IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 4, December 2024, pp. 4675~4687
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i4.pp4675-4687

Sentiment-electroencephalogram fusion for efficient product review prediction using correlation-based deep learning neural network

Rahul Kumar Sharma, Arvind Dagur
School of Computing Science and Engineering, Galgotias University, Greater Noida, India

Article Info

Article history:

Received Dec 8, 2023
Revised Mar 29, 2024
Accepted Apr 17, 2024

Keywords:

Correlation-based deep learning neural network
Entropy value
Grasshopper optimisation algorithm
Sentiment analysis
Weighting factor

ABSTRACT

Various techniques have been proposed and implemented in previous work for sentiment analysis prediction. However, achieving satisfactory quality of description and fault prediction remains a challenging task. To overcome these limitations, this study proposes an efficient prediction technique that utilizes sentiment analysis of product reviews and electroencephalogram (EEG) signals using correlation-based deep learning neural network (CDNN). The study employs two types of datasets: EEG signals and Amazon product reviews. During the pre-processing phase, EEG signals undergo normalization, while Amazon product reviews undergo tokenization, stop word removal, and weighting factor application to convert unstructured data into a structured format. Subsequently, the pre-processed EEG signals and reviews are analyzed to extract features like emotion, demographic information, personality traits, and sentiment. These features are then employed in sentiment analysis via an entropy-based deep-learning neural network. The proposed CDNN utilizes the grasshopper optimization algorithm (EGOA) to optimize hyperparameters for each layer. Comparative performance assessment against established methods like convolutional neural network (CNN), long short-term memory (LSTM), multiclass support vector machine (M-SVM), and bidirectional encoder representations from transformers (BERT) is conducted, and the results are evaluated. Experimental result reveal that the proposed system outperforms traditional approaches.

Corresponding Author:

Rahul Kumar Sharma
School of Computing Science and Engineering, Galgotias University
Greater Noida, India
Email: rahulpccs1988@gmail.com

1. INTRODUCTION

People now use a variety of e-commerce websites to exchange items because the commercial sector has mainly moved to online platforms. Before making a purchase, analyzing products has become a common practice. Additionally, customers are increasingly relying on reviews to make their purchasing decisions [1]. Business leaders can learn more about how consumers feel about their products by using the relatively new academic area of sentiment analysis, which analyses text from reviews, blogs, survey replies, and other sources. In marketing and customer service applications, this kind of analysis is frequently utilized to comprehend the voice of the consumer [2], [3].

Sentiment analysis also known as emotion analysis or opinion mining, involves identifying key attributes within unstructured, raw text commonly found on social media platforms and networks [4], [5]. In the classification process, sentiment analysis plays a crucial role in opinion mining, as it involves evaluating customer opinions about a product and categorizing them as positive or negative factors for analysis [6], [7]. Star ratings are a popular way to quickly convey the emotional tone of a review in consumer assessments. Nevertheless, star ratings possess certain constraints. Occasionally, they may exhibit bias, leading to ratings that do not consistently reflect the genuine emotion conveyed in the review [8]. In some cases, the star rating may be high but the review may be negative or the star rating may be low but the review may be positive [9], [10]. As a result, reviews are often accompanied by textual information to provide a more comprehensive evaluation.

Emotional analysis is essential to the success of a company as it guides its efforts to improve its operations and the products it offers [11], [12]. To extract emotions from customer reviews, two deep learning models were used. Extracting emotions from social media in multiple languages is a critical issue in the field of sentiment analysis and perception analysis [13], [14]. With the increasing online presence of major global activities, social media users use these platforms to express their views and opinions about them.

Brain signals can now be used to evaluate products through a technique known as “neuromarketing,” which involves monitoring brain waves to understand consumer psychology [15]. Obtaining accurate responses through this method can help companies save money on product advertising [16]. Many people do not want to fully communicate their sentiments and preferences regarding items when explicitly questioned. However, neuroimaging instruments like electroencephalogram (EEG) can gather information from a customer's brain even during the generation of desire or observation of a product. Therefore, these brain imaging tools aid marketing researchers in making decisions about future product advertisements [17], [18].

2. RELATED WORK

Gauba *et al.* [18] watch a video advertising while simultaneously recording their EEG signals. For every movie, valence scores were calculated based on self-report. A higher valence is indicative of the user's inherent beauty. Additionally, the natural language processing (NLP) technique was used to extract and evaluate the multimedia data, which included the comments left by viewers worldwide, to do sentiment analysis. The sentiment of the video was evaluated through the analysis of textual feedback in review comments to assign a score. EEG data was utilized, employing a random forest regression technique to forecast the rating of an advertisement. To bolster the predictive accuracy, the EEG-derived rating and the sentiment score from NLP were ultimately combined.

Fan *et al.* [19] suggested an innovative approach to product predictive analysis, integrating the bass/norton model with sentiment analysis using historical sales data and online review data. To enhance prediction accuracy, they augmented the imitation coefficient of the bass/norton model with the naive Bayes technique and mood index. Their study spanned both physical and online automotive industries. However, the page lacks statistics regarding user agreement or disagreement with the reviews, as well as the frequency of review readership.

Shrestha and Nasoz [20] employed sentiment analysis to assess the alignment between Amazon.com reviews and their associated ratings. Their study aimed to identify and categorize the positive and negative emotions conveyed in textual data through sentiment analysis. Despite customers providing polarity ratings in their reviews on e-commerce platforms like Amazon.com, discrepancies between the review content and the rating may arise. By leveraging deep learning sentiment analysis on Amazon.com product review data, the researchers identified reviews spanning diverse ratings. They transformed product reviews into vectors using a text vectorization process and subsequently trained a gated recurrent unit of a recurrent neural network.

Asghar *et al.* [21] investigated sentiment analysis of public product feedback, analyzing word semantic orientation to classify emoticons, modifiers, general-purpose terms, and domain-specific words into positive and negative categories. They also introduced an enhanced sentiment analysis method utilizing a rule-based classification framework grounded in lexicons to improve effectiveness within online communities. However, a notable limitation of their study is the necessity for automatic word categorization and scoring, potentially impacting the classification accuracy of domain-specific terms.

Kaur *et al.* [22] investigated the response of EEG to positive and negative emotions, specifically tranquility, anger, and happiness. They recorded EEG signals from ten volunteers in real time while they watched emotional video clips for two minutes. To categorize the signals gathered to identify emotional states, fractal dimension features were derived from the raw EEG data. A support vector machine (SVM) using a radial basis function (RBF) kernel was employed to obtain greater accuracy, with an average accuracy of 60%. However, it should be highlighted that finding a model that is optimal for identifying emotions gets harder as the number of individuals rises.

Wang *et al.* [23] utilized eye tracking and EEG response data as input for a multimodal fusion technique aimed at recognizing design decision-making. Results from the experiment suggest that the performance of the fusion strategy aligns well with expert decision-making outcomes when incorporating EEG signals and eye movement characteristics. By integrating eye tracking data and EEG, the multimodal fusion approach holds significant potential to mitigate the effects of subjectivity, bias, and superficiality in decision-making, offering a novel approach to guiding design practice with objective evidence and support.

Sharma and Dagur [24] utilized a vast dataset comprising over 500,000 online instant video reviews to develop a sentiment polarity categorization technique. The reviews were categorized into five groups, with consideration given to three polarity features (verbs, adverbs, and adjectives) for review-level classification. The findings demonstrated a promising accuracy rate of 81%, surpassing many prior systems by 3%. While automated sentiment analysis aids in processing large volumes of text data, it still encounters limitations; for example, the software employed in this study struggles with interpreting diverse styles like sarcasm. Refer to Table 1 for a comparison and evaluation of previous work.

Table 1. Analyzing and comparing previous works

References	Technique	Efficiency	Security level	Computational overhead
Gauba *et al.* [18]	NLP	Medium	Medium	Medium
Fan *et al.* [19]	BN model	Medium	High	High
Asghar *et al.* [21]	RBC scheme	High	Medium	High
Kaur *et al.* [22]	RBF & BCI	Average	Medium	High
Wang *et al.* [23]	Multimodal fusion strategy	High	Medium	High
Kausar *et al.* [25]	RB and RBS	Average	High	High

3. PROPOSED METHODOLOGY

Machine learning-based sentiment analysis that incorporates customer feedback and EEG signal data has grown in importance in recent years. The suggested study offers to address the current issues by utilizing a correlation-based deep learning neural network (CDNN). The machine learning and pattern recognition communities are currently actively researching deep learning. NLP, speech recognition, and computer vision represent only a handful of domains in which it has demonstrated exceptional performance. With the growing size of data, deep learning is becoming increasingly important in providing predictive analytics solutions. The dataset used in the proposed study is the input and has been pre-processed using stop word removal, tokenization, and a weighting factor for product reviews. Normalization is used to convert unstructured data into a structured manner when an EEG signal is employed. Various attributes such as emotion, demographic indicators, personality traits, and sentiment features are derived from the pre-processed data. The study introduces a hybrid CDNN, which is fine-tuned and optimized for hyperparameters using the grasshopper optimization algorithm based on entropy (EGOA) for each layer. Figure 1 illustrates the suggested block diagram. This method’s objective is to address the problems with sentiment analysis and produce more accurate outcomes.

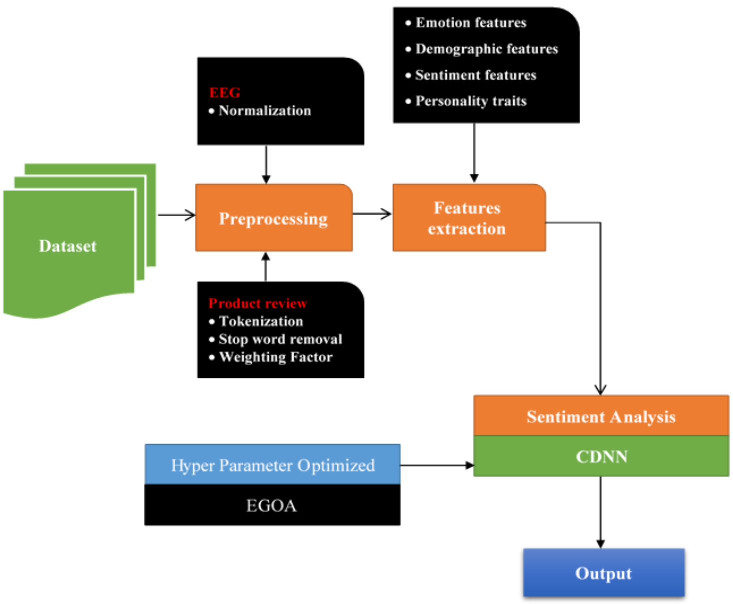

Figure 1. Proposed block diagram

As shown in Figure 1; product review, as well as EEG signal datasets, are used. Deliberate ΔTDS and is the Amazon product review data set $\Delta TDS \in \{TDS_{1^1}, TDS_{2^2}, TDS_{3^3}, \dots TDS_{n^j}\} \Delta EEG$ and is the EEG signal data set $\Delta EEG \in \{EEG_{1^1}, EEG_{2^2}, EEG_{3^3}, \dots EEG_{n^j}\}$ where *n* is the total amount of emotions experienced by humans based on EEG signals and the review of products. The vector function of each signal and the product reviews of a database is given as *i=1 to n*. EEG signals is first pre-processed, followed by pre-processing of the following set of data, such as product reviews.

3.1. Electroencephalogram signal: pre-processing

3.1.1. Signal transformation

Signal conversion is an important step in preparing the EEG signal data for further processing and analysis. This entails converting the signal data from its initial format, which may be categorized or non-numeric, into a numerical representation that machine learning algorithms can analyze. Once the signal data has been converted, it can be represented as a feature vector that contains numerical values for each component of the signal. These feature vectors can then be used to train a classifier to recognize different patterns in the EEG signals, such as the presence or absence of specific emotions or cognitive states.

3.1.2. Normalization

Normalization of an EEG signal refers to the process of converting an unstructured signal into a structured format. The EEG signal is linearly transformed to fit into a specific range during normalization. For the standardization of data, min-max normalization is used, which linearly changes the signals. The accompanying condition is used to perform min-max normalization regularly.

$$NY = \frac{NY - NY_{min}}{NYmin_{max}} \tag{1}$$

Where, NY_{min} and NY_{max} are the minimum and maximum values in NY, and $NY \in \Delta EEG$ is the set of values in the input EEG signal dataset. After completing the pre-processing stage of EEG signals, the product review of datasets is pre-processed which is represented as follows.

3.2. Amazon product review pre-processing

The product review dataset serves as the input source. The initial step in handling this dataset, which contains unstructured signals, involves converting these signals into structured ones. This process entails employing tokenization, stop word removal, and weighting variables to achieve structured data. The first step, solution creation, is described in detail as follows $\{TDS_{s^1}, TDS_{s^2}, TDS_{s^3}, \dots TDS_{n^j}\}$ implies the documents on the Amazon product review dataset.

$$\Delta TDS_s = \{TDS_{s^1}, TDS_{s^2}, TDS_{s^3}, \dots TDS_{n^j}\} \tag{2}$$

3.2.1. Tokenization

Tokenization is the first step in breaking down lengthy strings of product reviews into smaller tokens or units. This involves splitting larger sections of a product review into phrases and breaking down sentences into individual words. Tokenization is also referred to as product segmentation and lexical analysis. Tokenization is a method used to break down a set of input datasets into meaningful segments, or tokens, which can include words, phrases, and symbols. The resulting input text is then organized into a list of token collections for further processing. However, the nature of natural language presents challenges during tokenization; while many languages use white spaces to separate words, others do not.

Challenges in tokenization: indeed, the system of writing and typographic layout of text, such as product reviews, can significantly influence tokenization. These factors can introduce additional challenges that need to be addressed when tokenizing text. Furthermore, languages can be categorized into three primary types based on their structure:

- Isolating: in isolating languages, the Amazon product review words are typically composed of single morphemes, and word order and context are crucial for conveying meaning. There is little to no use of inflectional or derivational morphology. Chinese and Vietnamese are examples of isolating languages. In these languages, words are not inflected for tense, number, gender, or case, but instead, context or additional words are used to convey these grammatical features.
- Agglutinative: agglutinative languages use affixes extensively to denote grammatical relationships, but each affix generally represents a single grammatical meaning. These languages tend to have a relatively fixed word order, and words can have many affixes attached to them. Turkish, Finnish, and Swahili are examples of agglutinative languages.

– Inflectional: fusional languages often express multiple grammatical meanings within a single affix, resulting in complex word forms. These languages typically have more flexible word order compared to isolating and agglutinative languages. Examples of fusional languages include Latin, Greek, and Spanish.

3.2.2. Stop word removal

Stop words are commonly used words that often do not significantly change the meaning or context of a phrase. Although they are frequently employed in sentences to connect other words, they generally do not add meaningful content to the text. In text mining, the prevalence of stop words can complicate the understanding of document content. Therefore, it is widely accepted that eliminating stop words during pre-processing enhances the precision and effectiveness of text analysis. Examples of stop words include ‘and’, ‘are’, and ‘this’. As they do not contribute substantially to a document’s overall meaning, stop words are typically removed from the text. However, compiling a comprehensive list of stop words can be challenging due to inconsistencies across different text sources and their frequent occurrence in text. These challenges can impede the processing of textual data and the implementation of effective stop-word filtering.

3.2.3. Weighting factor

This involves assigning a weight to each term within a document, indicating its relative significance. This process of assigning weights to each phrase is commonly referred to as the “weighting method”. The frequency of the weighting factor is quantified numerically as:

$$Freq(W_i) = count[W_i] \tag{3}$$

$$Count[W_i] = G \tag{4}$$

Let the obtained $Count[W_i]$ be stocked up on the equivalent G. G signifies the frequency set of an Amazon product review. The pre-processed product review data then moves on to the step of feature extraction. The pre-processed data is utilized for extracting sentiment characteristics, personality traits, demographic factors, and emotional attributes.

3.3. Feature extraction

Following pre-processing, both the EEG data and Amazon product reviews proceed to the feature extraction phase. Feature extraction is pivotal in the classification process, involving the extraction of pertinent signals and review attributes from the pre-processed data to facilitate categorization. Extracting useful features from EEG signals and product reviews can be challenging, and there are various approaches to feature extraction. In this study, we extract emotion, demographic, personality, and sentiment features from the pre-processed EEG signals and Amazon product reviews.

3.3.1. Feature extraction based on emotion features

The methods and resources in this section concentrate on collecting emotion or mood states from a text excerpt using emotional qualities. A message needs to be put into a process that produces specific emotional categories, such as surprise, joy, or grief, among many others, and is emotion-oriented. A list of words or expressions categorized by various emotion states should be provided by emotion-oriented lexical resources in Table 2.

Table 2. Emotion features are categorized into the subsequent classes

Scope	Feature	Source	Description	Range
Emotion	NJO	NRC	number of product reviews and EEG signals that match the joy word and moment list	{0, 1, 2..., n}
	NTR		... matches the trust word and moment list	{0, 1,2 ..., n}
	NSA		... matches the sadness word and moment list	{0, 1,2 ..., n}
	NANG		... matches the anger word and moment list	{0, 1,2 ..., n}
	NSU		... matches the surprise word and moment list	{0, 1,2 ..., n}
	NFE		... matches the fear word and moment list	{0, 1,2 ..., n}
	NANT		... matches the anticipation word and moment list	{0, 1,2 ..., n}
	NDIS		... matches the disgust word and moment list	{0, 1,2 ..., n}

3.3.3. Feature extraction based on personality traits

Personality trait scores are continuous values that can be used as input for EEG signals and Amazon product ratings right away; however, to do classification, these scores must be discretized. In this study, five distinct approaches are tested, and the results are evaluated based on the character traits.

– Continuous: continuous in the context means that personality trait scores are used in their original, unaltered form, without categorization or transformation. In regression analysis, these scores are directly utilized as numerical variables to understand how they relate to other variables, without converting them into categorical or discrete groups.
– LAH: which stands for "low average high," is a method of categorizing individuals into three groups based on their scores or performance. These groups are typically labeled as low, average, and high. The essence of LAH is to divide participants into these three categories by establishing partition boundaries which are defined mathematically as (5):

$$LAH(s) = \begin{cases} high, if s > \mu + \frac{SD}{2}; \\ low, if s < \mu + \frac{SD}{2}; \\ average, otherwise. \end{cases} \tag{5}$$

– LH: LH is an abbreviation for low high, which refers to the division of participants into two groups: those with higher scores and those with lower scores. However, participants who are closer to the boundary may receive similar scores. This approach is scientifically characterized as a binary classification method.

$$LH(s) = \begin{cases} high, if s > \mu; \\ low, if s < \mu; \end{cases} \tag{6}$$

– LHNA: "stands for "low high, no average". It is a term used to differentiate between maximum and minimum scoring by disregarding any average values. This approach focuses solely on extremes, whether high or low, without considering the middle ground represented by average scores. Mathematically, LHNA is represented as (7):

$$LHNA(s) = \begin{cases} high, if s > \mu + \frac{SD}{2}; \\ low, if s < \mu - \frac{SD}{2}; \\ omit, otherwise. \end{cases} \tag{7}$$

– LHNASD: low high, no average, and even whole standard deviation, is a statistical method used to analyze data by focusing on extreme values while disregarding averages. In LHNASD, the highest and lowest values are emphasized by setting a threshold at ±1 standard deviation from the mean. This means that data points beyond this threshold are considered significant outliers. By doing so, LHNASD aims to highlight extreme values and detect any deviations from the typical pattern in the data. LHNASD which is mathematically represented as (8):

$$LHNASD(s) = \begin{cases} high, if s > \mu + SD; \\ low, if s < \mu - SD; \\ omit, otherwise. \end{cases} \tag{8}$$

3.3.4. Feature extraction based on sentiment features

Sentiment refers to a person's feelings or judgments. Traditionally, whenever a person is looking to purchase a computer, there are several factors to consider, He consults his friends and family members for advice. People nowadays, on the other hand, read reviews on the internet before deciding which computer to buy. Opinion mining/sentiment analysis captures a person's impressions and otherwise feelings about something like a product. Opinion mining and sentiment analysis are two interchangeable terms.

Scope: entrepreneurs can use sentiment analysis to evaluate whether a new product will succeed or fail. It can assist them in determining which features clients like. For example, a website evaluation claims that the laptop is efficient but the battery is inadequate. This type of data provides a clearer picture of end users' opinions, which may be used to improve features in future releases.

Challenges: the most difficult aspect of sentiment analysis is ambiguous word meaning. In one scenario, a word may be positive, while in another, it may be negative. Take the term "short," for example. Positive feedback would be if a customer reports that the computer's startup time is fast, while negative feedback would be if a customer complains about the computer's short battery life. It is crucial to remember that without appropriate training and customization, a system that has been trained on one sort of product feedback cannot be used for another product. Surveys, news, word-of-mouth, and internal statistics such as client opinion since contact centers, email, and other sources are used to obtain opinions.

3.4. Classification stage using correlation-based deep learning neural network

A correlation analysis entails a statistical evaluation of the strength and direction of the relationship between two variables. The correlation values typically range between -1.0 and 1.0, with any value beyond this range indicating an error in the correlation calculation. Correlation is a measure of the relationship between two sets of data, and the most common mathematical measure of correlation is depicted by (9), which measures the linear relationship between the input EEG signals and the product reviews.

$$Z = \frac{\sum(a1_i - \bar{a}2)(b1_i - \bar{b}2)}{\sqrt{\sum(a1_i - \bar{a}2)^2 \sum(b1_i - \bar{b}2)^2}} \tag{9}$$

Where z → correlation coefficient of EEG signal and Amazon product review, $a1_i$→ values of the 'a' variable in a sample, $\bar{a}2$→ mean of the value of the 'a' variable, $b1_i$→ values of the 'b' variable in a sample, $\bar{b}2$→ mean of the value of the 'b' variable. After finding the correlation coefficients of the EEG signal as well as Amazon product reviews the outcomes are moved to the next stage of classification which is explained in detail as: following feature selection using correlation coefficients, classification is performed using a deep learning neural network (DNN). Multi-layered artificial neural networks with hidden inputs and outputs make up DNNs. To maximize parameter learning, the learning process includes numerous pre-training and fine-tuning stages. The purpose of this study is to discover the best weights that can be used to precisely classify the output by training the data features, such as EEG signals and Amazon product review data sets. The DNN categorizes the data for sentiment analysis based on the extracted features. Figure 2 shows the DNN structure in diagrammatic form.

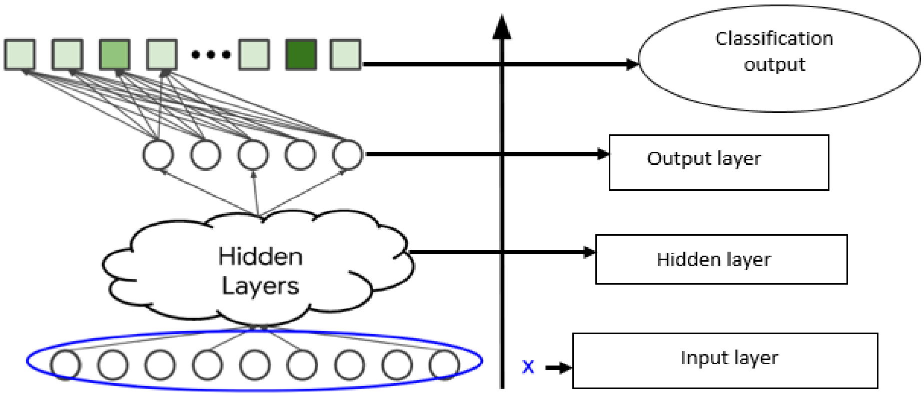

Figure 2. DNN structure

3.4.1. Using a deep belief network as a pre-training stage

We employ the deep architecture feed-forward neural network (DBN), which continues to be a deep architecture network with several degrees of concealment, during the training phase. The DBN input is currently only offered with a limited set of features. The DBN is generatively pre-trained using the learned weights after which it is used as its initial weights. The DBN model asserts that it employs a network based on the states of its hidden units and permits the activations to be made visible. This layer is made up of an input layer that encloses the input units, several hidden units, and an output layer that measures one unit for each class. Amongst the layering units $i - 1$ and i, the biases $B(i)$ → layer, weights are the parameters of a DBN W_i. Optimizing the parameters is one of the most difficult parts of DNN training. Today, a hyperparameter optimization technique is produced via random initialization. We employ a restricted boltzmann machine to address the issue. DBN can learn using a stacked set of easy-to-understand learning modules. The name of this straightforward learning module is results-based management (RBM).

3.4.2. Fine-tuning stage

The weights are fine-tuned via backpropagation to enhance the scheme's accuracy once the network has been pre-trained as RBM-stack model. To characterize the system's performance, an output layer is placed on top of the DNN. Moreover, the training dataset is refined until the optimal weight or high performance is achieved. The DNN classifier offers several advantages, including the ability to handle missing data during classification, where it automatically incorporates available information for further processing. Leveraging the acquired features, a deep-learning neural network categorizes the data for sentiment analysis. Subsequently, the weight parameter for each layer is adjusted using the EGOA.

3.5. Entropy-based grasshopper optimization algorithm

In this approach, an EGOA is employed to optimize hyperparameters. Utilizing the entropy-based grasshopper algorithm, the following processing steps are executed to yield optimal results. By employing a hybrid DNN that integrates machine learning with EEG signals and Amazon product review data, the objective is to conduct sentiment analysis effectively.

3.5.1. Entropy calculation

Calculating entropy is a key takeaway: entropy (ENTR) is a probabilistic measure of disorder or randomness in a macroscopic system, reflecting the number of possible arrangements of its constituent molecules. It quantifies the system's tendency to move towards a more disordered state. Mathematically, entropy can be calculated as the natural logarithm of the number of possible configurations divided by Boltzmann's constant assuming each configuration is equally probable: $ENTR = p_Q NLS$

$$ENTR = p_Q NL\Omega \tag{10}$$

ENTR→ entropy, p_Q→ Boltzmann constant, NL→ natural logarithm, Ω → number of microscopic configurations. The best solution is created using the procedures listed below after the entropy value has been calculated. The first step, solution creation, is described in detail as follows:

Step 1: Initialization: To optimize the hyperparameters, the EGOA algorithm begins by populating the solution with any number of people. An optimization algorithm's solution development is a crucial stage that aids in the rapid identification of the best solution. We select optimal weight settings from among the n range of features and weights in each data set. Solution generation is based on the chosen features and their weights. Assume that each flower has N pollen and that there are M flowers or solutions in the total population. The population of flowers as a whole is depicted as $S = (F_1, _{F2}, \ldots, F_M)$, anywhere, F_m is the m^{th} flower, and $m \in [1, M]$ is the flower's population's order number. Each flower has a different representation $F_m = (P_1, P_2, \ldots., P_N)$, where, P_n is the n^{th} pollen (weight parameter) in the m^{th}flower, and $n \in [1, N]$ is the pollen index. The obtained answer will be used in the next stage, which is the fitness assessment.

Step 2: fitness calculation: the fitness function evaluates the solution after it is generated, and then selects the best option. To find the optimum solution, the optimization algorithm primarily relies on its fitness function. A major feature of EGOA is the choice of fitness.

$$Fitness_i = \frac{1}{WF * ENTRV} \tag{11}$$

Where, WF→ weight factor, ENTRV→ entropy value, each person's fitness level is assessed. and saved for future reference once the first solution, as well as the opposing solution, has been developed. The equation is used to create the fitness function (11). The solution obtained after the fitness function computation is then given for the evaluation of the update phase, which comes next.

Step 3: OGWFS-based updating solution: in the grasshopper optimization algorithm (GOA), updating the solution based on entropy typically involves adjusting the positions of the grasshoppers in the population to encourage exploration of the solution space. In (12) is likely a mathematical representation used for this purpose. Let's denote the current position of a grasshopper i x_i.

$$x_i = Sa_i + Ga_i + Aa_i \ , \quad i = 1,2,\ldots,N \tag{12}$$

Where, x_i indicates the position of the i^{th} grasshopper, Sa_i represents the social interaction between grasshoppers, Ga_i denotes the gravitational force on the i^{th} grasshopper, and Aa_i is the wind advection. In (12) can be rewritten to introduce a random behavior of grasshoppers as (13):

$$Sa_i = \sum_{j=1, i \neq j}^{N} Sa_i(db_{ij})\hat{db}_{ij}, \quad db_{ij} = |xa_i - xa_j| \tag{13}$$

A range between i^{th} as well as j^{th} grasshoppers is indicated by in any situation db_{ij}, $db_{ij} = |xa_i - xa_j|$ denotes the Euclidean distance between $i^{th}$and j^{th} grasshopper, N denotes the number of grasshoppers, s, on the other hand, denotes the intensity of the social forces function, that can be expressed mathematically as (14):

$$Sa_i(y) = fe^{\frac{-y}{l}} - e^{-y} \tag{14}$$

Anywhere, $f \longrightarrow$ intensity attraction, and $l \longrightarrow$ scale with an appealing length, respectively. The social interaction among grasshoppers can be characterized by attraction and repulsion. Ga_i and Aa_i describes both gravity force as well as wind advection again for i^{th} grasshoppers, which could be quantitatively described as monitors.

$$Ga_i = -g\hat{e_g}, Aa_i = u\hat{e_w} \tag{15}$$

$$x_i = c(\sum_{j=1,i\neq j}^{N} c^{\frac{u-l}{2}} Sa_i(|x_j - x_i|)\frac{x_j - x_i}{d_{ij}}) + \hat{T}d \tag{16}$$

Wherever, $g \longrightarrow$ constant of gravitation and $u \longrightarrow$ constant drift, although $\hat{e_g}$ and $\hat{e_w}$ represent the wind direction and also the unity vector to the earth's center, $\longrightarrow$ Upper bound of the weight, $l \longrightarrow$ lower bound of the weight, $\hat{T}d$ $\longrightarrow$the best solution in the d^{th}dimension space, $Sa_i$is the social interaction between grasshoppers respectively.

Step 4: termination criteria After executing the optimization algorithm, the described processes, such as fitness evaluation, solution updates, and termination criteria, are repeated iteratively until the desired outcome is achieved. This outcome could be the identification of an optimal response or a set of characteristics that meet the specified criteria or objectives of the optimization problem. Once this optimized solution or set of features is obtained, it can be further analyzed, implemented, or utilized according to the specific goals of the optimization task.

4. RESULTS AND DISCUSSION

Assess the results of effective sentiment analysis utilizing one of the CDNN detailed in this chapter. The proposed methodology is implemented using Python, and a series of tests were conducted on a PC operating on Windows 7, equipped with a 2 GHz dual-core processor, 4 GB RAM, running a 64-bit version of Windows 2007.

4.1. Dataset description

4.1.1. Amazon product review

The 142.8 million reviews collected between May 1996 and July 2014 for the Amazon product review dataset encompass product reviews and Amazon-related information. This dataset provides diverse details about products, including their descriptions, categories, price, brand, and image properties. Furthermore, it includes links to related products that customers have viewed or purchased.

4.1.2. Electroencephalogram signal

The outcomes of our analysis are presented in this section using the CDNN-based efficient prediction technique for analyzing the sentiment of an EEG signal. For this study, we utilized EEG signal databases. The dataset contained 11,500 samples, with each sample having 178 properties that followed a normal distribution.

4.2. Evaluation result

Tables 3 and 4 present the accuracy and log loss values of the EEG signal and Amazon product review datasets across training, validation, and testing phases. Our suggested EEG signal dataset achieved a training data accuracy of 98.35% with a log loss of 0.045, while validation data accuracy and log loss were 98.20% and 0.046, respectively. For the test data, accuracy and log loss values were 98.20% and 0.057, respectively. On the other hand, the Amazon product review dataset exhibited training data accuracy and log loss of 98.55% and 0.054, respectively. Validation data accuracy and log loss were 98.35% and 0.058, while test data accuracy and log loss stood at 98.40% and 0.061, respectively. Our proposed system outperforms existing approaches based on these results.

Table 3. The EEG training, validation, and testing dataset's accuracy and log loss values

Dataset	Accuracy (%)	Log loss
Training data	98.35	0.045
Validation data	98.20	0.046
Test data	98.20	0.057

Table 4. The product review's training, validation, and testing of datasets' accuracy and log loss values

Dataset	Accuracy (%)	Log loss
Training data	98.55	0.054
Validation data	98.35	0.058
Test data	98.40	0.061

4.3. Experimental result

The performance of the suggested strategy when utilizing the following configuration is shown in the accompanying Figures 3 to 9. Figure 3 depicts the performance and comparative analysis of accuracy values. Accuracy serves as a measure of true outcomes within a general population, encompassing true positives or true negatives, and it evaluates the precision of data classification. The analysis indicates that our proposed methodology surpasses convolutional neural network (CNN), long short-term memory (LSTM), multiclass support vector machine (M-SVM), and bidirectional encoder representations from transformers (BERT) methods in terms of results.

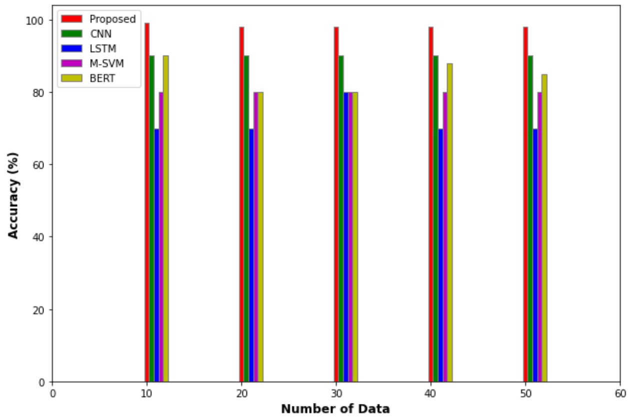

Figure 3. Performance and comparative analysis of accuracy

Figures 4 to 6 illustrate the precision, recall, and F-score plots. The analysis reveals that our proposed method exhibits consistent improvement across precision, recall, time, and F-score metrics when compared to other methodologies. These results demonstrate the superior performance of our proposed approach over CNN, LSTM, M-SVM, and BERT methods in terms of precision, recall, time, and F1-score rates.

Figure 7 scrutinizes the performance and comparison of log loss values. Log loss serves as a metric assessing the proximity of the predicted probability to the true number, typically 0 or 1 in binary classification. A higher log loss value signifies a greater disparity between the expected and actual probability. The analysis reveals that our proposed methodology outperforms CNN, LSTM, M-SVM, and BERT techniques in terms of performance.

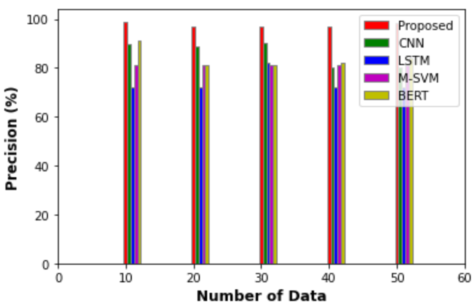

Figure 4. Performance and comparative analysis of precision

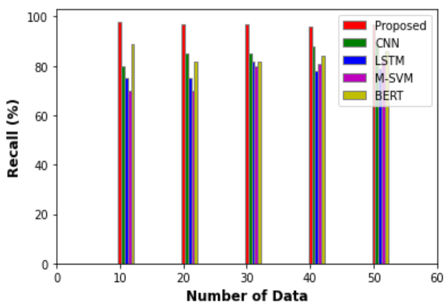

Figure 5. Performance and comparative analysis of recall

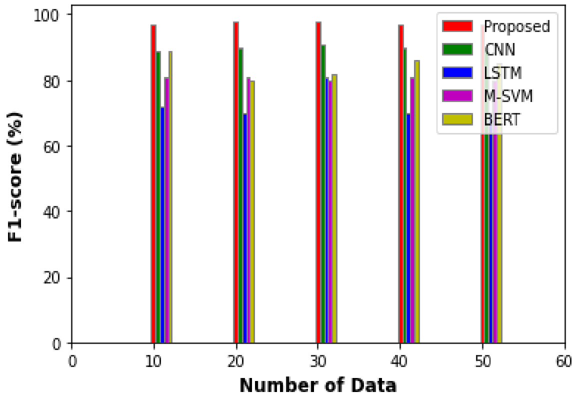

Figure 6. Performance and comparative analysis of F1-score

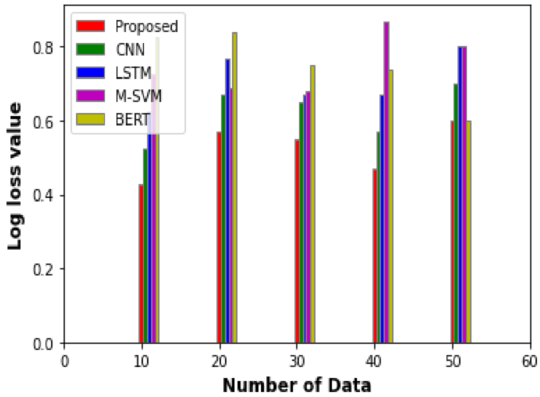

Figure 7. Performance and comparative analysis of log loss value

In Figure 8, our proposed methodology is juxtaposed with other existing techniques including CNN, LSTM, M-SVM, and BERT, employing performance analysis and comparing RMSE values. Root mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently employed statistic for evaluating the accuracy of a model or estimator by comparing projected values with observed values. Typically, a smaller RMSE is preferred over a larger one. The analysis indicates that our proposed methodology outperforms the other methods, showcasing superior results.

Figure 9 illustrates a performance analysis and comparison of R-score values. The R-squared statistic quantifies the proportion of variance in a dependent variable. Our proposed methodology is juxtaposed with existing methods including CNN, LSTM, M-SVM, and BERT. The analysis demonstrates that our proposed technique yields significantly superior results compared to these existing methods.

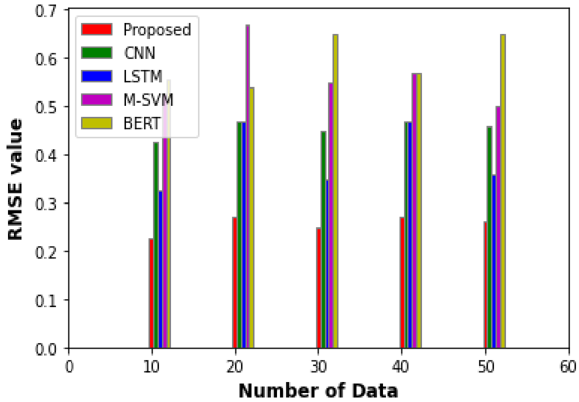

Figure 8. Performance and comparative analysis of RMSE value

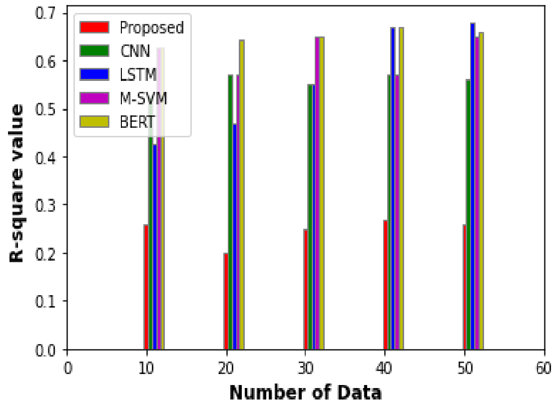

Figure 9. Performance evaluation and comparison of R-score value

4.4. Comparative analysis

We conducted a comparison between our proposed method and existing methodologies documented in the literature, alongside evaluating our proposed method. Although different datasets are utilized across various techniques, their performance serves as a crucial benchmark for gauging the effectiveness and applicability of our proposed approach. Notably, EEG signals and Amazon product reviews are among the most widely employed datasets. Our classification algorithm achieved comparable performance to all these strategies in terms of accuracy and area under the curve, with less complexity in the feature extraction step. This can be attributed to the proposed approach's efficacy in effectively mining the underlying distribution patterns of the data, as demonstrated by the results presented in Table 5.

Table 5. Comparison of the suggested algorithm with cutting-edge methods conducted by analyzing several performance metrics

State-of-the-Art-Work	Year	Accuracy	Sensitivity (%)	Specificity (%)	RMSE	R-square
MM framework	2017	80.19%	80.19	80.19	Minimum	Average
ADASYN	2016	98%	97	97	-	-
DEAP	2012	High	-	-	-	-
EP-SVM	2014	High	-	-	-	-
ERP	2011	Medium	89.00	89.00	-	0.80
NCA	2018	Low	-	-	-	-
R-CNN	2019	86.4%	86.4	86.4	-	-
SAP	2017	High	-	-	-	-
SACF	2019	Medium	85	85	-	0.7
SA-SPP	2017	Medium	-	-	-	0.88
Random forest model	2017	Medium	-	-	0.714	0.68
Proposed	-	99.00	98.0	98.0	0.234	0.200

5. CONCLUSION

The focus of this paper is an efficient prediction technique that combines sentiment analysis of product reviews and EEG signals using a CDNN. The proposed methodology includes preprocessing steps for both EEG signals and Amazon product review datasets, followed by feature extraction and classification utilizing the CDNN. Optimization of the CDNN is accomplished through the EGOA. To evaluate the proposed methodology, it is compared to other existing techniques such as CNN, LSTM, M-SVM, and BERT. The results show that the suggested approach surpasses these alternative techniques and delivers satisfactory outcomes.

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BIOGRAPHIES OF AUTHORS

Rahul Kumar Sharma is a research scholar in the School of Computing Science and Engineering at Galgotias University, Greater Noida, India. He is currently working as an Assistant Professor in the Department of Computer Science and Engineering, KIET Group of Institutions, Ghaziabad, India. He has completed his B.Tech. from Priyadarshini College of Computer Science and M.Tech. degree from Shobhit University, Meerut, India. He has various research papers in various refereed journals and international conferences. He has published several national and international patents. He can be contacted at email: rahulpccs1988@gmail.com.

Arvind Dagur is currently working as Professor and Program Chair in the School of Computing Science and Engineering, Galgotias University, Greater Noida, India. He worked as a Professor and Dy. Head, in the Department of Computer Science and Engineering, KEC (KIET Group) Ghaziabad. He completed his Ph.D. (Computer Engineering) from Jamia Millia Islamia, New Delhi, India (A Central University), M.Tech. (Computer Science and Engineering) from MNNIT, Allahabad, and B.Tech. (CSE) from UPTU Lucknow. He has published more than 40 research papers in reputed international journals and conferences. His research papers are indexed by SCI, SCOPUS, DBLP, and UGC approved journals. He has also published 5 book chapters in Springer Book series such as LNCS, AICS Series, and LNICST. He has chaired many conferences and many sessions in various conferences. He also served as reviewer of many conferences and journals. He can be contacted at email: arvinddagur@gmail.com.