








# Social Media Sentiment Analysis Using Deep Learning Approach

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**Abstract.** Compared to more traditional social media channels, Facebook and Twitter are far more effective at spreading information. Social media has developed into a great data origin for businesses or researchers to create models to analyse this repository and harvest practical insights for marketing policy for word-of-mouth (WOM) trading. However, the vocabulary used in social media is rather condensed and includes specialised words and symbols. Such brief communications are not well suited for the majority of natural language processing (NLP) techniques, which concentrate on processing formal phrases. In this paper, we suggest a brand-new paradigm for social media sentiment analysis based on deep learning models. We gather information from which we create a dataset. We aim to create a semantic dataset after processing these particular phrases in order to support future study. Future applications will benefit greatly from the retrieved data. Several social media platforms have been crawled to gather the trial data.

**Keywords:** Sentiment analysis · deep learning · social network

## 1 Introduction

User reviews are gathered in great numbers on social media sites like Facebook and YouTube, providing businesses with a wealth of information about their target market. Word-of-mouth (WOM) marketing initiatives also have a favourable impact on consumer purchasing choices. Social media posts have a significant influence on decision-making and offer direction for people, organisations, and social communities [1].

These comments and evaluations can be used to examine how people feel about various organisations, businesses, items, and even specific people. The technique of figuring out if a text or voice is favourable, negative, or neutral is known as sentiment analysis. NLP methods including part-of-speech tagging (POG), syntactic parsing, and other

forms of linguistic analysis constitute the foundation of many text mining algorithms [2].

As Web 2.0 has grown in popularity, sentiment analysis has as well. However, social media platforms do not always benefit from the usage of natural language processing methods [3]. Microblogs (such as tweets) and messages posted on fan pages are brief and casual prose, in contrast to product reviews and long comments. Social media jargon, emoticons, emphasis words, and other special words are all part of the brief social media language. Characters with specific functions are used in emoticons to convey emotions. Lol and omg are two slang terms. Although they are frequently crucial for sentiment analysis, these words are not always present in sentiment lexicons [4]. Such text cannot be processed using traditional NLP techniques. Haque et al. [5] proposed the deep learning-based opinion mining technique, in which they examine movie reviews gleaned from IMDb fan pages using opinion mining algorithms. We provide a deep-learning-based architecture in this study to manage slang and other unique social languages. We mine crowd intelligence by processing user reviews from various social media platforms while accounting for such specific phrases. For additional investigation, we'll publish our own semantic database.

## 2 Related Work

The SentiWordNet vocabulary, presented by Esuli [6], includes the opinion strength for every term. Reviews have been classified [7] and review elements have been identified [8] using SentiWordNet. Tokenization, filtering, lemmatization, and stemming are suggested as text preprocessing techniques by Allahyari, Pouriyeh, Assefi, Safaei, Trippe, Gutierrez, and Kochut [2]. Rout and Williams [9] use supervised and unsupervised methods to analyse tweet sentiment. Their experiment serves as an example of a supervised technique in which the union of unigram, bigram, and part-of-speech features is demonstrated to be effective in detecting the emotion and sentiment of unstructured data. A set of neuron layers, each layer of deep neural networks (DNNs) outputs a modified version of its input to the one below it. Various tasks have been successfully completed using DNN, a type of supervised machine learning [10]. A common form of DNN made up of convolutional layers and pooling layers is a convolutional neural network (CNN). Recurrent neural networks (RNNs) are efficient methods for modelling sequential data because they maintain hidden states for a long history. An input layer, one or many hidden layers, and an output layer make up long short-term memory (LSTM) based networks. Many NLP methods have been successfully completed using LSTM networks [11]. Bidirectional long short-term memory (BiLSTM) networks use a bidirectional RNN and NLP techniques to extract relations from unprocessed text data [12]. The use of gated recurrent units (GRUs) in applications requiring sequential or temporal data has been successful [13]. We use GRUs, BiLSTM, and LSTM in this work.

### 3 Proposed Framework

A successful avenue for movie WOM marketing is social media. This paper suggests a deep learning-based architecture for processing movie reviews. The suggested framework is depicted in Fig. 1 and consists of many modules. We go into further detail about these modules below.

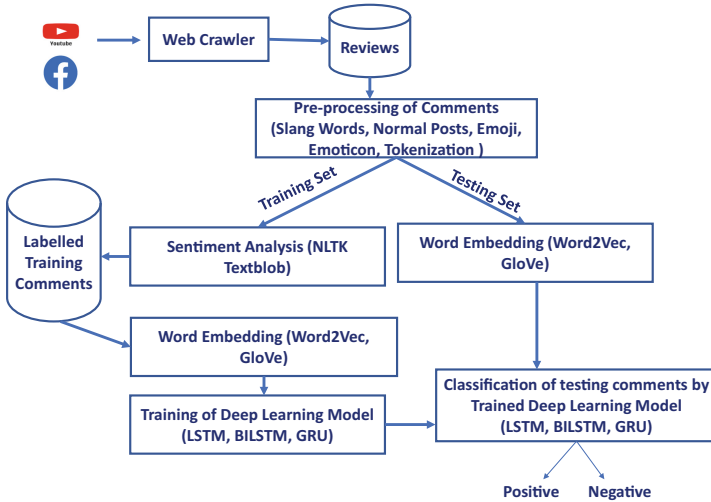


Fig. 1. The architecture of the Proposed Method

Crawler for the web: In the initial step, the proposed technique utilize a Python BeautifulSoup API as a crawler to gather review information regarding mobile and movie reviews from sites like Facebook and YouTube.

Preprocessing: The brief communications use slang and unusual phrases and symbols, such as emoticons, in an informal manner. As a result, we are unable to preprocess these reviews using conventional natural language processing (NLP) technologies. A basic example of a brief message is shown in Fig. 2. It is a casual post that uses emoticons(“:”)”, emoji (😊), acronyms, and special terms like LOOOL.

**“LOOL. The Mobile is looking gr8 😊 :))) :) :)”**

Fig. 2. Simple Review message

Haha, lol, rofl, and lmao are all symbols for laughter. To accentuate their feelings, authors utilise terms with repeated letters, such as OMGGGGG [14]. We establish rules in our algorithm to get rid of these unnecessary letters. In the aforementioned illustration, we divide the components shown in Fig. 3. LOOOL, which can be translated to token lol, makes up the first component.

“LOOL. The Mobile is looking gr8 😊 :))) :) :)”

Fig. 3. Simple Review message with different components

Chat messages frequently use slang. The polarity of slang must therefore be recognised, translated, and identified in order to ascertain the sentence’s semantic orientation. Using the online slang word dictionary shown in Table 1, we change these slang terms into their standard versions before adding them to the text.

Table 1. Slang. Dictionary

Slag Term	Explanation
TBH	To be Honest
GOAT	Greatest of all time
YOLO	You only live once
...	...

The second portion is gr8, which is equivalent to great in slang. Frequently used abbreviations, like omg, are stretched into their recognised whole forms (oh my god) [15].

Comments also contain emoticons like:),:D, of:(, and;). 20% of all posts on social media platforms utilise emoticons, which are frequently used. A comprehensive list of emoticons, including:-), (^ ^), (> <), and others, can be found on Wikipedia.

Labelling of training comments: Sentiment analysis may be utilized to gather, and examine the ideas and emotions expressed in comments made about a certain target movie and mobile. In the proposed work, we use NLTK Textblob, the Google Natural Language Cloud(GNLC) API, and three other technologies to assess the sentiment of user postings. The Python library known as NLTK, or Natural Language Toolkit, helps programmers resolve issues with natural language processing [16]. To get a sentiment score, we assess each statement using these three criteria. Each sentence is given a favourable or bad label based on the vote results. Table 2 provides examples.

Table 2. Example reviews sentences.

ID	Comment	NLTK	GNLC API	Proposed Method Label
100	That film it’s super	1	1	1
102	I don’t want the actress action	0	0	0
103	It’s the best one ever, Hardy.:)	1	1	1

As seen in Fig. 4, each sentence is examined using a number of techniques, such as tokenization, downsizing, slang mapping, and sentence classification.

**Comment 1:** "LOOL. The Mobile is looking gr8 😊 :))) :)"

**Shrink** : "LOL. The Mobile is looking gr8 😊 :))) :)"

**Slang Mapping** : "laugh out loud. The Mobile is looking great 😊 :))) :)"

**Sentence Labeling** : "laugh out loud. The Mobile is looking great 😊 :))) :)" **Label= 1(positive)**

**Tokenization** : ['lol', 'the', 'mobile', 'is', 'looking', 'great', '😊', ':)', ':)', ':)']

**Stop word Removal** : ['lol', 'mobile', 'looking', 'great', '😊', ':)', ':)', ':)']

Fig. 4. Sentiment Analysis outcome for simple message

Word Embedding: Bag of words (BOW) and term frequency inverse document frequency are two popular methods for representing a document as a vector (TF-IDF). These two approaches are inappropriate [17] because the typical social media content is only twenty eight characters long and has a relatively shallow data matrix. Using a neural network language model, Each word’s vector representation is learned by the model using word2ve, a novel word-embedding approach [18]. GloVe, a particular weighted least-squares model, maps tokens onto a meaningful space where the separation among words are correlated with their semantic resemblance [19]. For token representations of input tokens, we employ word2vec [20] and GloVe [21].

The proposed method train 3 deep learning techniques with every of these embeddings to test the efficacy of semantic embedding for emotion identification. Figure 5 illustrates how we experiment with the GRU, LSTM, and BiLSTM models.

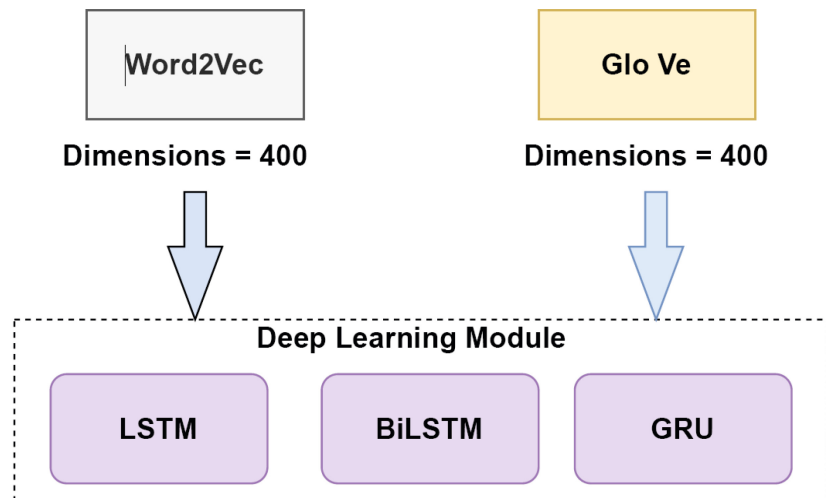


Fig. 5. Suggested Sentiment Analysis Model

To create a training dataset with the same size of + ve and -ve comments, the proposed method label every comment with a sentiment. The 3 deep learning-based sentiment classification techniques are built after the training dataset has been preprocessed with word embeddings. We browsed YouTube trailer comments in order to gather experimental data in order to test the efficacy of the suggested technique. Figure 6 displays a snapshot of the data that was crawled.

MIDin	Channel Name	video Title	VideoId_resp	CommentID	authorDis	Like	PublishedAt	UpdatedAt
IMDB					playName	TextDisplay	count	
tt1413493	Warner Bros Pictures	Infinity War- Official Trail DencilleSoA	UgyAcId-c49h74pocA4Baq	Slav Bakari	what spercall force	5	2018-01-17T11:25:09:002	2018-01-17T11:25:09:002
tt1413493	Warner Bros Pictures	Infinity War- Official Trail DencilleSoA	UgyAcId-c49h75pocA4Baq	Alpha	This mo vie deserves an Oscar like if agree	0	2018-01-18T11:25:09:003	2018-01-18T11:25:09:003
tt1413493	Warner Bros Pictures	Infinity War- Official Trail DencilleSoA	UgyAcId-c49h76pocA4Baq	Omega	this looks like in the COD black ops 2	0	2018-01-18T11:25:09:004	2018-01-18T11:25:09:004
tt1413493	Warner Bros Pictures	Infinity War- Official Trail DencilleSoA	UgyAcId-c49h77pocA4Baq	Tim Tiger	Nice Propaganda for brainless sheep	6	2018-01-20T11:25:09:005	2018-01-20T11:25:09:005
tt1413493	Warner Bros Pictures	Infinity War- Official Trail DencilleSoA	UgyAcId-c49h78pocA4Baq	Hot Spot	It's like a pirate had a baby with an angel	4	2018-01-22T11:25:09:006	2018-01-22T11:25:09:006

**Fig. 6.** Screenshot of Dataset Utilized

We chose 4000 positive and 4000 negative statements from this data. A classifier that can predict sentiment was created using the suggested sentiment classification models and trained on the labelled dataset. By comparing the classification performance of the three suggested sentiment classification techniques in terms of precision, recall, F-measure, and accuracy. Table 3 provides a summary of the findings. The graphical representation of the performance of the deep learning methods are presented in Fig. 7.

**Table 3.** Experimentation Findings

	Accuracy(%)	Precision(%)	Recall(%)	Specificity(%)	F1 Score(%)
LSTM	79.80	80.01	79.89	73.40	79.81
BiLSTM	86.15	84.70	87.80	81.84	86.19
GRU	63.89	63.80	64.89	62.91	63.84

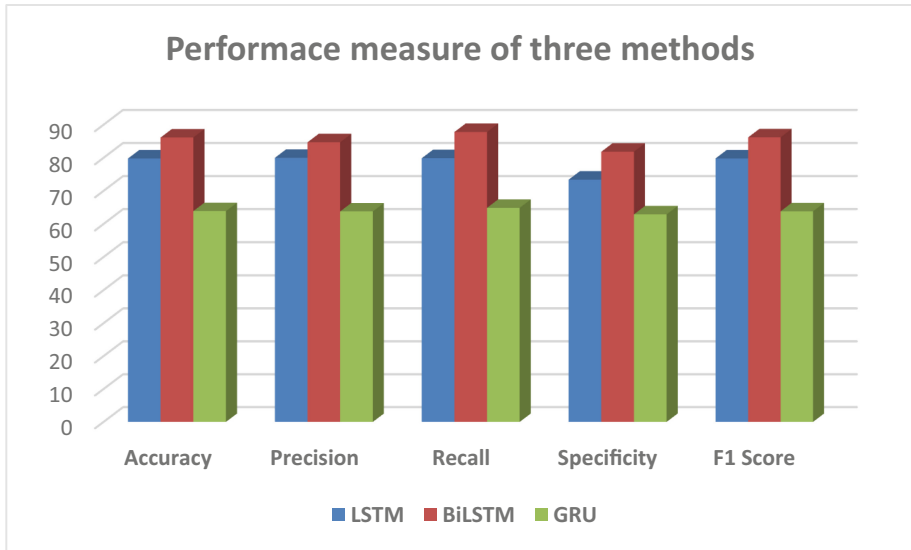


Fig. 7. Performance measures of three methods

## 4 Conclusion

User-generated content on social networking platforms can be analysed using sentiment analysis. However, it is challenging to precisely determine sentiment due to the intricacy and dynamic essence of social network information. We gather testimonials from social media sites in order to create a dataset for next studies. We offer three deep learning-based models to categorise review sentiment for the analysis of comments taken from social media networks. We will create a framework in the future to test the crawling intelligence from our review dataset based on the suggested sentiment techniques.

## References

1. Mohamed Iqbal, M., Latha, K.: A parallel approach for sentiment analysis on social networks using spark. *Intell. Autom. Soft Comput.* **35**(2), 1831–1842 (2023)
2. Subramani, Sudha, M., Sandra, W., Hua, W., Frank Heyward, Benjamin.: Text mining and real-time analytics of twitter data: a case study of Australian hay fever prediction. *Int. Conf. Health Inf. Sci.*, 134–145 (2018)
3. Kundi, F.M., Ahmad, S., Khan, A., Asghar, M.Z.: Detection and scoring of internet slangs for sentiment analysis using SentiWordNet. *Life Sci. J.* **11**(9), 66–72 (2014)
4. Chinthala, Santhi, M., Ramesh, M., Vemuri, S., Sindhura.: Sentiment analysis on twitter streaming data. In: *Proceedings of the 49th Annual Convention of the Computer Society of India (CSI)*, pp. 161–168 (2015)
5. Haque, M.R., Akter Lima, S., Mishu, S.Z.: Performance analysis of different neural networks for sentiment analysis on IMDb movie reviews. In: *2019 3rd International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE)*, pp. 161–164, (2019)
6. Esuli, A., Sebastiani, F.: Sentiwordnet: a publicly available lexical resource for opinion mining, 417–422 (2006)

7. Husnain, M., Missen, M.M.S., Akhtar, N., Coustaty, M., Mumtaz, S., Prasath, V.B.S.: A systematic study on the role of SentiWordNet in opinion mining. *Front. Comp. Sci.* **15**(4), 1–19 (2021). <https://doi.org/10.1007/s11704-019-9094-0>
8. Mandal, S., Gupta, S.: A novel dictionary-based classification algorithm for opinion mining. In: 2016 Second International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), pp. 175–180 (2016)
9. Rout, J.K., Choo, K.-K. R., Dash, A.K., Bakshi, S., Jena, S.K., Williams, K.L.: A model for sentiment and emotion analysis of unstructured social media text. *Electron. Commerce Res.* **18**(1), 181–199 (2018). <https://doi.org/10.1007/s10660-017-9257-8>
10. Martin-Gutierrez, S., Losada, J.C., Benito, R.M.: Semi-automatic training set construction for supervised sentiment analysis in political contexts. In: 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 715–720 (2018)
11. Monika, R., Deivalakshmi, S., Janet, B.: Sentiment analysis of US airlines tweets using LSTM/RNN. In: 2019 IEEE 9th international conference on advanced computing (IACC), pp. 92–95 (2019)
12. Vimali, J.S., Murugan, S.: A text based sentiment analysis model using bi-directional LSTM networks. In: 2021 6th International Conference on Communication and Electronics Systems (ICCES), pp. 1652–1658 (2021)
13. Zouzou, A., Azami, I.E.: Text sentiment analysis with CNN & GRU model using GloVe. In: 2021 Fifth International Conference on Intelligent Computing in Data Sciences (ICDS), pp. 1–5 (2021)
14. Kouloumpis, E., Wilson, T., Moore, J.D.: Twitter sentiment analysis: the good the bad and the omg! *ICWSM* **11**(538–541), 164 (2011)
15. Chatterjee, A., Gupta, U., Chinnakotla, M.K., Srikanth, R., Galley, M., Agrawal, P.: Understanding emotions in text using deep learning and big data. *Comput. Hum. Behav.* **93**, 309–317 (2019). <https://doi.org/10.1016/j.chb.2018.12.029>
16. Jha, N.K.: An approach towards text to emoticon conversion and vice-versa using NLTK and WordNet. In: 2018 2nd International Conference on Data Science and Business Analytics (ICDSBA), pp. 161–166 (2018)
17. Al-Ghuribi, S.M., Noah, S.A.M., Tiun, S.: Unsupervised semantic approach of aspect-based sentiment analysis for large-scale user reviews. *IEEE Access* **8**, 218592–218613 (2020). <https://doi.org/10.1109/ACCESS.2020.3042312>
18. Li, Q., Shah, S., Ghassemi, M., Fang, R., Nourbakhsh, A., Liu, X.: Using paraphrases to improve tweet classification: comparing WordNet and word embedding approaches. In: 2016 IEEE International Conference on Big Data (Big Data), pp. 4014–4016 (2016)
19. Pennington, J., Socher, R., Manning, C.: Glove: global vectors for word representation, pp. 1532–1543 (2014)
20. Lei, S.: Research on the improved Word2Vec optimization strategy based on statistical language model. In: 2020 International Conference on Information Science, Parallel and Distributed Systems (ISPDS), pp. 356–359 (2020)
21. Zouzou, A., Azami, I.E.: Text sentiment analysis with CNN & GRU model using GloVe. In: 2021 Fifth International Conference on Intelligent Computing in Data Sciences (ICDS), pp. 1–5 (2021)