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Article

A Hybrid Deep Learning Framework for Sentiment Analysis of Social Media's Heterogeneous Data

Seema Rani[1], Manoj[2*], Sunila Godara[2], Sanjeev Kumar[2], Jai Bhagwan[2], Yati[2], Rajat[2]
[1]State Institute of Engineering & Technology, Panchkula, Haryana, India.
Sirsa, India.
Email: seemarajput1028@gmail.com.
[2]Department of Computer Science & Engineering, Guru Jambheshwar University of Science & Technology, Hisar, India.
[*] Corresponding Author : Manoj, manojkoslia91@gmail.com.

Abstract: Sentiment analysis of social contents posted by people has become an essential task for understanding public opinion, customer feedback, and brand perception. However, the informal nature of Twitter (X) posts, short textual contents and the visual information make sentiment analysis a challenging task. This paper proposes a deep learning model for sentiment analysis of Twitter data using CNN. The textual sentiment analysis has been done using LSTM and CNN has been used for graphical data. The proposed framework uses inclusive preprocessing, tokenization, feature extraction, word embedding and deep feature learning to improve the results of while reducing noise and training complexity. Our experiment evaluation demonstrates that the LSTM model achieves 99% training accuracy and 94% validation accuracy for textual sentiment analysis. The CNN model improves the graphical sentiment analysis by improving overall accuracy from 92.48 to 94.92% compared to conventional CNN approach. The proposed framework also improves precision, recall, and F1-score across multiple sentiment classes. The results demonstrate that the combining deep learning architecture for textual and graphical modalities provides a robust and scalable solution for multimodal sentiment analysis using twitter data.
Keywords: CNN, Deep Learning, Opinion mining, Sentiment analysis, Twitter data.

1. Introduction

Sentiment analysis may be utilized in advertising, customer service feedback and healthcare and other fields. The current study analyzes Twitter users' emotions. We categorize data using a CNN and a textual-trained LSTM in this work. Training a neural network using textual input may improve response accuracy. Many pleased consumers are polled in emotional research. The sentiment analysis technique may solve the challenges of quantifying human emotions, customers satisfaction etc. The modeling efforts have yielded a Twitter data mood assessment method. Many scientists are in the opinion that the sentiment analysis strategy may provide more accurate and reliable outcomes than the standard and ordinary methods. Text mining is utilized to extract relevant information from online product reviews which is a rich source of consumer input. Several computational linguistics experiments are covered in the literature in past. Sentiment analysis may be utilized for healthcare services, internet and social media platforms, review and survey responses, and more. This might benefit medical, advertising, and business marking and planning services. Many researchers have examined how to use Twitter sentiment analysis effectively. Sentiment analysis may be applied to numerous consumer resources, making it valuable in advertising, research, healthcare, and customer service. Recent technological developments are transforming the world dramatically [1]. Everyone needs the Internet nowadays, online platforms like Instagram, Facebook and other platforms for entertainment and message spreading and advertisement purposes. These platforms become more and more popular day by day. So, many people are utilizing them to express their opinions and complaints about the world. Consumer responses to public services, products, etc. must be collected and studied. Sentiment analysis is used in discussion preparation to determine the feelings behind different texts' opinions. Several sentiment analysis tools employ machine learning techniques for decision making.

1.1 Natural Language Processing

People are studying NLP research and implement it to make the machines more intelligent. These techniques are becoming popular day by day and the goal of these techniques is making the machines quite intelligent like human beings. That mean the machine automatically should understand different types of texts, signs etc. and convert those in understanding form irrespective of geographical areas.

Lots of people are using AI to make things like chatbots, voice interfaces etc. NLP is one of the most important technologies of 4th Industrial Revolution and has become a popular field. There are a lot of useful applications that come from the field of NLP [2]. From simple to complicated these can be found in many places. A sub-field of NLP called Sentiment Analysis is called "opinion mining", "emotional AI", or "sentiment mining". It is used to find and extract opinions from text across different types of media like blogs, reviews, social media, forums, news, and many more.

1.2 Neural Network

ANN is a kind of AI that can emulate brain's computational abilities to solve the complex problems. With the use of linked nodes grouped in a hierarchical structure evocative to the human brain the DL is a form of ML. The DL methods cannot function without NN. The neural network structure has been borrowed from the brain of human beings. Its structure is almost same as like as human's brain. The input, output, and hidden layers make up the neural networks simplest. There is a node at each layer that connects to the one below it, creating a network of nodes. For the human brain's neural network, the node is the equivalent of a neuron. It is facilitating the identification, classification, and enhancement of patterns. Countless fields could benefit from this type of data processing from fighting credit card fraud to improving medical diagnoses. Neural networks which humans use to classify items, make predictions etc. are called as multi-layer networks of neurons [3][4].

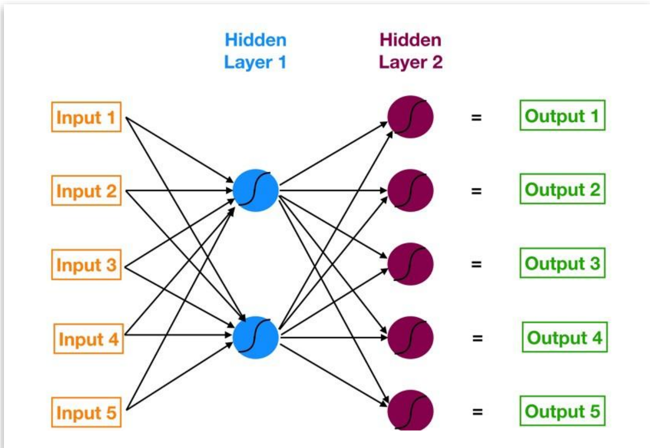


Fig. 1. Neural Network

Figure 1 depicts a simple neural network consisting of five inputs, five outputs, and two layers of hidden neurons. Being the backbone of machine learning, the deep learning algorithms rely heavily on ANN. They are modeled like real neurons and act similarly to send and retrieve the signals or information.

1.3 Sentiment Analysis Approach for Prediction

Emotions and other forms of subjective data may be identified and quantified. Opinion mining and emotional artificial intelligence are known as other names for sentiment analysis. Review and survey data, as well as internet and social media content, healthcare documents are all common sources for sentiment analysis. It has wide-ranging applications in business, healthcare, IT application business, and helping customers to choose right products and services. NLP and biometrics may be used to extract, quantify, and assess emotional states and subjective data in real life usages and research. When referring to the study of customers' attitudes towards certain goods or services, the terms opinion mining and SA are sometimes used interchangeably. Sentiment analysis examines how individuals communicate their feelings about a topic, person, or an object. Expressions may be positive, negative, or neutral. Natural language processing uses sentiment analysis to automatically extract text feelings or views to classify the feeling as positive, negative, or neutral. This technique is vital to understanding public opinion, consumer feedback, and social media engagement [5]. Traditional ML models like Naive Bayes and Support Vector Machines as well as more advanced deep learning models like RNNs, LSTMs, CNNs, and transformer-based models like BERT and GPT can be used for predictions. Sentiment analysis may measure brand perception, product reviews, and social media sentiment etc. Tokenization and text representation utilizing word embedding or TF-IDF are necessary for its efficacy. Adapting to changing language patterns and predicting sentiment requires continuous monitoring and model modification.

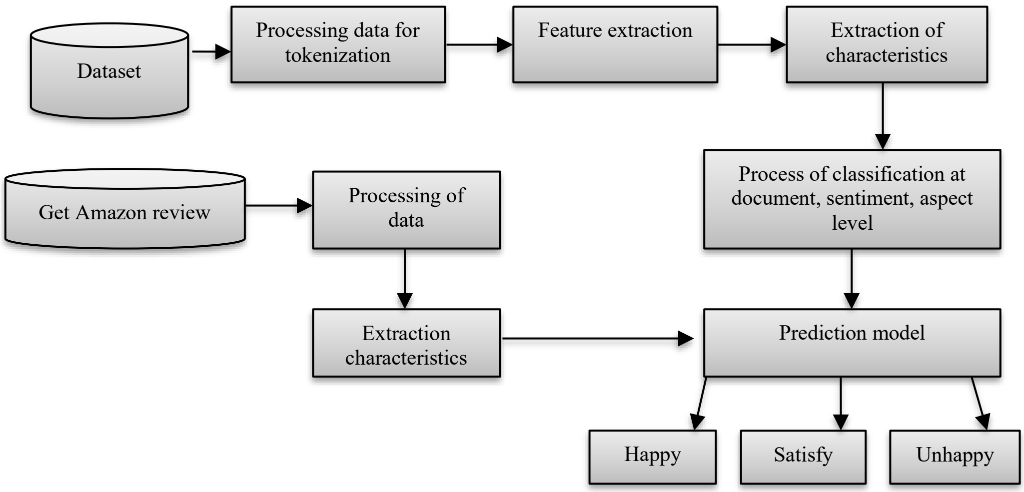


Fig. 2. Prediction Model for Sentiment Analysis

Figure 2 [11] represents prediction model used for sentiment analysis in this research. In this model, firstly data is preprocessed for tokenization, and then features are extracted in order to get the characteristic that supports classification at document, aspect, sentiment level. After this, the predication model predicts happy, satisfy and unhappy state of people. The Amazon's real world dataset has been used for experiments purpose and it is processed by the prediction model to declare sentiment. Opinion mining and sentiment analysis both approaches related to natural language processing (NLP) computer algorithms are used to identify and extract attitudes, feelings, and opinions from text. The main objective of sentiment analysis is to understand the subjective information in the text and labeling it as good, negative, neutral, or sometimes more nuanced emotions. The main parts and features of sentiment analysis are as follows:

1) *Text Input:* Sentiment analysis primarily works with textual data including user reviews, social media posts, customer feedback, articles, and any other form of written communication available on various sources.

2) *Natural Language Processing:* NLP techniques are employed to process and analyze text and breaking it down into meaningful components such as words, phrases, or sentences etc.

3) *Feature Extraction:* Sentiment analysis involves extracting relevant features from text which may include words, phrases, or even context-related information. These features are used to identify patterns indicative of sentiment.

4) *Classification:* After the feature extraction a machine learning model classifies the text into predefined sentiment categories. Common classes include positive, negative, and neutral sentiments.

5) *Machine Learning Approaches:* Machine learning algorithms are often used in case of sentiment analysis and other areas as well. Supervised learning involves training a model on labeled data where the sentiments are known and then using the trained model to predict unknown data.

6) *Rule-Based Approaches:* Rule-based systems use predefined linguistic rules and patterns to identify sentiments. These rules may include the presence of specific words, sentiment lexicons, or syntactic structures associated with positive or negative sentiments.

7) *Sentiment Polarity:* The sentiment polarity represents the overall sentiment expressed in the text. It can be binary (positive or negative), ternary (positive or neutral or negative), or more granular depending on the level of detail required.

8) *Applications:* Brand tracking, consumer feedback analysis, social media tracking, product evaluations, market research, and many more uses are a few of the numerous that sentiment analysis may be placed to use for. In order to manage their reputation, making educated judgments, and comprehend consumer sentiment, businesses use sentiment analysis.

Sentiment analysis is a valuable tool in the field of natural language processing helping businesses and organizations to gain insights into public opinion, customer satisfaction, along with overall sentiment toward products, services, or topics etc.

1.4 Different Types of Sentiment Analysis

Sentiment analysts assess textual opinions such as positive, negative, or neutral. This may be done by phrase, feature and document. Sentiment classification specialists evaluate pleasure, wrath, contempt, grief, fear, and surprise. Such users go beyond polarity. The General Inquirer released text pattern counting rules and before sentiment analysis psychological investigations investigated mental health by monitoring speech patterns. Volcani and Fogel patented a method that analyzes text for emotional tone and extracts words and phrases. Based on their study effect check provides different word options that increase or decrease emotional reaction. Choose a synonym from this list to change emotion strength. Turney and Pang employed simpler ways to assess how many individuals liked or disliked a product or movie reviews [6]. Like Pang and Snyder, one may use a multi-dimensional polarity scale to determine document orientation. Pang and Lee made judging movie reviews harder. Snyder studied restaurant assessments to predict food quality and ambiance using 3–4 star ratings. Neutral texts are typically removed from statistical categorization since they are in between two groups. Some experts believe that every polarity problem requires three classes. Some categorization schemes benefit from neutral categories. This is because neutral classes improve Max Entropy and SVM classification. A neutral class may be worked with in two ways. In-and-out: The system both finds neutral language first and then evaluates the rest for positive and negative attitudes or it determines all three feelings at once. The second method estimates group probability [7]. Some situations may benefit from ignoring neutral language and concentrating on positive and negative sensations. If the proof isn't conclusive use neutral language. If the data is mainly agnostic or has positive and negative outliers is unclear. Determining the sentiment represented in a piece of text is the goal of sentiment analysis which is a natural language processing (NLP) activity. Another name for this is opinion mining. A variety of sentiment analysis methods exist and each tailored to a certain facet or degree of emotion. Some examples of frequent kinds are:

1) *Binary Sentiment Analysis*
   - *Description:* Classifies the sentiment as positive or negative.
   - *Use Case:* Simple sentiment classification where the goal is to determine whether overall sentiment of text is positive or negative.
2) *Multi-class Sentiment Analysis*
   - *Description:* Classifies the sentiment into more than two categories such as positive, neutral, and negative.
   - *Use Case:* Provides a more nuanced understanding of sentiment, allowing for a neutral category to capture sentiments that are neither explicitly positive nor negative.
3) *Fine-grained Sentiment Analysis*
   - *Description:* Classifies sentiment into multiple, fine-grained categories, often on a scale (e.g., very positive, positive, neutral, negative, very negative).
   - *Use Case:* Offers a more detailed analysis of sentiment, enabling a more nuanced interpretation of opinions.
4) *Aspect-Based Sentiment Analysis (ABSA)*
   - *Description:* Analyzes sentiment at a more granular level, focusing on specific aspects or features mentioned in text.
   - *Use Case:* Useful in case of understanding sentiment towards different aspects of a product, service, or topic, providing more detailed insights.
5) *Emotion Analysis*
   - *Description:* Identifies and classifies emotions expressed in the text, such as joy, anger, sadness, fear, etc.
   - *Use Case:* Useful for understanding the emotional tone of user reviews, social media posts, or customer feedback.
6) *Temporal Sentiment Analysis*

- *Description:* Analyzes how sentiment changes over time.
- *Use Case:* Helps track sentiment trends, identify patterns, and understand how opinions evolve.

7) *Multimodal Sentiment Analysis*

- *Description:* Integrates analysis of multiple modalities, such as text, images, along with audio, to capture a more comprehensive understanding of sentiment.
- *Use Case:* Useful in scenarios where sentiment is expressed through various channels, such as social media posts with both text and images.

8) *Irony and Sarcasm Detection*

- *Description:* Identifies instances of irony or sarcasm in text, as these can convey sentiments opposite to literal meaning of words.
- *Use Case:* Ensures a more accurate understanding of sentiment, especially in cases where the surface-level meaning may be misleading.

These types of sentiment analysis cater to different requirements and provide varying levels of insight into the emotional tone of text data. The choice of appropriate type depends on specific goals and context of the analysis.

2. Literature Review

Ronan Collobert [8] and others have employed convolution networks to achieve data mining goals. The author demonstrates how to do part-of-speech tagging, chunking, named entity identification, along with semantic role labelling using a single NN and a learning technique. The purpose of this research was to accomplish just a goal by collecting and analysing client feedback gleaned through K. Dave's [9] product evaluations. Due to the fact that the classifier makes use of information retrieval strategies to carry out tasks such as feature extraction and scoring, the actual results may vary depending on the configuration. When you are investigating new ways of learning, you are not limited to just the conventional form of machine learning. It was difficult to conduct operations on certain search keywords because of the vast amount of results returned by search engines and the imprecision of those results. L. Maria Soledad Elli [10] was influenced by the comments and suggestions made by her customers. In response to the findings of the data analysis, the business's strategy has been adjusted. The primary thesis of the book is that the suggested technology offers a higher level of precision than that which is now available. The naïve multinomial Bayesian analysis was used by the researchers. Classifiers are responsible for the vast majority of the laborious work at this location. Vector machines, on the other hand, make use of mechanisms. It was also possible to spot phony trends and evaluations by making use of approaches including machine learning. KNN classifier was used by M. S. Hota and S. Pathak [11] in order to do multi-class sentiment analysis on Twitter data. The archaic word "sentiment," which was formerly often used, has been replaced by the more contemporary term "feelings," when referring to emotions. Opinion mining is a kind of data mining that evaluates to discover public opinion on a broad variety of issues, such as news events, companies, goods, and brands. Sentiment analysis is another name for opinion mining. Opinion mining along with sentiment analysis is similar. Micro-blogging services, social networks, online news, as well as user reviews, all fall under the category of user-generated content. In this particular research project, the participants' feelings were categorized using a multidimensional framework. When compared to the standards of the industry, we find that the innovative approach performs significantly better overall. Opinion Mining and Sentiment Analysis were used in the survey work that L. Zhang and K. Liu [12] carried out. Learn how the general population feels about a subject by using a method called as sentiment analysis, which is also sometimes referred to as opinion mining. Rain [13] provided a summary of many researches that examined various NLP ideas and frameworks. In these experiments, the researchers made use of a variety of classification methods, including decision lists and naïve Bayesian classifiers. The categories that might be used for the overview are given above. It's possible that this review is excellent, but it might also be bad. More and more research are adopting deep neural networks. In recent years, neural networks have gained popularity as a tool for use in the research and analysis of emotional states. Customers were asked to provide feedback on Amazon after they had received their items after being given the opportunity to do so. Recursive neural networks, which M. R. Socher [14] popularized, are currently being used to learn more about compositionality in areas such as sentiment recognition. These networks are being used to learn more about compositionality in these domains. Traditional methods such as naive Bayesian analysis, k-nearest neighbor search, and supporting vector machine are only some of the techniques that will be coupled with cutting-edge Dl approaches. The computer science methods of perceptron, naive bayes, and supporting vector machines were used in the study that was conducted by N. Xu Yun et al. [15]. It was put to productive use to the extent of 70% of the total. Opinion mining and sentiment analysis were the subjects of a thorough examination that was carried out by N. Kumar Ravi and Vadlamani Ravi [16]. Throughout the course of the past ten years, more than a hundred articles have been written and published that investigate various strategies, approaches, and applications of sentiment analysis. In this study, the methodologies are investigated in more detail than before. In this article, almost a hundred different publications are summarized, and the essay concludes with a list of potential study ideas. The implementation of O. Zainuddin's [17] suggestion to make advantage of Twitter's aspect-based sentiment analysis in order to categorize hybrid sentiment took place in 2017. We used Twitter's aspect-based sentiment analysis in order to delve further into the data. This study explains how a feature selection method was used in order to categories the emotions expressed on Twitter. According to N. M. Z. Asghar's [18] research, it is possible to study the sentiment on Twitter by using a method that uses hybrid categorization. An method known as cross-categorization was used by the researchers in this study so that they could explore these problems. O. Alsaeedi, Abdullah, along with Mohammad Khan [19] has only recently brought their study on approaches for analyzing sentiment in Twitter data to a successful conclusion. They believed that the development of new technologies was to blame for the lightning-fast pace of world change. P. Shathik and Anvar [20], who also gave a review of the relevant research, were the pioneers in advocating for use of ML algorithms in the process of conducting sentiment analysis.

3. Problem Statement

The Conventional study has produced a method that makes use of just a few characteristics. To categories tweets, the conventional method looked at the contents only. Researchers are looking at a system that can automatically recognize sarcastic tweets. It has been shown that sentiment analysis is more reliable. Politics, sports, movies, and other forms of electronic machinery all were given a serious consideration for inclusion. Using ordinary models achieved an accuracy of over 80%. SVM outperforms Naive Bayes and Maximum Entropy in terms of accuracy. In conventional research on tweets textual sentiment analysis, challenges emerge across various facets, impacting critical metrics such as training accuracy, validation accuracy, along with F1-score. The brevity of tweets poses a significant hurdle, leading to limited context for models during training. Consequently, achieving high training and validation accuracy becomes challenging as models may struggle to capture the nuanced sentiment within the constraints of short texts. The prevalence of informal language, slang words and abbreviations in tweets or comments further makes complicate the task potentially lowering accuracy and F1-score. Imbalanced dataset is a common problem in sentiment analysis. It can result in biased models that may favor the majority sentiment class, affecting F1-score, particularly for minority classes. The limited availability of labeled datasets for graphical content compared to textual data adds a challenge potentially influencing the precision and recall of models. Finally, achieving scalability and efficiency in processing large volumes of image and textual data particularly with deep learning approaches is a practical concern that can impact overall accuracy in graphical sentiment analysis. This stresses the need of designing a sentiment analysis framework that can deliver more precise results.

4. Methodology

There have been several researches in existence that are related to sentiment analysis, machine learning and accuracy. Issues faced in conventional research are accuracy, reliability and lack of flexibility. Thus novel framework has been proposed to perform sentiment analysis on textual and graphical tweets. Researchers are using sentiment analysis on a dataset culled from Twitter, which contains both visual and textual user comments, to get a sense of user attitude. Rapid transformation is occurring all around the globe as a consequence of recent scientific and technical developments. The study of consumer attitudes has gained attraction in recent years. The proposed research integrated LSTM and CNN model allows for comprehensive sentiment analysis capturing the combined impact of text and visual elements in tweets.

4.1 Process of Classification of Textual Content

Classifying textual content using (LSTM) networks is a common approach in natural language processing. LSTMs are suitable for sequential data making them effective for text classification tasks. Firstly, a labeled dataset of textual content is gathered where each text document is associated with a specific category or class. Then, preprocess the text data by removing special characters, punctuation, and irrelevant symbols. In next step, tokenization is done that determine the text into words or sub-word units and converting text to lowercase ensure the uniformity. After that, make ready-to-use LSTMs by transforming preprocessed text input into numerical sequences. Construct a word list and a relationship matrix between words and numerical indexes. To make sure all the input data is having same length and pad otherwise trim the sequences. Separate sets are created for training, validation, and testing from the dataset. In order to train an LSTM model use a training set. In order to fine-tune the hyper parameters use a validation set and finally, to assess the model's performance use a testing set from the data.

The architecture of LSTM-based neural network has been displayed in Figure 3. Common choices are included using a standalone LSTM layer or a combination of LSTM along with other layers. Decide number of LSTM units, the number of dense layers, activation functions, and dropout rates. Now add one or more LSTM layers to the model. LSTMs can capture sequential patterns along with dependencies in text data. Configure the number of LSTM units in each layer, return sequences or not, and specify any recurrent dropout. Further one or more fully connected dense layers are added in case of feature extraction and classification. Use activation functions like ReLU (Rectified Linear Unit) or sigmoid and introduce dropout layers to prevent over fitting. We added an output layer with digit of neurons equal to digit of classes or categories. We use a soft max activation function to obtain class probabilities. LSTM-based neural network is trained using the training data. The model learns to map sequential text inputs to their corresponding categories during this phase. Monitor model's performance on validation data to avoid over fitting. Evaluate trained model's performance on testing dataset.

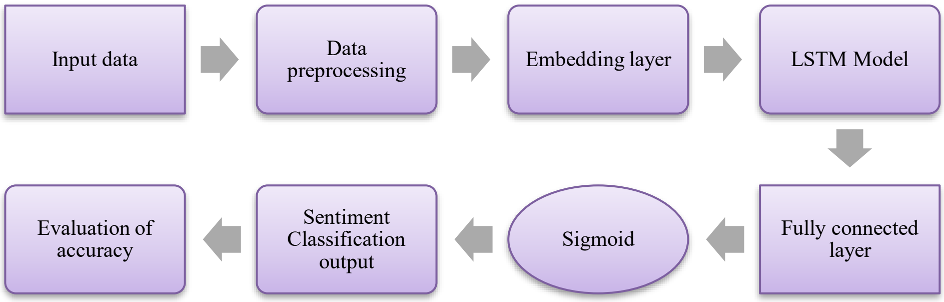


Fig. 3. LSTM Model

Figure 3 is presenting proposed work for LSTM model by considering the classification of textual content. LSTM networks are particularly effective for tasks that require capturing long-range dependencies and understanding the context of words in a text sequence. Textual tweets are taken and tokenizer is applied over sentences during preprocessing. Keywords that help in identification of sentiment are extracted during tokenization. Then, the dataset is split for training along with testing. Hyper parameters such as batch size, learning rate, epoch, and optimizer are set. Then, training operation takes place and finally testing is made to find confusion matrix. Confusion matrix involves the parameters such as Recall, precision along with F1-Score.

4.2 Process of Classification of Graphical Content Using CNN

Conducting graphical Twitter sentiment analysis using a hybrid (CNN) involves training a DL model to classify tweet sentiment and then visualizing the results. Here's we will also gather a labeled dataset of tweets in case of sentiment analysis. This dataset should include tweets categorized as negative, positive, or neutral sentiments. Clean and preprocess tweet text by removing special characters, URLs, along with mentions. It tokenizes the text into words or phrases and converts text to lowercase to ensure uniformity. Now dataset is spitted into training, validation, along with testing sets. Typically, 70-80% of data is used for training, 10-15% for validation, and 10-15% for testing. We preprocess the text data further by using word embedding, Word2Vec, GloVe, or FastText, to represent words as numerical vectors and create a vocabulary and map words to their corresponding word vectors. Now we will design a CNN model for sentiment analysis. This model typically consists of convolutional layers in case of feature extraction along with pooling layers in case of down sampling, followed by one or more fully connected layers in case of classification. It decides on hyper parameters, such as the number of filters, filter sizes, activation functions, and dropout rates and compiles the model with a suitable loss function, optimization algorithm, and evaluation metrics. CNN model is trained on training dataset. Monitor model's performance on validation set to avoid over fitting. It uses back propagation to update the model's weights and biases during training. Last it evaluates model's performance on testing dataset using metrics like accuracy, precision, recall, along with F1 score and adjusts hyper parameters or the model architecture if necessary to improve performance. It uses the trained CNN model to predict sentiment labels (positive, negative, neutral) for a new set of tweets. Graphical representations are created of the sentiment analysis results.

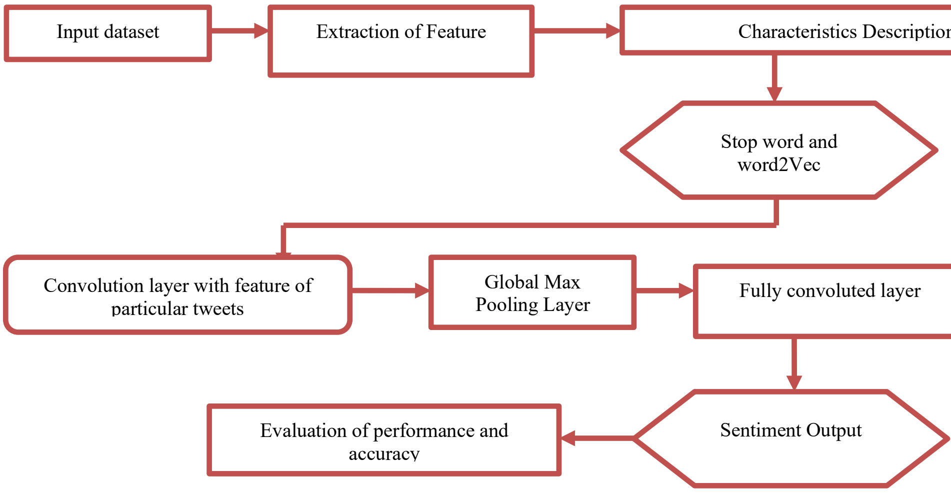
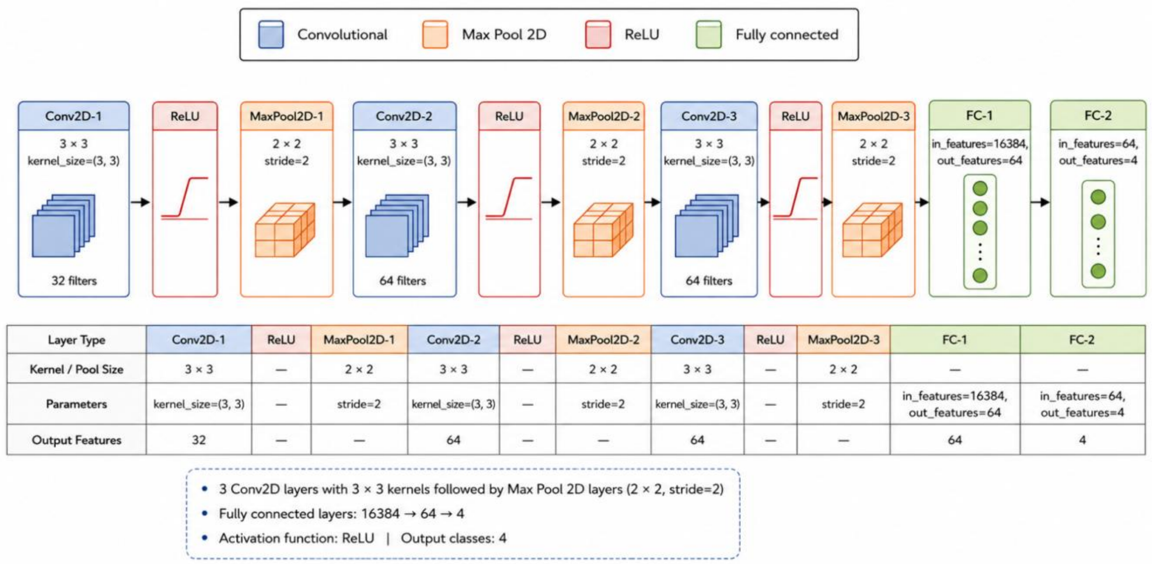


Fig. 4. Proposed CNN Model

Common visualization methods include bar charts, confusion matrix, roc curves, precision-recall curves, word clouds and utilize data visualization libraries, such as Matplotlib, Seaborne, or Plotly, to create graphical representations. Further we analyze visualizations to gain insights into the sentiment of tweets and the model's performance. Look for patterns and trends in data that can inform decision-making or marketing strategies. For example, Image are taken and compressed to reduce size then noise filter is applied on these images during preprocessing. After preprocessing hyper parameter for CNN based training are configured such as learning rate, Convolution layers, Dense layer, Batch size, epochs. Then CNN based train model consider twitter images for training and testing. After training CNN Model, testing operation is made to get accuracy, f1-score, recall and precision along with training and testing time. Use of a CNN in case of sentiment analysis in Twitter data allows for automated sentiment classification, which can be a valuable tool in case of businesses and organizations to gauge public opinion and track brand sentiment on social media platforms.



Layer Type	Conv2D-1	ReLU	MaxPool2D-1	Conv2D-2	ReLU	MaxPool2D-2	Conv2D-3	ReLU	MaxPool2D-3	FC-1	FC-2
Kernel / Pool Size	3 × 3	—	2 × 2	3 × 3	—	2 × 2	3 × 3	—	2 × 2	—	—
Parameters	kernel_size=(3, 3)	—	stride=2	kernel_size=(3, 3)	—	stride=2	kernel_size=(3, 3)	—	stride=2	in_features=16384, out_features=64	in_features=64, out_features=4
Output Features	32	—	—	64	—	—	64	—	—	64	4

Fig. 5. Proposed Layered Architecture

Figure 5 is representing layered architecture of proposed work where each max pool and ReLU layer is considering kernel size of 2 with stride 2, padding 1 and dilation 1. But convolution layer in each phase has different dimensions. However, kernel size is (3, 3), stride is (1, 1), padding is (1, 1) is same for all convolution layer.

5. Results and Discussion

5.1 Simulation of Textual Tweet Sentiment Analysis

The frequency of negative and positive tweets in the social media analytics offers cherished perceptions to understand the attitude towards the particular topic, product, or event.

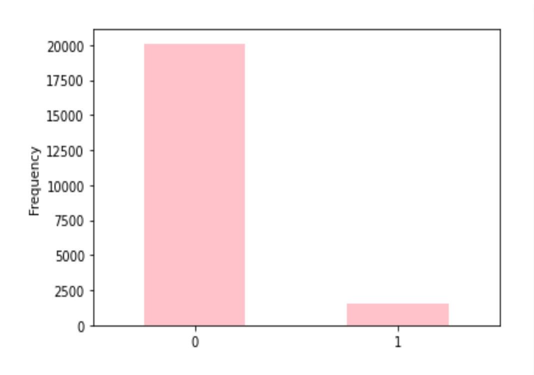


Fig. 6: Frequency of Negative and Positive Tweets

Counting negative tweets' number can help to evaluate the level of dissatisfactions, complaints, or even criticisms towards something. On the opposite, the positive tweets frequency demonstrates the support or satisfaction. While operating the simulation process, the python application was used. In the process, comma separated files of train and test textual tweets were taken into consideration. Figure 6 above represents analyzing the frequency of negative and positive tweets might be helpful to examine the opinions on particular topics or products. Through applying the sentiment analysis, it becomes possible to sort tweets into positive or negative ones based on their content. It might also become possible to evaluate positive and negative opinions' percentage and frequency distribution. Understanding the frequency distribution of positive and negative tweets is critical to analyze the social media audience. The main reason is that it helps to estimate the level of dissatisfaction or support in real-time. In cases of increased negativity towards a specific item or service, appropriate actions should be taken to improve the situation and address the existing issues. In cases of positive sentiment, companies can benefit from the situation and promote their products/services among their audience by engaging them in the process. Training accuracy and validation accuracy are two essential metrics to learn when designing a machine learning or deep learning model. The training process shows how much the model can predict correctly the results demonstrated in the train set or how much it can repeat the same data. On the opposite, the validation accuracy shows how much the model can predict correctly the results demonstrated in the data, which were not used during the training process. Table 1 below represents Education and verification with accuracy in f-score discovered during the simulation process for two various positive and negative cases.

Table 1: Training and Validation Accuracy

Case	Training Accuracy	Validation accuracy	F1 -score
1 (Positive)	0.99	0.94	0.58
2 (Negative)	0.99	0.935	0.55

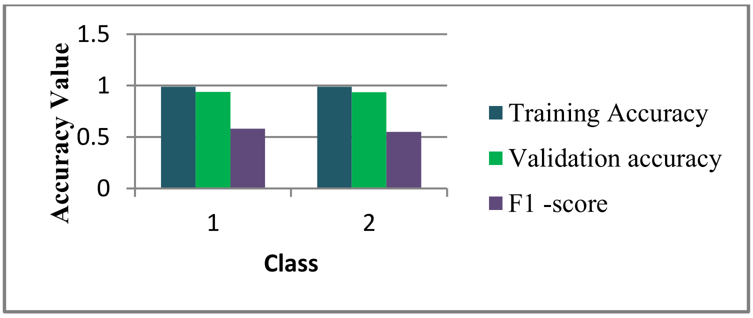


Fig. 7. Training Accuracy, Validation Accuracy and F1-Score Results for Textual Analysis

Figure 7 shows an analysis in the form of pictorial representation for the training accuracy, validation accuracy, and F1-score for positive and negative situation using the displayed in Table 1.

5.2 Simulation for Sentiment Analysis of Graphical Tweets

Simulating sentiment analysis of graphical tweets works as follows: it includes producing and analyzing tweets as graphic texts. It uses computer vision and natural language processing to extract text and image data. It analyzes the image and sentiment of text to classify them based on emotions, such as very happy, happy, normal, unhappy, sad. By simulating it, you get to know how tweets and texts convey users' emotions and influence the way the brand is perceived. Then the marketing team can optimize its strategies and improve customer outreach and engagement on social media. Our dataset includes expression pictures. There are also very happy, happy, normal, sad, unhappy. Table 2 below presents the confusion matrix obtained by training the visual data with a standard CNN network with no preprocessing.

Table 2: Matrix of Conventional Work

	Very happy	Happy	Normal	Unhappy	Sorrow
Very happy	465	4	0	0	31
Happy	1	463	3	3	30
Normal	0	2	464	2	32
Unhappy	3	8	6	461	22
Sorrow	17	12	5	7	459

After considering Table 2, the accuracy parameters were calculated, which results are depicted in Table 3. The classes are represented by very happy, happy, normal, unhappy, and sad for conventional CNN model.

Table 3: Accuracy of Conventional Work

Class	**n (truth)**	**n (classified)**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
1	486	500	97.76%	0.93	0.96	0.94
2	489	500	97.48%	0.93	0.95	0.94
3	478	500	98%	0.93	0.97	0.95
4	473	500	97.96%	0.92	0.97	0.95
5	574	500	93.76%	0.92	0.80	0.85

Table 4 represents the confusion matrix resulted from the training process and testing conventional CNN model using preprocessed visual data.

Table 4: Confusion Matrix for Proposed Work

	Very happy	**Happy**	**Normal**	**Unhappy**	**Sorrow**
Very happy	484	4	0	0	12
Happy	1	473	3	3	20
Normal	0	2	474	2	22
Unhappy	3	8	6	473	10
Sorrow	17	2	5	7	469

Table 5 below represents the calculated accuracy parameters based on the data in Table 4. Similarly to Table 3, the classes are very happy, happy, normal, unhappy, and sad.

Table 5: Accuracy of Proposed Work

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
1	505	500	98.52%	0.97	0.96	0.96
2	489	500	98.28%	0.95	0.97	0.96

3	488	500	98.4%	0.95	0.97	0.96
4	485	500	98.44%	0.95	0.98	0.96
5	533	500	96.2%	0.94	0.88	0.91

Table 5 below illustrates the comparison of overall accuracy between conventional and proposed methods for graphical Twitter sentiment analysis.

Table 6: Comparison of Overall Accuracy

Conventional model	Proposed model
92.48%	94.92%

Considering Table 6, Figure 8 is showing comparison results for overall accuracy for better understanding.

Fig. 8. Accuracy Comparison

The proposed work leads to several advantages over conventional methods in the case of text and graphical classification, including accuracy, performance, scalability, flexibility, and addressing the questions of under fitting and over fitting. First, the proposed work provides better accuracy in the case of textual classification using the DL models like LSTMs or CNNs. These DL algorithms help in achieving better accuracy in classifying the text data as compared to conventional methods. Second, the proposed method leads to better performance as compared to conventional methods. DL-based models can achieve fast performance because of a higher degree of parallelism. This is especially helpful in cases when dealing with big datasets, which traditional ML algorithms may not be able to handle easily. Third, the proposed work provides better scalability, especially in case of graphical classification. By leveraging the power of GPUs, and using the deep learning paradigm, the proposed work would be able to scale well to bigger graphical datasets. Fourth, the proposed work provides more flexibility in terms of being able to deal with both textual as well as graphical data. Traditional methods are often limited to either one or the other and sometimes need extensive feature engineering in either case. The fifth and the last advantage is the ability of the proposed work to address the questions of under fitting and over fitting. Deep learning-based models can be regularized to a great extent, and therefore, can avoid the problems of under fitting and over fitting to a great extent. This property is especially useful in cases when dealing with smaller datasets. Sixth, the proposed work in the case of textual and graphical classification is better than the traditional methods in several aspects, including accuracy, performance, scalability, flexibility, and addressing the questions of under fitting and over fitting. The DL-based models can be regularized to a great extent, and therefore, can avoid the problems of under fitting and over fitting to a great extent. This property is especially useful in cases when dealing with smaller datasets.

Table 7: Detailed Comparison of Conventional and Proposed Research

	Conventional research	Proposed work
Accuracy	92.48%	94.92
Performance	Slow	Fast
Scalability	Limited to either textual or graphical	Considers both textual and graphical
Flexibility	Comparatively less flexible	Comparatively more flexible
Under fitting issue	Considers under fitting issue slightly	Considers under fitting issue

		seriously
Over Fitting issue	Does not considers over-fitting issue	Considers over fitting issue.
Textual classification	Made by ANN that provided limited accuracy	Made by LSTM that provided high accuracy
Graphical classification	Made by conventional CNN model	Made by hybrid CNN model

Table 7 is representing the detailed analysis of conventional and proposed research.

6. Conclusion and Future Scope

This paper proposes a hybrid deep learning framework for performing sentiment analysis of Twitter (X) data through the joint consideration of textual and graphical information by convolutional neural networks. It was found that the suggested model, which exploits preprocessing mechanisms, feature extraction steps, and deep learning-based features, leads to improved performance on both textual and graphical sentiment analysis tasks. Indeed, the obtained results showed that the model achieved 99% accuracy on training data and 94% - on test data for textual sentiment classification. For graphical sentiment analysis, an increase in accuracy from 92.48% to 94.92% was achieved compared to the conventional CNN model. Additionally, positive changes in precision, recall, and F1-score were observed for most classes. This indicates that the proposed approach is beneficial for solving the given task and is able to address the challenges posed by the high noise level and heterogeneity of social media data. Hence, it is possible to conclude that the CNN-based model suggested in this study is a viable solution for performing multimodal sentiment analysis. It has the potential to be applied in social media monitoring systems to perform customer sentiment analysis, assess brand image, and support business decision-making.

Further research should be conducted to incorporate transformer-based language models, such as BERT, RoBERTa, or DistilBERT, to achieve better performance on textual sentiment analysis. To address graphical sentiment analysis, it is possible to utilize computer vision models, such as Vision Transformers or multimodal transformers.

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