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AI-Based Techniques for Online Social Media Network Sentiment Analysis: A Methodical Review

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***Abstract*—**Online social media networks have long served as a primary arena for group conversations, gossip, text-based information sharing and distribution. The use of natural language processing techniques for text classification and unbiased decision making has not been far-fetched. Proper classification of these textual information in a given context has also been very difficult. As a result, a systematic review was conducted from previous literature on sentiment classification and AI-based techniques. The study was done in order to gain a better understanding of the process of designing and developing a robust and more accurate sentiment classifier that could correctly classify social media textual information of a given context between hate speech and inverted compliments with a high level of accuracy using the knowledge gain from the evaluation of different artificial intelligence techniques reviewed. The study evaluated over 250 articles from digital sources like ACM digital library, Google Scholar, and IEEE Xplore; and whittled down the number of research to 52 articles. Findings revealed that deep learning approaches such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Bidirectional Encoder Representations from Transformer (BERT), and Long Short-Term Memory (LSTM) outperformed various machine learning techniques in terms of performance accuracy. A large dataset is also required to develop a robust sentiment classifier. Results also revealed that data can be obtained from places like Twitter, movie reviews, Kaggle, Stanford Sentiment Treebank (SST), and SemEval Task4 based on the required domain. The hybrid deep learning techniques like CNN+LSTM, CNN+ Gated Recurrent Unit (GRU), CNN+BERT outperformed single deep learning techniques and machine learning techniques. Python programming language outperformed Java programming language in terms of development simplicity and AI-based library functionalities. Finally, the study recommended the findings obtained for building robust sentiment classifier in the future.

***Keywords*—**Artificial Intelligence, Natural Language Processing, Sentiment Analysis, Social Network, Text.

I. Introduction

MORE people are using social media as a tool for sharing ideas, discussions, gossip, and other information in real-time by freely expressing their opinions on various topics and in various contexts based on their moods or sentiments on web pages, thanks to the rapid development of the Internet and online social media networks such as Twitter, Facebook, and WhatsApp.

In its most basic form, sentiment can be defined as an attitude or judgment based on feelings or experience [1]. One key type of sensation is people's opinions after consuming specific products, such as attending a football match, seeing a popular movie, conducting election or voting processes, governmental issues, academic matters, and so on [1]. According to [2], the online social media networks revolution plays a critical and crucial role in acquiring public opinion data. It has also been noted that these sentiments are mostly textual in nature and can reflect positive, negative, or neutral tones or emotions [2]. It is worth noting that previous reviews of product comments might have a favorable or negative impact on a decision-making process [3]. A crucial goal of sentiment classification that should not be overlooked is the correct assessment of sentiment polarity and the accurate prediction of textual information [4]. Reference [5] found that social media networks are a valuable source of data for sentiment analysis.

Public opinion is collected from replies acquired from social media in [6], in order to achieve subjective and factual outcomes. Based on theoretical and technical challenges in constructing a powerful and robust sentiment classifier, the reliability of projected outcomes from sentiment analysis is still a major difficulty in natural language processing [7].

Sentiment analysis (SA), also known as mood extraction or opinion mining, is a strategy for assessing people's or groups' feelings or opinions on a specific product or context from online social media networks, blogs, online forums, news groups, and other sources using techniques such as natural language processing, text mining, computational linguistics, machine learning, and deep learning [2], [5], [8], [11], [15]-[18], [20], [30]-[43].

Fig. 1 depicts a block diagram for predicting and classifying hidden information from online social media network data in terms of user feelings, intents, and opinions.

SA may categorize a text's polarity on three levels: sentence, document, and aspect [2]. Sentiment analysis could be helpful for corporate intelligence, recommender systems, business strategies, and decision-making. Noise (abbreviations and slangs), unstructured data, contextual information, word sense ambiguity, and language structures are some of the primary issues in SA [2].

Our research will concentrate on multiple aspects of SA of textual material from social media networks in various contexts. The fundamental goal of this research is to summarize, assess, and evaluate the experimental evidence on artificial intelligence-based SA systems. For the sentiment classifier's evaluation, we looked at the datasets utilized for some existing models, commonly used prediction approaches, programming

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language, metrics, and performance measures. As a result, in future trials, we will be able to gain the desired strategies and methodologies for developing a powerful sentiment classifier that can effectively handle sentiment classification in terms of inverted compliments.

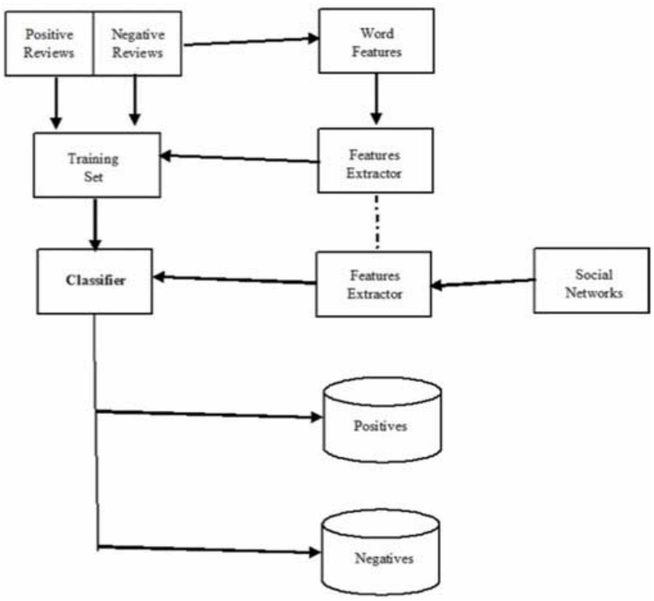

Fig. 1 Structure for SA data from Social Networks [2], [10]

The following is how the rest of the paper is organized: The process for finding comparable studies was covered in Section II as well as how the research questions are defined. The results and discussion of the research topics and other findings were discussed in Section III. Finally, Section IV brought the paper to a close and made a suggestion for future research.

II. Methodology

A Systematic/Methodical Literature Review (SMLR) was used as the study's technique. This method was deliberately selected to analyze recent papers on SA based on the detailed review of previous work [29]. SMLR is a well-known review process that entails locating, evaluating, and weighing existing research data in order to answer to pre-defined research questions [12].

A. Research Question

Research questions are defined to assist us in assessing and evaluating previous studies. The goal of this systematic review is to present and assess empirical evidence from previous studies on the use of Artificial Intelligence (AI) techniques such as Machine Learning (ML) and Deep Learning (DL) methods for developing powerful sentiment classifiers or models that can detect and analyze textual sentiments.

The research questions that will be addressed in this review are as follows:

- RQ1 - What kind of AI-based methods have been chosen for textual information SA?
- RQ2 - Which datasets and dataset sizes are most commonly utilized for SA?
- RQ3 - Which programming language is best for creating a sentiment classifier for online social networks?
- RQ4 - What are the most commonly used metrics for SA?
- RQ5 - In terms of accuracy, which AI-based solution performs better?

B. Appraisal Procedure

Choosing digital repositories, generating the search string, doing an initial search, and collecting the first list of main studies from the digital repositories that matched the search string are all steps in the process of searching past literature research.

Table I lists the appropriate digital repositories as well as the databases that were used to conduct the search.

TABLE I
Selected Digital Databases

S/N	Digital Database
1	Google Scholar
2	IEEE Xplore
3	ACM Digital Library

C. Data Mining

The main studies are culled from different repositories such that the data collected can help answer the research questions in this SMLR. The data extraction method was created to collect information from the major studies that is required to answer the research questions.

Table II shows the qualities that were used to answer the study questions.

TABLE II
Summary of Search Results

S/N	Digital Database	Initial List	Final List
1	Google Scholar	150	26
2	IEEE Xplore	70	25
3	ACM Digital Library	32	1
	Total	252	52

III. Results and Discussion

When it comes to textual classification on online social media networks, SA is one of the most recent and challenging fields in the field of natural language processing. In order to find the appropriate answers to the research questions, this part discusses the most important topics to consider while creating and executing a robust sentiment classifier, including development settings, dataset source, methodologies, algorithms, and performance evaluation.

A. AI Based Methods

Based on the 31 major investigations, two primary AI-based methodologies for SA (ML and DL) are provided in the linked literatures. Based on the investigations, Fig. 2 displays the distribution of the major approaches.

In both the ML and DL methodologies studied, researchers employed distinct algorithms. LSTM [20], [26], [39], [42], [45], CNN [30], [31], [34], BERT [23], Naïve Bayes (NB) + Support Vector Machine (SVM) [16], Ruled based [17], SentaNLP [27], NB [13], [19], [40], and OneR [25].

TABLE III
SUMMARY OF RELATED WORKS

Study ID	Year	Reference	Comments based on findings
S1	2021	Wassan et al. [15]	ML, NLTK, Python, 28,000 product review from data world website
S2	2013	Schulz et al. [13]	ML, Naïve Bayes Multinomial Model, 150,000 tweets from Twitter, 65.75% accuracy
S3	2014	Malandrakis et al. [14]	ML, Naïve Bayes + SVM, Python, 315 million tweets on election
S4	2019	Bahrawi [16]	ML, Random Forest Algorithm, Python, 14,640 dataset from Kaggle.com, 75% accuracy
S5	2019	Bahrawi [18]	DL, Lexicon + Rule-based, Python, Raw data from Twitter API Stream service,
S6	2016	Nurhuda et al. [19]	ML, Naïve Bayes, Legislative election dataset, 90% accuracy
S7	2017	Xu et al. [20]	DL, Bi-LSTM, Python 3.5, TensorFlow and scikit-learn libraries, 15,000 hotel comments crawled from https://www.ctrip.com, Precision = 91.54%, Recall = 92.82%, F1-Score = 92.18%
S8	2021	Cheng et al. [21]	DL, CNN + RNN (BiGRU), Python, 50,000 dataset from American movie review, 91.5% accuracy
S9	2021	Xuanyuan et al. [22]	DL, CNN + RNN, Python, 38,000 dataset from Weibo, 90.2% accuracy
S10	2020	Tang et al. [23]	DL, BERT, Python, 6,000 code switching dataset from NLPCC2018 shared task, 62% accuracy
S11	2021	Naqvi et al. [24]	DL, CNN + LSTM, Python, 6,000 sentences and 117,685 words collected from Urdu blogs & news website, 77.9% accuracy, 72.7% F1-score
S22	2019	Liu et al. [36]	DL, CNN+TWAM, chnSentiCorp-Htl-ba-10000 hotel reviews. NLPCC-ECGC dataset from online comments on weibo with over 1,000,000 dialogues, 90% accuracy
S23	2021	Wang et al. [38]	DL, Word2vec + Glove, SemEval, SST1, SST2, IMDB & Yelp2012 datasets
S24	2020	Hameed & Garcia-Zapirain [39]	DL, Bi-LSTM, Python 3.7 with Keras and TensorFlow, MR (10,662), IMDB (50,000), SST2 (9,613)
S25	2020	Li et al. [40]	ML, Naïve Bayes, Sentiment Dictionary, Python, Datasets from Danmako video reviews, Accuracy = 88%, Recall = 78%, F1-Score = 82%
S26	2019	Wu et al. [41]	Rule-based, Sentiment Dictionary + Semantic Rules, 25,720 Chinese micro-blogs, Precision = 84.9%
S27	2020	Jelodar et al. [42]	DL, LSTM, Python with Keras Library, 563,079 comments from sub-Reddit forums, 81.2% accuracy
S28	2019	Zheng & Zheng [44]	DL, CNN + RNN, Python, Dataset from Yahoo, Sogou news, Yelp review, short reviews
S29	2019	Hameed et al. [45]	DL, LSTM, Python, Movie review, Stanford sentiment tree dataset, F1-score = 85.75%
S30	2021	Venkatesh et al. [46]	DL, CNN + LSTM, Python, Football fans tweets on twitter, Accuracy = 92.56%
S31	2019	Li et al. [47]	DL, BERT + CNN, Python, Dataset collected from a MOOC platform, Accuracy = 81.3%, F1-Score = 92.8%
S12	2017	Singh et al. [25]	ML, OneR, Python 3.5 using NLTK, Amazon 7465 IMBB Movie Review, 91.3% accuracy, 92.4% F1-score, 97% precision
S13	2019	Deng et al. [26]	DL, Sparse Self Attention, LSTM, Python, 1,600 tweets, 80% accuracy
S14	2017	Bouazizi & Ohtsuki [27]	ML, SENTA NLP, Java & Java FXML, OpenNLP, 40,740 tweets, 81.3% tweets
S15	2020	Sanagar & Gupta [28]	DL, Corpus-Generated Polarity Seed Words, Python using NLTK and Gensum, 103,000 dataset from Stanford network analysis project DB, 86% accuracy
S16	2021	Feng & Cheng [30]	DL, CNN, 10,000 Tan Songbo's Chinese Hotel Review collected from http://ctrip.com, 86.32%
S17	2020	Dong et al. [31]	DL, CNN, Python, 55,421 sentences from NLPCC2014, 76% accuracy
S18	2016	Zhou et al. [32]	DL, CNN +RNN [BiLSTM], Python 3.6 Keras & TensorFlow, SemEval Task4 & SemEval 2017 Task4 datasets, 75% accuracy
S19	2020	Aydin & Gungor [33]	DL, Recursive NN + Recurrent NN [GRU], (R-RNN), Python, SemEval Task4, 81.38% accuracy
S20	2016	Phan et al. [34]	DL, CNN, Python, 60,000 Synset from SentiwordNet, 14,865 tweets, Precision = 81%, Recall = 82%, F1-Score = 81%
S21	2018	Fu et al. [35]	DL, RNN [LSTM], Python, 147,668 dataset from IMDB, Yelp2013, MR, NB-4000, Book4000, Accuracy = 80.8%

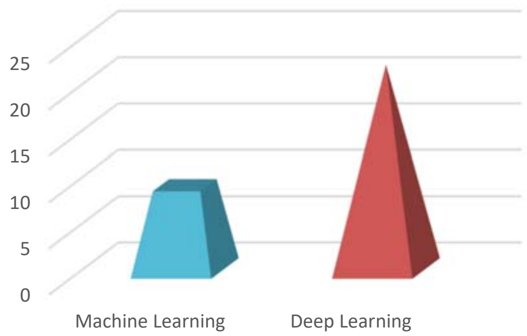

Fig. 2 AI based methods for SA

There is also research into the usage of mixed algorithms or strategies to improve performance over single algorithms. CNN + LSTM [24], [32], [46], CNN + RNN-GRU [21], CNN + RNN [22], [35], [44], RNN + RNN-GRU [33], CNN + TWAM [36], WORD2Vec + GloVe [38], CNN + BERT [47].

This study also discovered that RNN [50] with LSTM unit is explicitly designed to avoid gradient disappearance and produces better results when compared to RNN such as Bidirectional-LSTM (commonly referred to as Bi-LSTM) [20], [32], [39], Tree Structured LSTM referred to as Tree-LSTM [51], and Nested LSTM referred to as NLTM [52].

B. Datasets

Datasets are recognized pool of evidence that is used in a certain domain to address an issue. According to Kamei and Shihab [48], AI researchers can use diverse datasets that are publicly available to create sentiment classifiers. It should be highlighted, however, that the quality of publicly accessible datasets cannot be guaranteed [49].

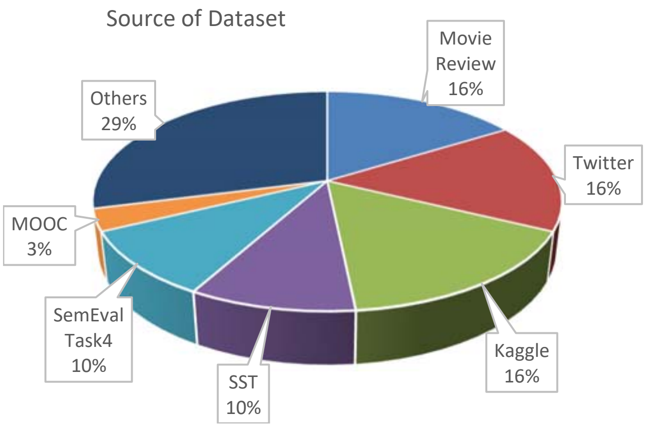

Fig. 3 Percentage of frequently used dataset

The fraction of datasets that were regularly utilized in previous studies is shown in Fig. 3. Based on the findings, we can conclude that Twitter [9], Kaggle.com, and movie reviews are the most commonly used dataset repositories for SA by previous researchers. For example, [13]-[16], [20], [22], [24], [27], [28], [30], [31], [34], [35], [39], [41], [42] employed large datasets to train their sentiment classifier, which was quite accurate. This demonstrates that, as predicted by [36], a large dataset is required for a high-accuracy sentiment classifier to be efficient and successful.

C. Programming Language

The prototype sentiment classifiers were written in a particular programming language. In comparison to implementation using Java programming language [27], more researchers advocated the use of Python programming language for implementation due to its simplicity and more AI-based library functions [14]-[16], [18], [20]-[26], [28], [31]-[35], [39]-[42], [44]-[47]. A graphical comparison of the two languages is shown in Fig. 4. As a result, we suggest Python as a preferable choice for future development.

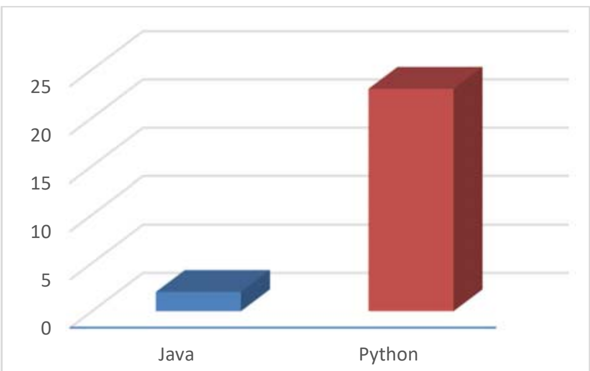

Fig. 4 Programming language

D. Evaluation Metrics

Researchers should analyze their proposed model or strategy to solving an issue since it allows them to check the model's efficiency and efficacy. Accuracy, Precision, Recall, and F1-Score are some of the numerical assessment metrics that can be utilized in SA measurement.

According to our research, accuracy is the most commonly used statistic. It is calculated by dividing the number of successfully identified feelings by the total number of sentiments. We utilize the F1-Score as the second most used statistic for SA. The recall value comes in third, followed by precision.

The distribution of the various numerical evaluation metrics is depicted in Fig. 5.

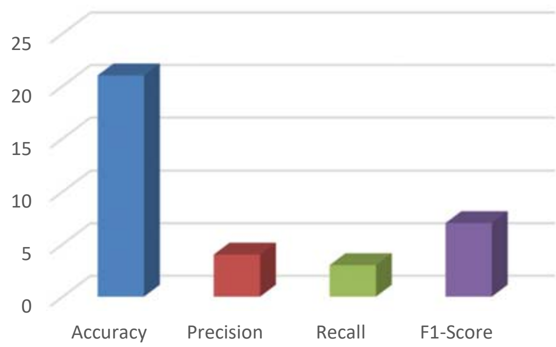

Fig. 5 Distribution of evaluation metrics

E. Model Performance Evaluation

DL models outperformed ML models in terms of model performance. Similar to the single models, the deep hybrid models outperformed them.

Now let us focus on the specific integrated algorithms that were used. The CNN + LSTM combination has the best accuracy. After then, CNN + BERT airs. CNN + RNN is in third place, followed by CNN + RNN (Bi-GRU). Fig. 6 shows the performance distribution of various DL hybrid models.

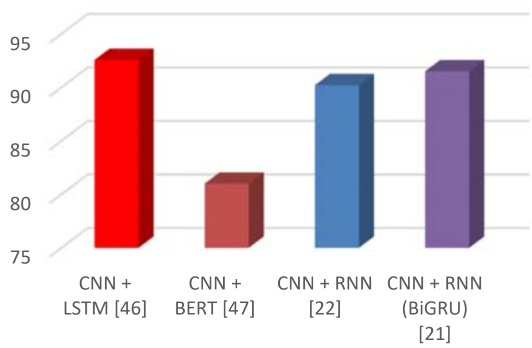

Fig. 6 Distribution of models' performance

Table IV depicts the relationship between the major studies and the research questions, as well as whether or not the studies answered the questions.

TABLE IV
SUMMARY OF DATA EXTRACTION

ID	References	RQ1	RQ2	RQ3	RQ4	RQ5
S1	Wassan et al. [15]	√	√	√		
S2	Schulz et al. [13]	√	√		√	
S3	Malandrakis et al. [14]	√	√	√		
S4	Bahrawi [16]	√	√	√	√	
S5	Bahrawi [18]	√	√	√		√
S6	Nurhuda et al. [19]	√	√		√	
S7	Xu et al. [20]	√	√	√		√
S8	Cheng et al. [21]	√	√	√	√	√
S9	Xuanyuan et al. [22]	√	√	√	√	√
S10	Tang et al. [23]	√	√	√		√
S11	Naqvi et al. [24]	√	√	√	√	
S12	Singh et al. [25]	√	√	√	√	√
S13	Deng et al. [26]	√	√	√	√	
S14	Bouazizi & Ohtsuki [27]	√	√		√	√
S15	Sanagar and Gupta [28]	√	√	√	√	√
S16	Feng & Cheng [30]	√	√		√	√
S17	Dong et al. [31]	√	√	√	√	√
S18	Zhou et al. [32]	√	√	√	√	√
S19	Aydin & Gungor [33]	√	√	√	√	√
S20	Phan et al. [34]	√	√	√	√	√
S21	Fu et al. [35]	√	√	√		√
S22	Liu et al. [36]	√	√		√	√
S23	Wang et al. [38]	√	√			√
S24	Hameed & Garcia-Zapirain [39]	√	√	√		√
S25	Li et al. [40]	√	√	√	√	
S26	Wu et al. [41]	√	√			
S27	Jelodar et al. [42]	√	√	√	√	√
S28	Zheng & Zheng [44]	√	√	√		√
S29	Hameed et al. [45]	√	√	√		√
S30	Venkatesh et al. [46]	√	√	√		√
S31	Li et al. [47]	√	√	√	√	√

IV. CONCLUSION

We used a systematic and thorough evaluation in this study to investigate and evaluate the performance of several AI-based SA algorithms. Following a thorough examination and a step-by-step process, the identified 31 key studies from 2013 to 2021 were assessed. The research was mostly reported in a tabular manner, with AI-based approaches, algorithms, datasets, programming languages, performance metrics, and model performance all taken into account.

The following are the most important conclusions from the studies:

(a) In previous literatures, ML and DL approaches were the most commonly employed AI-based methodologies.
(b) The ML approaches we identified were NB, NB + SVM, and Random Forest.
(c) Our research identified LSTM, CNN, BERT, CNN + LSTM, CNN + BERT, and CNN + RNN (GRU) as DL strategies.
(d) For training the sentiment classifier, a large dataset is necessary, and the most widely utilized sources were Twitter, Movie review, Kaggle, SST, SemEval Task4, and MOOC.
(e) The two major programming languages identified were Python and Java, with Python being the most widely used programming language due to its simplicity and more AI-based functional libraries.
(f) The most relevant measuring measures were determined to be accuracy, precision, recall, and F1-Score; accuracy was the most commonly utilized performance parameter in the key research.
(g) Finally, when compared to other methodologies employed in the primary studies, hybrid DL approaches performed better.

We urge that the study's findings are seriously considered while designing and developing a more robust and efficient sentiment classifier for textual categorization on online social media networks.

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