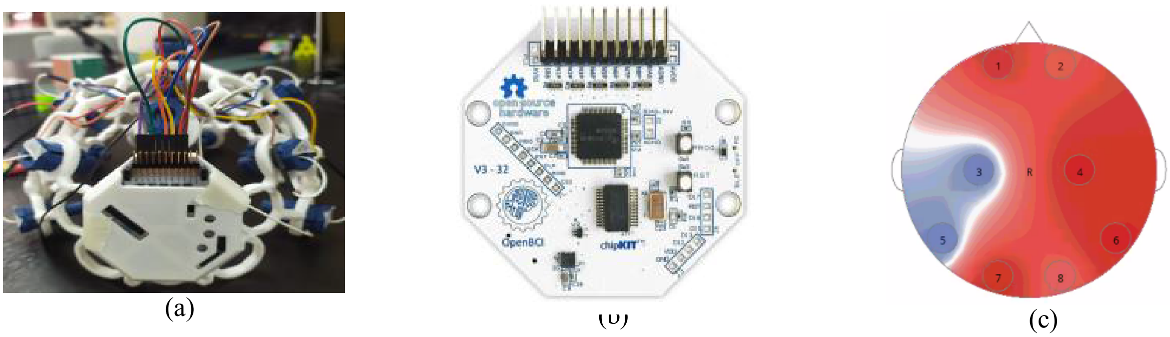

FIGURE 2. (a) OpenBCI Ultracortex headset, (b) Cyton Biosensing board, (c) Electrode location.

A. DATASET ACQUISITION

We used a brain-computer interface (BCI) Ultracortex Mark IV EEG headset to record the experiment's participants' EEG signal. The device had 8-channel dry electrodes for recording brain signals. To collect the EEG signal, it uses the Cyton Bio-sensing board with an 8-channel neural interface and a 32-bit processor. The board communicates wirelessly with a computer using a USB dongle (Figure 2.a and 2.b). The Cyton Bluetooth headband device allows for an open-source brain-computer interface that facilitates EEG data procurement and analysis.

We applied the 10-20 systems diagram with channels 1-8 of the OpenBCI default setting. Figure 2.c and Table 2 show the systems' electrode location, and the channel's positions used are shown inside a circle. Therefore, the Stock-Emotion dataset has EEG recordings using eight electrodes, 4 in each cerebral hemisphere.

The dataset corresponds to EEG signals of 10 healthy participants between the ages of 25 to 60 years old, five males and five females. The EEG brain waves of the subjects were recorded while they traded in the United States stock markets. The experiment used paper trading, i.e., with live market data and simulated money. The experiment required that each of the 10 participants have a session of paper trading. Participants self-reported their state of mind in two-minute intervals.

The protocol followed for the recordings started with a two-minute reference point, where the participants were asked to relax. This initial recording was labeled as a calmed state. After this, the individuals initiated trading.

TABLE 2. Cyton's channels and eight electrode's position.

Electrode's position	Channel
1	FP1
2	FP2
3	C3
4	C4
5	P7
6	*P8*
7	O1
8	O2

The participants were previously trained in a standardized trading methodology that used RSI, MACD, and Keltner channel indicators, plus momentum and mean reversal trading techniques. Our goal was to give participants the same theoretical trading framework and then analyze their EEG readings as they dive into the markets. We set up a carrot and stick reward dynamic for participants. As measured by their profits, the top-performing individuals were promised to receive a payout from the bottom participants. Here, we aimed to enhance the risk and reward dynamics inherent to stock trading and influence the participant's emotional states.

Participants tagged the data with a self-reported state of mind. The data was labeled using self-assessment manikin ([41] for the definition of valence – arousal in the VA space. We used the quadrants derived from the variables 1) valence and 2) arousal according to Russell's circumplex model [42].

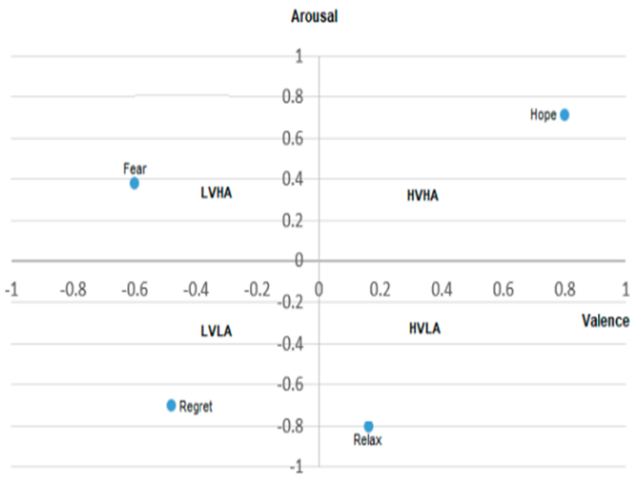

FIGURE 3. Russell's Circumplex Model is showing three key emotions related to stock trading and a relaxed state.

Then we translate the EEG readings to four possible emotional states: low valence – low arousal LVLA (quadrant 1), low valence – high arousal LVHA (quadrant 2), high valence – low arousal HVLA (quadrant 3), high valence – high arousal HVHA (quadrant 4). Figure 3 shows the Valence-Arousal plane and the related three key emotions of stock trading (fear, hope, and regret). In this figure, it is also located a relaxed state. A calmed condition is possibly the ideal affective state for a trader to make objective decisions.

One of our work's contributions is the delivery of the dataset called Stock-Emotion. It introduces an interactive emotion elicitation method that resembles a specific work scenario and constitutes an emotionally relevant stimulus. This method is efficient in motivating affective states that could be recognized by a machine learning system. Also, the Stock-Emotion database could be used for general emotion recognition purposes.

The experiments' design with 10 participants is justified by referencing similar studies analyzed in related work reviews. Regarding the duration of the sessions and the size of our dataset, it can be observed that the present work carries out 24-minute sessions with each participant, with self-labeling of emotions every 2 minutes. There are measurements on eight electrodes for 24 minutes (1440 seconds), at 128 Hz, all multiplied by 10 participants, for a total of more than 14 million entries.

Our dataset did not contain HVLA entries (relaxed state) except those obtained in the two-minute baseline. Therefore, the amateur participants never felt something resembling a calm state during trading. This outcome is expected for novice traders.

On the topic of the labeling frequency of segments of the dataset, it is worth noting that in the DEAP dataset, emotions are tagged for every one-minute long music video, with three seconds separating each clip. So, in this well-known dataset, one minute was considered enough to provoke, recognize, and tag an emotion. In our experiment, the participants labeled their emotions every two minutes, which was deemed sufficient to detect their current feelings.

Since emotions are gradually changed in humans, and they are possible higher on the last section of the time window, processing was made for the two-minute EEG records before a label. It was also executed, focusing on the final 30 seconds of EEG data from the two-minute segment. Classification accuracy was evaluated to see if it may lead to better performance, as Koelstra *et al.* has suggested this strategy in their work [43].

B. PREPROCESSING

In addition to the preprocessing embedded in the Cyton Open-BCI device, artifact removal is carried out using two Butterworth filters with zero-phase to preserve frequencies between 1 Hz and 80 Hz to ensure the elimination of the noise generated from eye movement and heartbeat. Additionally, a 60 Hz notch filter was utilized to remove electrical noise contamination.

C. FEATURE EXTRACTION

Appropriate feature extraction is the key to construct an efficient emotion recognition model. The features are expected to have the essential properties to discriminate among signals. We obtained features related to the electrode location and characteristics in the frequency-domain.

For EEG spatial information, the signals are obtained referenced to digitally linked ears (DLE) value, calculated in terms of the left and right earlobes (1).

$$V_e^{DLE} = V_e - \frac{1}{2}(V_{A1} + V_{A2}) \tag{1}$$

VA1 and VA2 are the reference voltages on the left and right earlobe. This way, the EEG data is broken down, considering each electrode. Thus, each channel contains the spatial evidence of the location of its source.

First, it is considered information obtained using FFT. Frequency filters in Python were used to separate the following bands: Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (13–30 Hz), gamma (30–100 Hz). As an example, Figure 4 shows five frequency bands from one of the experiment's subjects.

EEG signals are highly complex and non-linear. Spectral entropy reflects the amount of non-linearity presence in the EEG signal. It is a way to quantify, in a statistical sense, the amount of uncertainty or randomness in the pattern. This value serves to quantify the amount of information contained in the signal and its complexity. The differences in entropy generated by different emotional states are features proven to discriminate emotions [44]. For this reason, we computed as features Differential Entropy (DE) for each frequency band, and the combination for symmetrical electrodes: Differential Asymmetry (DASM) and Rational Asymmetry (RASM).

In the frequency domain, Differential Entropy (DE), and its derivatives Differential Asymmetry (DASM), and Rational Asymmetry (RASM) measure functional dissimilarities.

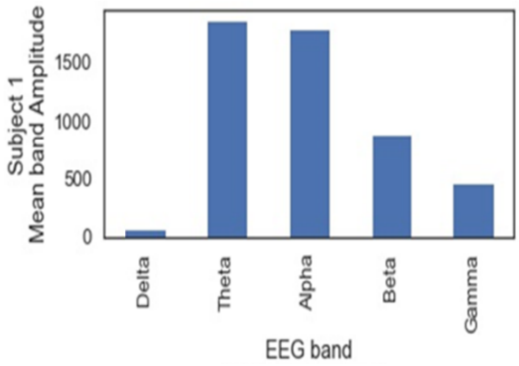

FIGURE 4. Five frequency bands for subject 1, trial 1.

These features are calculated from the logarithmic power spectral density for a fixed length EEG sequence and the difference and ratios between the DE features of hemispheric asymmetry electrodes [44]. These attributes are related to both the frequency domain and also take into account spatial considerations.

In the present work, we first transform the signal into the frequency domain and then calculate differential entropy over each band as a relevant feature. DASM and RASM are computed as a measure of the DE's differences between both cerebral hemispheres.

DE was defined in (2).

$$h(X) = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx$$
$$= \frac{1}{2}\log\left(2\pi e\sigma^2\right) \quad (2)$$

where the series X is a Gauss distribution N(μ, σ^2). for an EEG sequence of fixed length, DE is equivalent to the logarithm ES in a particular frequency band [45]. DE will correspond to a feature in each one of the five power bands.

DASM and RASM were calculated for each trial as the differences and ratios, respectively, between DE of 4 pairs of electrodes. Each pair of electrodes are located in the right and the left cerebral hemispheres, as shown in Figure 2 (c) and Table 3.

$$\text{DASM} = \text{h}(\text{X}_\text{i}\text{left}) - \text{h}(\text{X}_\text{i}\text{right}) \quad (3)$$
$$\text{RASM} = \text{h}(\text{X}_\text{i}\text{left})/\text{h}(\text{X}_\text{i}\text{right}) \quad (4)$$

Figure 5 shows the distribution of the initial 20 features (Power Bands-Mean Band Amplitude (MBA), DE, DASM, and RASM, for each band) and their respective labels for a sample case.

D. FEATURE SELECTION

As was mentioned, features with information that has proven to be the most important for emotion recognition were extracted, taking into account the frequency domain and spatial information related to the electrodes' symmetrical location. Power bands, DE, DASM, and RASM, were calculated for each of the five frequency bands of the EEG signal: Delta (0-4Hz), Theta (4-7Hz), Alpha (8-12Hz), Beta (12-30Hz), and Gamma (30-80Hz). Consequently, this yielded a vector of characteristics made up of 20 attributes.

TABLE 3. Pairs of symmetrical electrodes located in each cerebral hemisphere.

Pair No.	1	2	3	4
Electrode position	1,2	3,4	5,6	7,8
Channel Left	FP1	C3	P7	O1
Channel Right	FP2	C4	P8	O2

Feature selection is necessary to obtain an optimized feature vector to get a more precise classification with less possibility of overfitting and better performance evaluation to simplify and improve the dataset's quality. To feed the classifiers and compare performance, we used feature selection methods: Filter, wrapper, and embedded methods. The mutual information matrix is used as a filter algorithm that evaluates each pair of features' correlation. Chi-square statistics, a wrapper method, is used after trial classification to help discard features that are not significant since they do not influence the classification. Then, we combined the results of filter and wrapper methods to select the features. Separately, the embedded method would be tested with a deep learning classifier.

Therefore, in the first step, we test if the features are statistically independent. The mutual information between two random variables x and y is calculated, defined using (5).

$$I(x;y) = \iint p(x, y) \log \frac{p(x, y)}{p(x)\, p(y)} dxdy \quad (5)$$

where p (x) and p (y) are the marginal probability density functions of x and y, respectively, and p (x, y) is their joint probability function. If I(x, y) equals zero, the two random variables x and y are statistically independent [46].

Figure 7 presents values for the mutual information matrix for each attribute. MBA represents Mean Band Amplitude. This matrix can be observed to detect a correlation between the different pairs of features. If two features are not statistically independent, it should be considered the elimination of one of them. However, it is also essential to consider the chi-squared statistics results, which evaluate each feature's significance related to the output classes. In our proposed feature selection method, both algorithms complement each other strengths.

The chi-square method is a statistical approach to evaluate the dependency between two variables and differences in distributions. This algorithm evaluates features individually concerning the output classes, so it is a method that is applied after classification results.

The algorithm evaluates each feature's significance. If a feature is not significant, it may be discarded from the model [47].

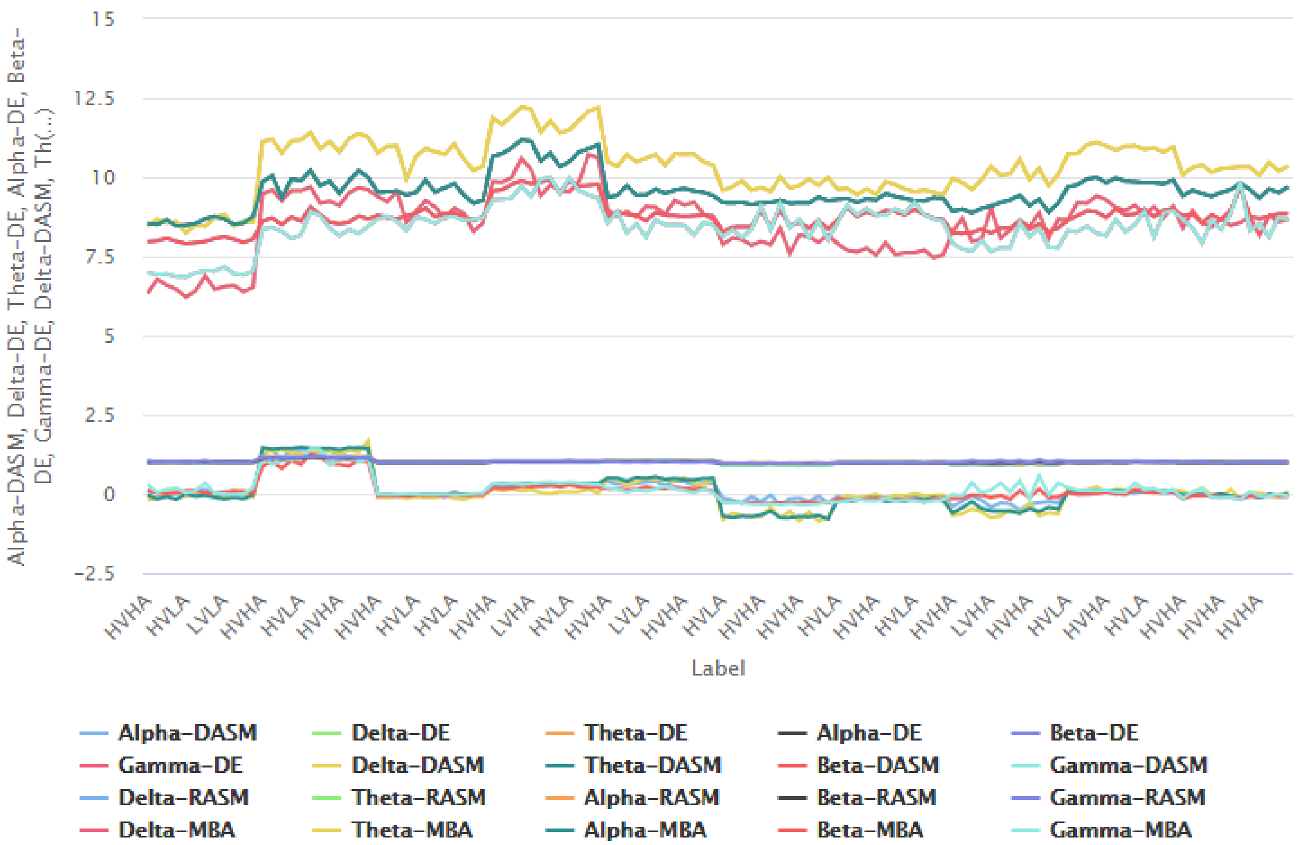

FIGURE 5. Initial features distribution vs. labels.

Let Nij be the number of samples of the Ci class within the jth interval, and Mij is the number of samples in the jth interval. The expected frequency, then, we have (6).

$$\text{Expected frequency of Nij} = \text{Eij } 0 \text{ Mij}|\text{Ci}|\text{N} \tag{6}$$

The chi-square statistic is defined in (7).

$$\chi 2 = \sum_{i=1}^{c} \sum_{J=1}^{I} \frac{(Nij - Eij)^2}{Eij} \tag{7}$$

I is the number of intervals. The larger the value of chi-square, the more significant is the feature, i.e., it has more influence in the emotion classification.

Chi-square statistics show the weight of the features in the classification. Less significant features appear to be the indexes RASM and DASM for the gamma and delta bands, respectively (Figure 7). Delta and its differential entropy have the most weight in the classification, followed by Alpha and Gamma bands and their differential entropy. These findings align with assertions made in other works. In [48], the authors stated that the delta band increased the synchronized activity between the two cerebral hemispheres, particularly in the emotions with negative valence; this feature can be associated with the power band's amplitude and the differential entropy. In [43], a negative correlation was reported in the Alpha and Gamma bands for arousal.

Figure 8 shows the remaining features after the selection made considering Mutual Information Matrix and Chi-square statistics. According to the matrix, there is a strong correlation between the power bands and their differential entropy. Thus, power bands were omitted from the remaining features.

E. CLASSIFICATION

A classification algorithm is used to infer the emotional states of the experiment's participants. The system uses two phases: 1) training to generate models and 2) a test phase to evaluate them in new data. The classes that the algorithms recognize correspond to the four quadrants of the Valence-Arousal space, related to the critical emotions associated with stock trading: fear (LVHA), hope (HVHA), sorrow or regret (LVLA), and a calm state (HVLA) as seen in Figure 3.

The system trains the data from the Stock-Emotion database. Testing is carried out in a new set of data from Stock-Emotion and in a DEAP database subset.

Necessary adaptations are made to test the models in DEAP. Firstly, DEAP has information from 32 EEG channels configured with the 10-20 system. From DEAP, only eight electrode data are taken into account to correspond to the eight channels configuration of the Cyton BCI device used to obtain Stock-Emotion data (Figure 2 and Table 2). This correspondence is possible because the devices use the same 10-20 system for electrode location.

Furthermore, from the attributes from DEAP, only valence, and arousal labels are utilized because our approach does not

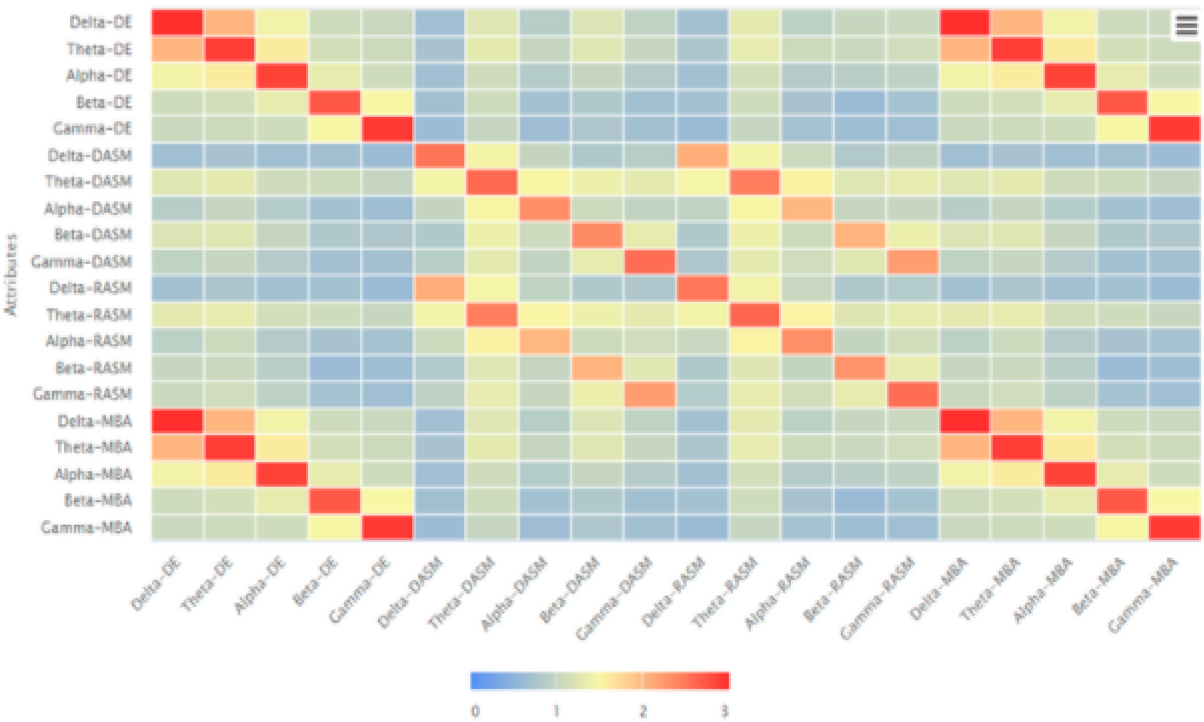

FIGURE 6. Mutual information matrix.

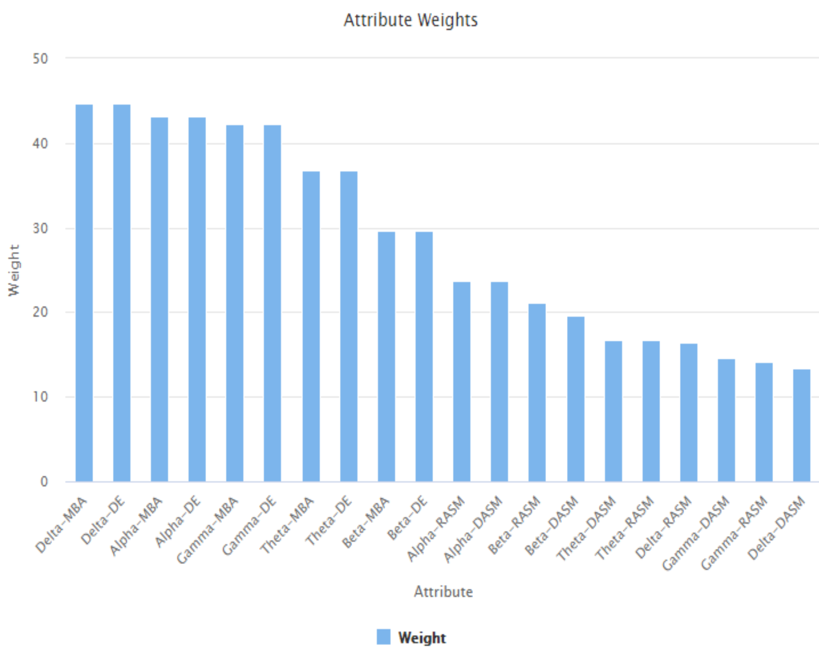

FIGURE 7. Attribute weight by chi-square statistics.

consider dominance nor liking. Finally, physiological signals were not included.

For classification, Random Forest [49] and Neural Networks [50] algorithms were selected for having the best performance, after several tests with Sklearn Python functions. The system performance was evaluated using 10-fold cross-validation using the tests carried out in Stock-Emotion and DEAP.

1) CLASSIFIER TRAINING PHASE

In the present investigation, Random Forest, and Deep Learning algorithms, were used to classify emotions using the feature vectors described in Section 4.4. The purpose is to compare results from two different types of classifiers that were proved to deliver the best results for emotion detection using EEG. Additionally, were tested the following classifiers: Naive Bayes, Generalized Linear Model, Logistic

Regression, Fast Large Margin, Decision Tree, Gradient Boosted Trees, and Support Vector Machines. These seven algorithms yield the accuracy values of less than 65%. Therefore, we chose the Random Forest and Deep Learning algorithms because of their superior performances over the mentioned available functions in the Sklearn Python library.

The classifiers are trained and tested using the already described original feature: five frequency bands, DE for every band, DASM y RASM for eight pairs of channels in each frequency band, for a total of 20 initial features. The process also uses a feature selection procedure with filter and wrapper algorithms to obtain a feature vector with only seven chosen features. Embedded methods included in a Deep Learning classifier were also used to evaluate results.

For comparison purposes, the system was trained and tested using all the initial features and processing the selected attributes. The objective is to observe changes in the classification performance using a subset of the original features. The result that the performance is maintained or improved is possible if only the redundant information were eliminated while retaining the features relevant to emotion recognition.

2) RANDOM FOREST

This algorithm uses a set of decision trees. Each tree performs a classification, and the class with the highest number of votes is the one included in the model prediction. This model works very well based on the logic that multiple classifiers that function as a committee work better than a single classifier. On the other hand, even though many trees may have the wrong classification, others are included in the correct categorization. The final decision will be accurate as long as the trees have a low correlation between them.

For this algorithm, we set the parameter of 100 random trees. The criterion to estimate the quality of a split is Gini impurity [51], maximum depth of the tree = none, so the nodes are expanded until all leaves are pure or until all leaves contain less than two split samples.

3) DEEP LEARNING

In this research, Deep Learning was implemented to compare its results with those obtained with the shallow Random Forest method. The recognition of the four emotional quadrants was investigated. The H2O Deep Learning operator was used based on a multi-layer artificial feedforward neural network. Hidden layer sizes = 100, activation function for the hidden layers is a rectified linear unit. The solver is adam, a stochastic gradient-based optimizer [52], alpha = 0.0001, learning rate = constant, and the maximum number of iterations = 200.

Deep learning algorithms received raw data and carried out internal processes to extract and select features. For this reason, it is said they had an embedded feature extraction and selection process.

4) CLASSIFICATION PERFORMANCE

Classification training was done with and without feature selection. The training was carried out with the Stock-Emotion dataset. For testing, data from Stock-Emotion and a subset of DEAP datasets were used. Both Stock-Emotion and DEAP are unbalanced datasets with more labels in two classes; this could introduce a bias in the classification. Consequently, to avoid a lack of significance in our results, we applied 10-fold cross-validation. Average accuracies for the different experiments are shown in Table 4.

The same feature extraction and selection procedures were applied to the DEAP dataset to test the classifiers' models. Table 4 presents classification performance results with and without feature selection.

The outcomes have a performance comparable to the State-of-the-Art's best results, corresponding to a similar number of classes [40].

The test phase applied in a subset of DEAP using Random Forest yields the following values of accuracy: 78.92% with feature selection, and 72.62% without feature selection. We used a subset of eight channels from the DEAP dataset using the corresponding 10-20 standard electrode's layout. It is worth mentioning that authors in [52] experimentally determined that it is just needed to extract information from eight channels to obtain enough performance in an emotion recognition system for practical use.

On the other hand, Table 4 results demonstrate that feature selection improves the accuracy (82.51%) compared with classification made without this process (73.22%), using Random Forest in our dataset. Embedded feature selection carried out in a deep learning algorithm produces an accuracy of 70.12% in Stock-Emotion and 69.02% in DEAP.

Training and testing were also proved using only a segment of the EEG signals. Remarkably, the results of processing only the last 30 seconds of the two-minute component of the signal assigned to a label were slightly better than the performance obtained using all the EEG signals' two-minute segment. The same strategy was applied with the DEAP dataset, using the last 30 seconds of each one-minute part, and also an improvement was noted.

Results validated our proposed feature selection method because combining Mutual Information Matrix and Chi-square statistics for feature selection has better performance results than using the initial vector or applying an embedded method via Deep Learning.

V. DISCUSSION

This article has presented an emotion elicitation technique that uses a specific work scenario: trading in a competitive stock market. The dataset recordings had more than 14 million entries preprocessed to eliminate artifacts. This dataset will be publicly available.

The emotions provoked by stock trading activities were tagged using the self-assessment manikin method. The user-made labels were moved to four discrete states in each of the four quadrants of the Valence-Arousal space: HVHA, HVLA, LVLA, LVHA, to further differentiate emotional states in our classification models.

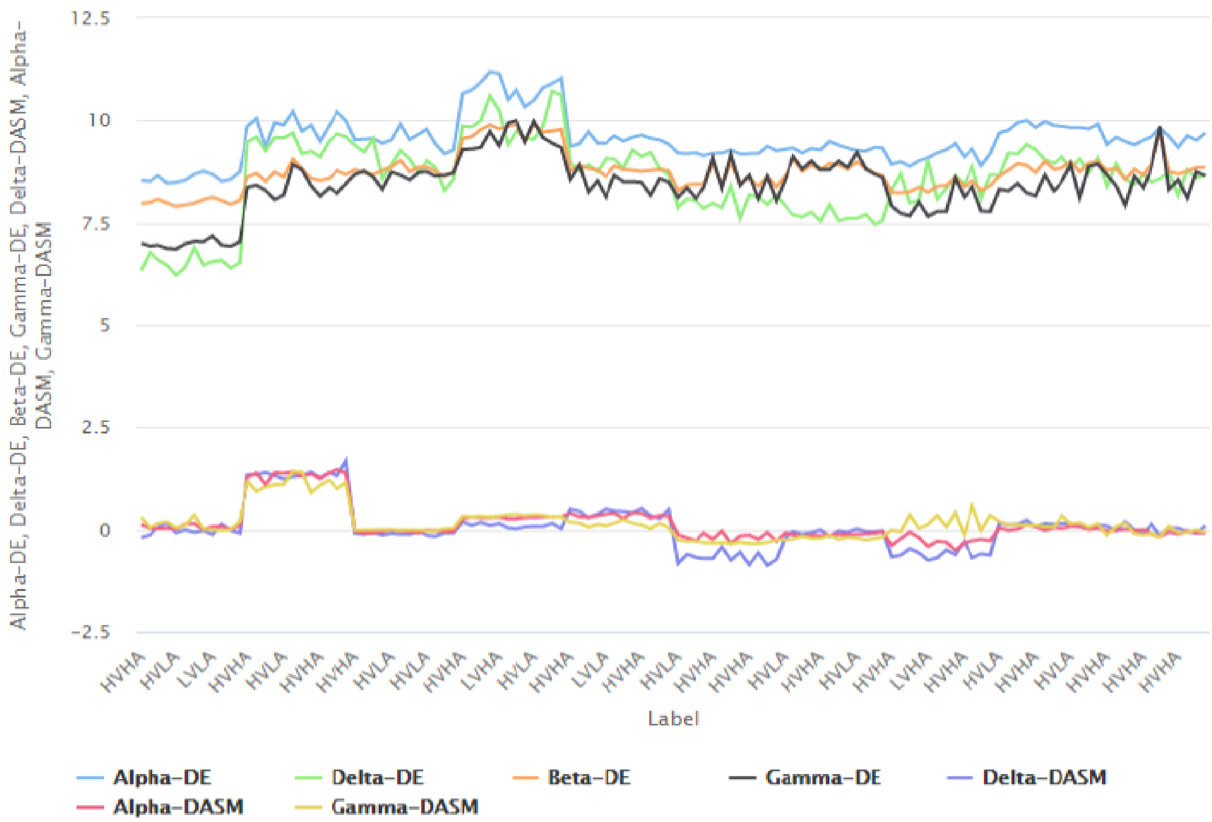

FIGURE 8. Remaining features after feature selection vs. labels.

TABLE 4. Classifiers performance.

		Processing using two-minute EEG signals			Processing using the last 30 seconds of the two-minute signals		
Dataset	Classifier	Accuracy with embedded feature selection (%)	Accuracy with the initial feature vector (%)	Accuracy with feature selection (%)	Accuracy with embedded feature selection (%)	Accuracy with the initial feature vector (%)	Accuracy with feature selection (%)
Stock-Emotion	Deep Learning	70.12	-	-	71.22		
	Random Forest	-	73.22	82.51	-	73.25	83.18
DEAP	Deep Learning	69.02	-	-	69.82	-	-
	Random Forest	-	72.62	78.92	-	72.73	79.17

The proposed system included feature extraction and selection processes. Feature extraction is essential when manipulating EEG signals that involve a large amount of data. We combined frequency and spatial information to define the calculated features. The mean amplitudes of five frequency bands (Delta, Theta, Alpha, Beta, and Gamma) were calculated in the frequency domain. Additionally, Differential Entropy (DE), and its derivatives Differential Asymmetry (DASM), and Rational Asymmetry (RASM) were obtained to measure functional dissimilarities between the cerebral hemispheres.

After feature selection, seven characteristics were chosen using Mutual Information Matrix and Chi-squared statistics: the differential entropies for Delta, Alpha, Gamma y Beta bands, and the DASM for Delta, Alpha, and Gamma bands were the most influential in the four-classes emotion classification.

The findings concerning each feature's relevance in the classification align with assertions made for other papers corresponding to the relationship among information associated with frequency bands and emotions. For example, our dataset does not have calm state-related samples (except for baseline), and interesting enough, the Theta band and its related features were eliminated. This finding supports what was already mentioned in [33], which linked this band with the presence of mindful states.

Another chosen feature was DASM obtained in the alpha band that could be associated with asymmetric activity at the frontal site, which is connected with emotion. This result agrees with [32]. On the other hand, RASM features were eliminated because they had redundant information already present in DASM.

The selected features had relevant and non-redundant information useful for an optimized emotion recognition process with the proposed selection method.

After several tests with Python's SKLearn machine learning algorithms, we chose the classifiers with the best performances: Random Forest and Deep Learning. Random Forest was used 1) with the initial features, and 2) with the selected features. Outcomes were compared, and it was noticed that the proposed feature selection method improves the classifiers' performance.

The Deep Learning algorithm has an embedded feature extraction and selection methods. Deep Learning accuracy results were lower than those obtained using the proposed selected features and Random Forest.

The results mentioned in the last two paragraphs validate the efficiency of combining a filter (Mutual Information Matrix) with a wrapper method (Chi-square statistics) for feature selection.

In the test phase, we used the Stock-Emotion database generated in our experiments and a subset of the DEAP dataset using arousal and valence labels.

As future work, we plan to collect more data for Stock-Emotion and continue applying feature engineering and parameter tuning for different algorithms. Additionally, we expect to use the proposed techniques to learn about emotion management and recognition in competitive workplace scenarios.

VI. CONCLUSION

In the present work, three main contributions were made. The first one was the dataset that will be publicly available. The second was a novelty and dynamic way for emotion elicitation: stock market trading activities. Each participant faced different and unique market conditions (inherent in simulated live trading), so the experiment offered new circumstances to other individuals. This proposed method provoked emotions that were tagged using valence - arousal definitions. The labels were related to the key emotions that influence trading: fear (low valence - high arousal), regret or sorrow (low valence - low arousal), hope (high valence - high arousal), and a relaxation state (high valence - low arousal). This fourth state is ideal for traders since it gives more objectivity to their decision making. Simultaneously, the other three emotions can somehow affect judgment and could lead to incorrect decisions. Thus, it would be intended that traders become aware of their emotions to facilitate their management and to achieve an optimal affective state for their work. Interestingly, in our experiments, the traders did not label any emotion as a relaxed state, except in the baseline.

The third contribution was the proposition of a feature selection process as a blend of two methods: Mutual Information Matrix that considers correlations between features; and Chi-squared statistics that take into account the significance of each feature related to the output classes.

In conclusion, our emotion elicitation method effectively provoked emotions related to trading, and our system was capable of recognizing them. Due to the subjective aspect that involves discriminating and self-labeling emotions, and the complexity of EEG signals, EEG-based BCI systems for emotion recognition do not readily have high accuracy. However, the system's performance in this research is comparable and even better than the state-of-the-art systems that recognize a similar number of categories for emotion recognition [2].

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