Enhancing Opinion Mining In Social Media Using A Multi-Edge Adaptive Deep Convolutional Neural Network Integrating Text And Emojis For User Sentiment Prediction

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Abstract

In the social media age, understanding and evaluating user sentiment is essential for various uses, including public opinion tracking, customer feedback analysis and marketing. Since social media sites like Twitter have become well-known forums for people to share their thoughts and feelings on various subjects, precise sentiment analysis of textual material combined with emojis may provide a detailunderstanding of user sentiment. The paper introduces a novel Twitter sentiment prediction method, utilizing a Multi-Edge Adaptive Deep Convolutional Neural Network (MADCNN) and an emoji sentiment lexicon, which serves as the foundation for the sentiment analysis model. The preprocessing stage comprises stop word removal to remove noise from the text data, and we use Word2Vec for feature extraction to capture the semantic meaning of words and emojis. Our emoji sentiment lexicon strengthens the sentiment analysis by linking emojis with emotion scores. The MADCNN framework is designed to handle social media data, which includes text and emojis. It incorporates multiple edges for processing text and emoji inputs separately, allowing the model to extract nuanced sentiment information from both textual and non-textual elements of posts.We evaluate the effectiveness of the suggested method by contrasting it with existing sentiment analysis approaches, employing evaluation metrics including precision, recall, confusion matrix, f1-score, and accuracy. The results indicate that the suggested MADCNN performs more than conventional techniques. The suggested MADCNN, in conjunction with the emoji sentiment lexicon, provides a strong tool for predicting user opinions.

Keywords: User Opinions, Sentiment Analysis, Social Media, Multi-Edge Adaptive Deep Convolutional Neural Network (MADCNN)

1. Introduction

Social media is becoming a key source of information on various challenges and an essential information-sharing platform. Online multimedia content shared on social media platforms that promote individual participation and community curation is referred as social multimedia [1]. In the big data era, enormous quantities of multimedia data are created on social networks.

Recognizing the data included in social multimedia is important as it's needed for many fascinating uses, such as user behavior research and forecasting [2]. Since sentiment analysis is essential to thinking, analysis, creativity, and decision-making processes, it has gained importance in today's world because of the large number of visual content available in social networks. Opinion mining studies people's thoughts, needs, beliefs, and feelings. Opinion mining becomes difficult to handle and manipulate due to the informal nature of human conversation. It expresses the ways that customers have opinions about an organization [3].

Customer reviews indicate the fact that the product should be purchased. Customers who shop online depend on product reviews from blogs and other media platforms, which help them to decide what to buy. Opinions can differ greatly based on a person's living location, taste, money, and other factors [4]. An opinion of a given product varies amongst blogs and social networks. Sentiment analysis, widely regarded as a natural language processing (NLP) approach, attempts to extract and identify the emotional states or subjective judgments from texts. Sentiment analysis fundamental duties include classifying a text's orientation and identifying when a phrase communicates a positive, negative, or neutral feeling. Sentiment analysis tasks involve a variety of classification techniques due to the development of machine learning (ML) and deep learning (DL) [5]. Due to the popularity of camera-enabled portable gadgets and social media platforms, multimedia content, encompassing images and videos, has acquired a crucial role in conveying individuals' emotions and viewpoints in social networks. Consequently, sentiment analysis for social multimedia has emerged as a prominent facet within the realm of Natural Language Processing (NLP), establishing interconnections with computer vision, pattern recognition, and other artificial intelligence (AI) domains [6]. Opinion mining in social media refers to obtaining and understanding user thoughts and views from the diverse and ever-changing social media environment using text and emoji analysis. The study's objective is to recognize, categorize, and interpret user feelings using sophisticated NLP methods. This allows for an enhanced understanding of public perception, preferences, and responses.

Contribution of the study

- Initially, we started gathering the Twitter dataset and data preprocessing method called stop word removal used to preprocess the data. The feature extraction process uses Word2Vec, making extracting semantic meaning from text and emoji data feasible.
- We introduce an innovative method called MADCNN to predict user sentiment in text and emoji.
- When managing social media data, the MADCNN architecture processes textual and non-textual inputs and extracts complex sentiment information from postings.

The structure of the paper as follows: Section 2 presents a summary of relevant literature, highlighting the existing research in the field. Section 3 provides a deeper explanation of the methods employed, offering a comprehensive understanding of the techniques used in the study.

The results and analysis are detailed in Section 4. Section 5 provides a conclusion, emphasizing the implications of the study's outcomes and suggesting potential directions for future research.

2. Related works

The study [7] investigatedemojis' potential to enhance automated sentiment analysis in text messages. The study focused on Arabic-language tweets, which were spoken but had a difficult morphology and limited reliable sources for sentiment analysis. The study [8] provideddistinctive method for predicting people's views using textual tweets and emoticons. They create an emoji sentiment lexicon as a result. The study [9] suggested a creative method for sentiment analysis in social media evaluations to address the problem. The input dataset was first preprocessed using tokenization, lemmatization, Stop Word elimination, and URL removal. The final characteristics were evaluated according to their significance. The study [10] suggested an emoji vectorization technique to produce emoji vectors, which could be used to categorize emotions of microblog evaluations using emojis in microblog social networks. Then, a sentiment analysis model called ET-BiLSTM (emoji-text integrated bidirectional LSTM) is demonstrated. A bidirectional LSTM network generated sentence representations based on review text in this model. The study [11] utilized a URL-based security method to gather 600 million public tweets, and they performed feature generation for sentiment analysis. The outcomes of user-sent tweets are collected, and the ternary classification is performed using preprocessing techniques.

The study [12] demonstrated the creation of an opinion-mining module. A dataset of opinions with tags for emotions was created to develop the module. A module for opinion mining has been placed into location, which analyses statements connected to computer programming and determines the kind and polarity of emotions expressed in them. Finally, the prior section was integrated into an intelligent learning environment. The study [13] illustrated an investigation of sentiment analysis on social media data to detect anxiety or despair using a variety of AI approaches. With several AI approaches, the study probed social media data texts, emoticons, and emojis for sentiment detection. Multi-class classification using the DL algorithm demonstrates a greater accuracy value during sentiment analysis. The study [14]suggested a novel approach to sentiment analysis called Domain Specific Ontology, which was grounded on common sense. Based on ConceptNet, they developed their own Oman tourist ontology. The tagger was used to extract entities from tweets, and those things were compared to concepts in the ontology related to the subject. In addition, the integrated sentiment lexicon technique determines the emotional state of the retrieved instances. Semantic orientations of domain-specific characteristics are blended concerning the domain. The study [15] introduced a sustainable machine intelligence method for mining Twitter opinions that focused on creating a conscious feedback loop. The outcomes of their experiments show their method works for categorizing tweets into categories for positive, negative, and neutral moods.The study [16] aimed to provide a methodology for examining emotional reactions to actual Twitter data. The data used in the proposed model was gathered for empirical research using the TWEEPY crawler, and it is based on supervised machine learning methods. Preprocessed, trimmed, and fed into several supervised models is collected data was used. Sentiment was assigned to each tweet according to the user's emotions: neutral, negative, or positive.

3. Methodology

A Twitter dataset was first collected for study, and the dataset followed meticulous preprocessing using stop word removal methods.Next, we use word2vec for feature extraction. The study concentrated on integrating the text and emoji using MADCNN to predict user sentiment. The results demonstrate the method's effectiveness in overcoming the difficulties associated with opinion mining. Figure 1 depicts the flow of the proposed methodology.

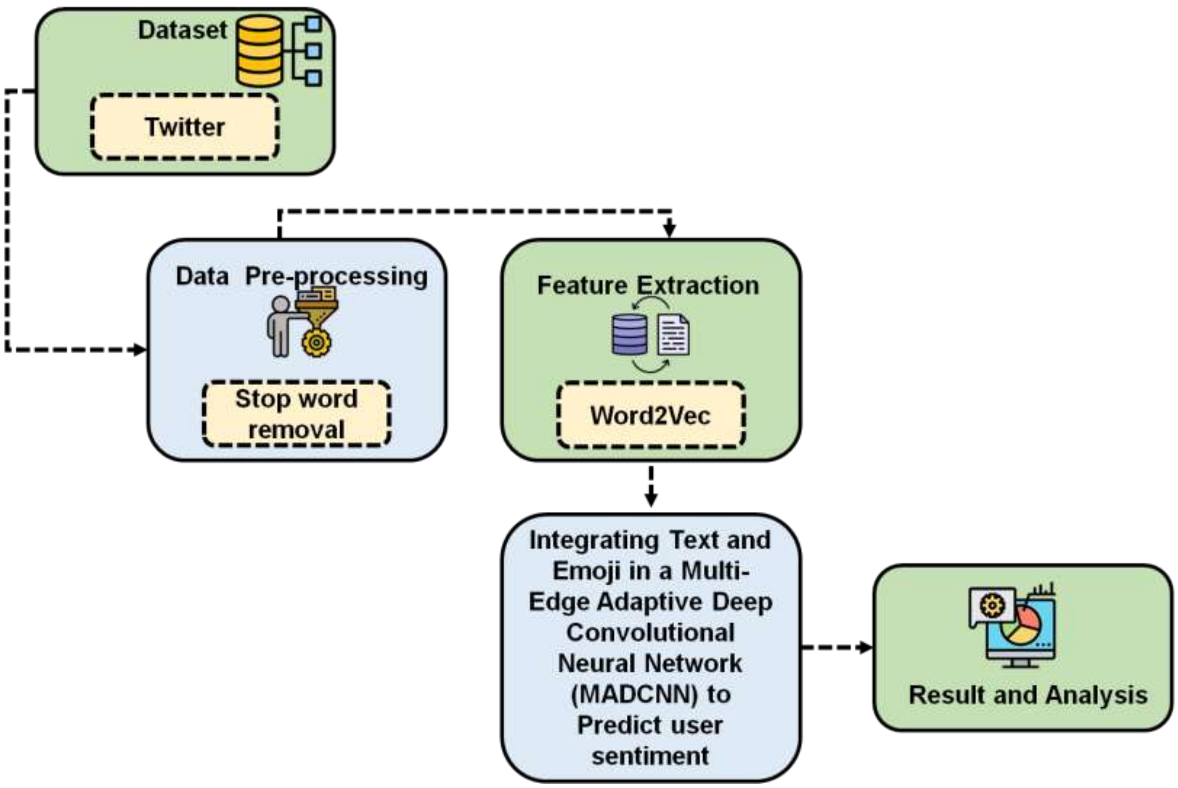


Figure 1: Proposed flow

3.1.Dataset

The research gathered the dataset from Twitter [17]. 164,880 Twitter tweets are included. Each tweet also consists of an emoji among the 35 most popular emojis, along with textual, graphic, and regional information. A list of keywords associated with YouTube and its videos was used to stream the raw dataset from Twitter API, from which the dataset is gathered. We create a prediction task in the experimental setup based on the 35 chosen emojis and their tweet locations.

3.2.Data preprocessing using stop word removal

Stop-words are usually recurring terms in a natural language regarded as irrelevant in specific applications related to NLP, such as information retrieval, text summarization, clustering, etc. Before analyzing files and queries, almost all text preprocessing systems eliminate the stop words.

As a result, system performance is improved. Terminology Based Random Sampling (TBRS) is one of these techniques used to preprocess the files. The method is to identify the stop words from online texts manually. Using a random selection process, this function iterates across distinct data segments.

$$t_y(d) = t_y(d).\log_2 \frac{B_y(d)}{b(d)} \quad (1)$$

$t(d)$is the normalize term incidence of d across the compilation, while $t_y(d)$ is the normalize term occurrence of a term d inside a mass y. The closing stop list is created after eliminate any potential duplication and selecting the least edifying phrases crosswise all chunks.

3.3.Feature extraction

Word2Vec is a feature extension bag of word (BOW) and skip-gram architectures intended to acquire non-numerical input and convert it back to numeric data. Numerous persons have been utilized as features for various text classification tasks since Mikolov's publication of Word2Vec for word embedding. Word2Vec appears in prance Gram and Continuous Bag of Words (CBOW). Using words as input, the skip-gram model attempts to predict the target context. The goal of CBOW is to predict the output when providing context based on the information, which is the reverse of Skip-gram. Words have been assigned to the center word to improve likelihood in context, and an attempt is scheduled to compute the maximum probability. The probability can be estimated and described using the following equation:

$$(\theta) = \prod_{d=1}^{D} \prod_{-n\leq i\leq ni\neq 0} B(U_{d+i}|U_d;\theta) \quad (2)$$

We define the window after determining the location of the word's intendedtarget in the first stage. Generate predictions for the target words inside a fixed-size-n window for each point $d = 1, \dots D$(corpus). A word can be described using the following equation to calculate the probability of context:

$$B\left(U_q \middle| U_j\right) = \frac{\exp\left(w_q^D c_v\right)}{\sum_{u=1}^{c} \exp(w_u^D c_v)} \quad (3)$$

The vector representation of the center word is denoted by C, whereas the context word is represented by W. The softmax function produce V, and the center target word provide q. Its probability is converted by the softmax process by normalizing it over the entire lexicon. In the subsequent stage, the Word2Vec output can be utilized for feature expansion. The expansion algorithm looks for rows in the corpus with a similarity vector with the word in concern.

3.4.Integrating Text and Emojis in a Multi-Edge Adaptive Deep Convolution Neural Network (MADCNN) to Predict User Sentiment

Using a different supervised corpus, the proposed MADCNN model that interpreting text and emoji for sentiment analysis. By examining each character individually, the embedding is created from the beginning. The word-level embedding and BOW techniques are intended to be defeated by text-level embedding.

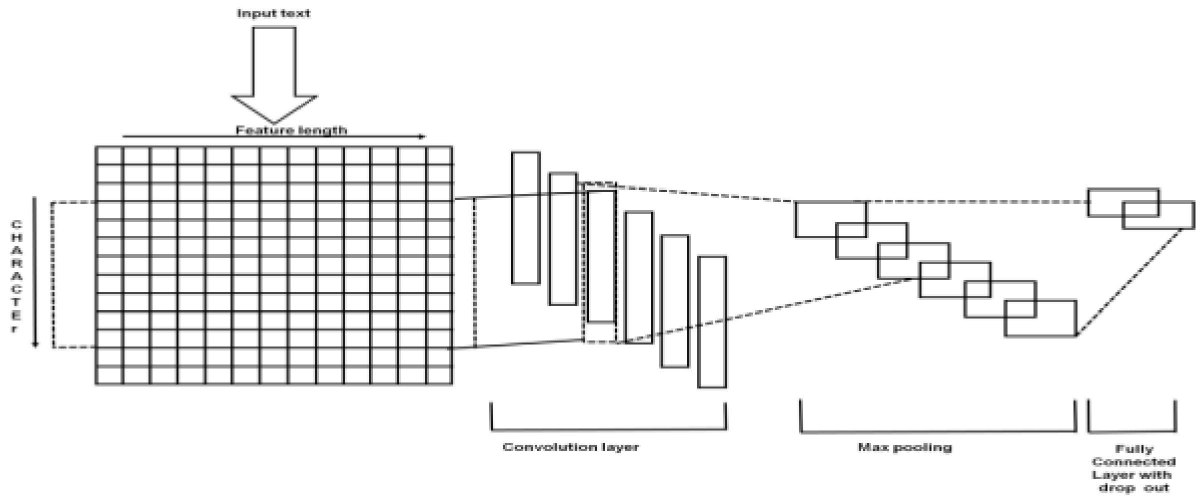


Figure 2: Structure of MADCNN

The structure of MADCNN network is shown in Figure 2. Convolution networks can be used on a sentence without understanding its linguistic semantics. Thus, character-level embedding in MADCNN enables cross-language work without requiring knowledge of a word's definition. The input is processed at the character level by the convolution layer. As a result, the character sequence is conveyed as fixed-length vectors. The character sequence that transfers to the character matrix$V \in K^{t\times|C|}$, while the format of sentences for the original tweet is specified as$G \in K^{t\times|G|}$, serves as the input for our model. It gets transmitted to the convolutional layer, which uses the filter $L \in K^{t\times n}$ to transmit the convolution process. The action of the convolution layer is represented as,

$$p_i = (G * L)_i \tag{4}$$

$$= \sum_{r,j}(G_{[:i-n+1:i]} \otimes L)_{rj} \tag{5}$$

Where the matrix of the phrase is defined by $G_{[:i-n+1:i]}$, column size (n), and $\otimes$ indicatesamatrix multiplication performed element-by-element. As a result, the productionp_i specifies the partially manufactured goods of the phrase matrix's column matrix and the filter$L$. The sentence matrix and single filter are defined by the preceding equation, where the feature matrix $L \in K^{n\times(|G|-n+1)}$is obtained by using a set of filters. Following the convolution procedure follows the corrected activation function. In this instance, the ReLU procedure produces feature maps with positive values. By using this technique, the network is trained to provide correct results. The definition of the pooling operation is:

$$p_{pool} = \begin{bmatrix} pool(\alpha(p_1 + s_1 * a)) \\ \ldots\ldots\ldots. \\ pool(\alpha(pm + sm * a)) \end{bmatrix} \quad (6)$$

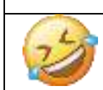
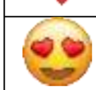
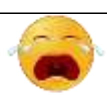
This operates on the form's columns containing the feature map:
$swimmingpool(o_j): K^{1\times|G|-n+1} \rightarrow K.$

$$B(x = i|y, c, p) = softmax_i(y^D u + p) \quad (7)$$

$$= \frac{a^{y^D u_i + p_i}}{\sum_{r=1}^{R} a^{y^D u_r + p_r}} \quad (8)$$

Where the mass vector and the matrix's prejudice value are defined by the variables $u_r$and p_r.To represent emojis using lexicon-based scores, we used the sentiment-based lexicon Emoji-Ranking Sentiment (ESR) for emojis. An 81 annotated the tweets with a neutral (0), positive $(+1)$, or negative (-1) classification. Emojis are assigned three $\{b- = M_-/M, b_q = M_o/M, b_+ = M_+/M\}$ based on the sentiment of tweets in which they appear. These values indicate the possibility of an emoji appearing in a particular sentiment category.M_- denotes the amount of times an emoji appear in a tweet with a negative sentiment, $M_+$and Mo indicates the amount of times an emoji appear in a tweet with a neutral sentiment, M_+ is the amount of times, an emoji appears in a tweet with a positive sentiment, and $M = M_- + M_q + M_+$. Each emoji's sentiment score is determined using the formula $gg = M_+ - M_-$. The top 5 emojis in the language are shown in Table 1.

Table 1: The top 5 emojis in the language

Figure [twemoji]	**Code point in Unicode**	**Amount [5... well]**	**Locatio n [0...1]**	**Neg [0....1]**	**Neut [0...1]**	**Pos [0....1]**	**Achiev e [-1..+1]**
	0x1f602	14622	0.805	0.247	0.285	0.468	0.221
	0x2764	8050	0.747	0.044	0.166	0.790	0.746
	0x2665	7144	0.754	0.035	0.272	0.693	0.657
	0xf60d	6359	0.765	0.052	0.219	0.729	0.678
	0xf62d	5526	0.803	0.436	0.220	0.343	-0.093

The number of occurrences and scores are used to extract the feature vectors. In tweet i, for emoji j, Fi_{ji} is calculated as:

$$i_{ji} = ai_{ji} * gg_j \quad (9)$$

Where ai_{ji} represents the frequency of emoji j in the tweet, i and gg_j denote the lexiconof the emoji's emotion scores.

4. Result and discussion

The study results are described in this section, along with a description of the MADCNN method, which seeks to provide an entire solution to predict user sentiment in text and emojis using criteria such as accuracy, precision, recall, F1-Score, and confusion matrix.

4.1.Accuracy

Accuracy is essential while estimating the user sentiment in text and emoji settings. Through meticulous training and fine-tuning of sentiment analysis models on various datasets, people can accurately identify moods. Using complex algorithms that consider the advantage of the distinctive characteristics of language and visual representations could enhance sentiment prediction accuracy and gain a greater understanding of user input and feelings. Table 2 and Figure 3 depict the accuracy of the suggested system.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (10)$$

Table 2: Mathematical outcome of accuracy

Methods	Accuracy (%)
CNN+LSTM [18]	88
Multi-Class SVM [19]	75
SWN+GB [20]	80
MADCNN [Proposed]	96

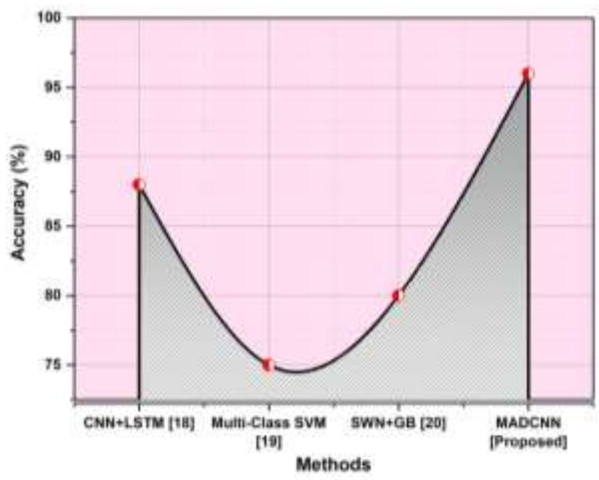


Figure 3: Accuracy comparison between existing and proposed

4.2.Precision

The percentage of detected positive or negative feelings among predicted positive or negative emotions can be measured by assessing the precision of sentiment analysis algorithms. Enhancing the model's capacity to identify certain emotions is necessary to maximize precision, which can result in more reliable and perceptive evaluations of user input and emotions.The precision of the suggested method is demonstrated in Table 3 and Figure 4.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FN}} \tag{11}$$

Table 3: Mathematical outcome of precision

Dataset	Precision (%)			
	CNN+LSTM [18]	Multi-Class SVM [19]	SWN+GB [20]	MADCNN [Proposed]
1	80	83	89	92
2	82	89	83	91
3	91	90	89	93
4	86	89	83	90
5	81	83	86	95

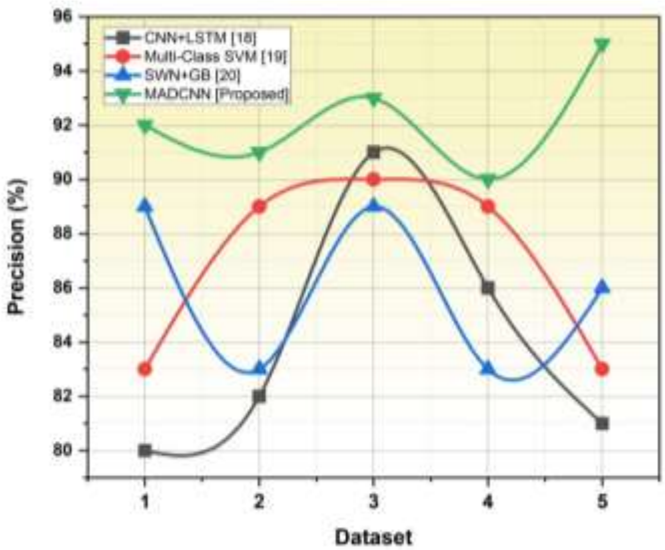


Figure 4: Precision comparison between existing and proposed

4.3.Recall

Assessing the model's capacity to detect each occurrence of positive or negative sentiment in the dataset highlights the importance of recall as a pivotal metric in user sentiment prediction. It is important to maximize memory and provide an accurate representation of user emotions and input while optimizing the model to find many instances of the target mood as practical.The proposed system's recall is shown in Table 4 and Figure 5.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{12}$$

Table 4: Mathematical outcome of recall

Dataset	Recall (%)			
	CNN+LSTM [18]	Multi-Class SVM [19]	SWN+GB [20]	MADCNN [Proposed]
1	78	80	87	91
2	80	85	88	93
3	79	80	83	89
4	79	85	86	90
5	75	82	89	95

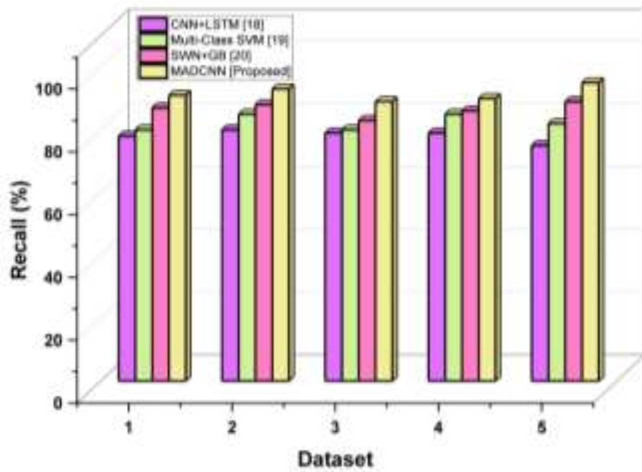


Figure 5: Recall the comparison between existing and proposed

4.4.F1-Score

The F1-Score combines accuracy and recall into consideration to provide a comprehensive evaluation of the model's ability to identify and classify user sentiments. A balance between precise sentiment detection and thorough sentiment coverage is needed to maximize the F1 score, resulting in a more reliable and robust analysis of user sentiments and comments.Table 5 and Figure 6 show the proposed system's F1-Score.

$$\text{F1 Score} = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP}+\text{FN})} \tag{13}$$

Table 5: Mathematical outcome of F1-Score

Methods	F1-Score (%)
CNN+LSTM [18]	64
Multi-Class SVM [19]	85
SWN+GB [20]	78
MADCNN [Proposed]	93

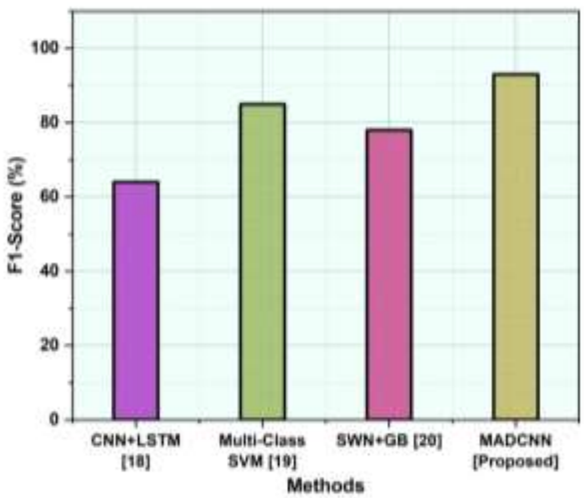


Figure 6: F1-Score comparison between existing and proposed

4.5.Confusion matrix

The confusion matrix is an essential tool for evaluating the effectiveness of sentiment prediction algorithms in text and emoji settings. Presenting the true positive, true negative, false positive, and false negative predictions provides a comprehensive overview of the model's predictive skills. By examining the confusion matrix, one can gain a greater understanding of the model's advantages and disadvantages. Thiscan help improve methods for enhancing sentiment analysis's precision and dependability, improving how user sentiments and feedback are evaluated.Figure 6 depicts the confusion matrix of the suggested system.

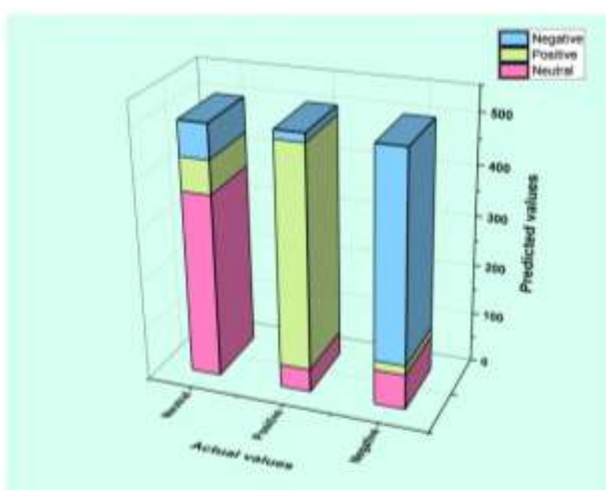


Figure 7: Confusion matrix of MADCNN

4.6.Discussion

Due to their primary focus on pattern recognition and sequential data processing, the Convolutional neural network+ long short-term memory (CNN+LSTM) [18] could not fully interpret the contextual nuances of both text and emojis. Multi-class support vector machine (SVM) [19] could operate less when handling complicated user views because it can be difficult to grasp the minute linkages and dependencies observed in textual and emoji-based feelings. SentiWordNet+Gradient Boosting (SWN+GB) [20] consists of its incapacity to classify emotion because it needs to understand the contextual complexities and details of current language usage. The use of MADCNN in social media platforms and other text-rich contexts improves the model's capacity to extract complex sentiment patterns, improving sentiment analysis's accuracy and dependability.

5. Conclusion

Opinion mining on social media is collecting and examining user-expressed views, attitudes, and emotions from various social media platforms. The MADCNN framework facilitates complex sentiment extraction from different user-generated material on social media and other platforms by processing text and emoji inputs independently. This method provides a greater understanding of user opinions and ideas by using emoji's emotional impact and capturing the semantic meaning of textual information. The parameters show the accuracy of the proposed methods (96%), precision (95%), high recall (95%), and F1-score (93%) and produce accurate predictions that are close to the actual values. The rapid development of online language and the release of new emojis can influence sentiment analysis's accuracy in maintaining consistent sentiment lexicons.The precision and dependability of sentiment analysis models should improve with advances in NLP and machine learning methods, allowing for more sophisticated understanding of user attitudes in various linguistic and cultural situations.

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