A Systematic Survey on Deep Neural Networks for Sentiment Analysis

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***Abstract* - Sentiment analysis is a powerful approach for processing, analysing, speculating, and summarising unstructured content to convert it into reliable information. With the increasing demand for sentiment analysis in real-life applications, new discriminate machine learning and natural language processing techniques have been introduced in past years. However, the deep neural network is an emerging approach that learns by multiple layer feature dimensions of data and predicts faultless for large corpora with minimum computational cost. These neural networks provide the automatic feature engineering and advanced word embedding (TF-IDF, One Hot Encoding, Word2Vec, and Glove) for feature vector presentations that are helpful in extracting the meanings from complex linguistic texts. Therefore, a systematic survey is presented to provide detailed knowledge about deep neural networks that are rapidly applied in sentiment analysis with enhanced linguistic capabilities. The prime contribution of the existing researchers is highlighted with the focal point of deep learning-based sentiment analysis. Additionally, several benchmark datasets, feature engineering techniques, and existing deep learning-based research performance are also discussed. The prime objective of this survey is to present the credibility of the deep neural network to handle the sentiment analysis tasks.**

Keywords- Sentiment Analysis, Deep Learning, Feature Engineering, Convolutional Neural Network, Gated Recurrent Unit, Artificial Intelligence

I. INTRODUCTION

Sentiment analysis combines information retrieval, Natural Language Processing (NLP), and Artificial Intelligence (AI). It is a growing field of research due to its wide adoption in various real-life applications. Presently, it is noticed that various people are actively participating on online social networks, and they are sharing their emotions in terms of comments, likes, posts, stories, and blogs. The tremendous growth of social media users increased the bulk of unstructured data on the internet, which can be mined to extract useful information. Therefore, efficient sentiment modelling is required to mine the amorphous content of social platforms effectively and generate reliable information in opinion, polarity, and subjectivity [1].Sentiment analysis examines attitudes, appraisals, evaluations, emotions, and thoughts. The famous phrase of sentiment analysis is "opinion mining," which is extrapolated from information retrieval and data mining procedure [2-3]. Many approaches like the lexicon, deep learning, machine learning, or hybrid have been introduced by different researchers to develop efficient sentiment analysis models [4]. These techniques rely on either supervised or unsupervised learning mechanisms. The supervised approach trains on labelled datasets, where a mapping function is used to map the input with the output and predicts reliable outcomes [5]. The unsupervised approach also identifies the patterns from unlabelled data [6-7]. Deep neural networks produce efficient results for multiple language processing. These models effectively work with Arabic and produce good accuracy for sentiment analysis tasks [8].

Most research focused on English language sentiment analysis, but deep learning networks have also advanced the Persian language [9]. A systematic survey is needed due to the increasing demand for deep learning neural networks in sentiment analysis. A systematic survey is presented to describe deep learning-based feature extraction and classification techniques. Figure 1 depicts the detailed methodology used in the survey. The contribution of the paper is presented below:

- Sentiment analysis-related feature engineering techniques, namely Term Frequency-Inverse Document Frequency (TF-IDF), Word2Vec, One Hot Encoding, and Glove, has been discussed in detail.
- Additionally, a comprehensive discussion of deep learning models, namely Recurrent Neural Network (RNN), Convolution Neural Network (CNN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Recursive Neural Network (Rec NN), and Memory Network (MN), and have been made.
- Furthermore, existing state-of-the-art models and datasets related to sentiment analysis tasks are presented to benefit future research in this field.

Further subsections of this survey are organised as follows: Section II discusses the detailed description of deep learning-based feature vectorization techniques. Section III presents the taxonomy of deep neural network models. Section IV presents the results of existing deep learning research and benchmark datasets. Finally, Section V concludes the work and discusses the future opportunities in sentiment analysis.

II. DEEP NEURAL NETWORK

Feature extraction and representation are essential to process before the final prediction and classification. This section presents a detailed description of different feature vectorization techniques applied before the final prediction.

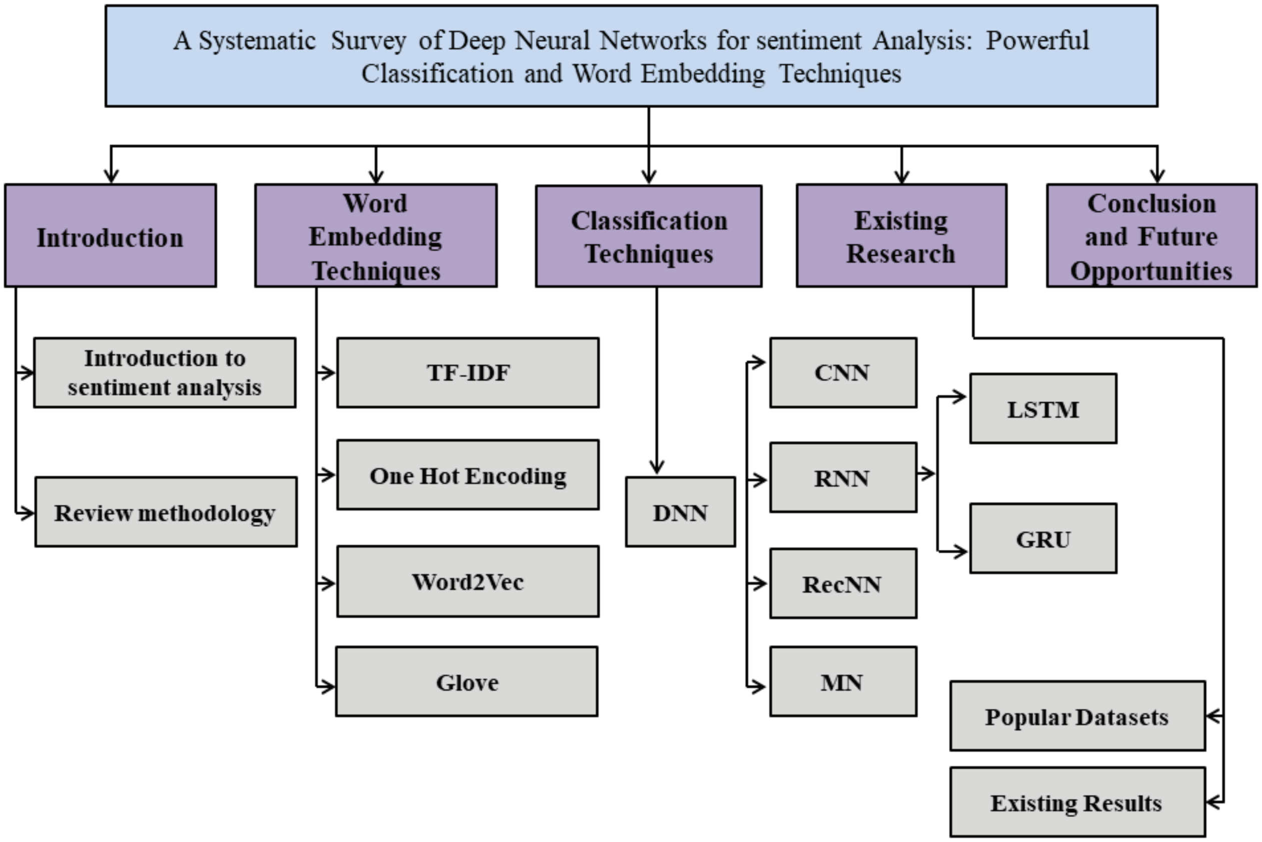

Fig. 1. Architecture of the Systematic Survey.

A. TF-IDF

It is a statistical approach used to check the mathematical contribution of a phrase in a document [10].

$$TF(term, doc) = \frac{F_{doc}(term)}{\max\limits_{w \in d} F_{doc}(w)} \tag{1}$$

$$IDF(term, D) = 1n\left(\frac{|D|}{|\{doc \in D{:}term \in doc\}|}\right) \tag{2}$$

where, $f_{doc}(term)$ the frequency of term t in documents d and D represent the document corpus, the frequency of the word decreases if it occurs in another document. Hence, the phrase is not essential if it frequently occurs in another document as well.

B. One Hot Encoding

It is a method of presenting a categorical variable into binary vectors to make the data machine-understandable. In this, vectors are created according to the size of the total distinctive words. The vector's values are organised in the manner that the index associated words value is assigned as 1 and 0 for others [11].

C. Word2Vec

It is an AI-based model that contains the input, output, and hidden layers. The aim of this method is to generate an embedding based on the probability of the particular phrase surrounded by other phrases.

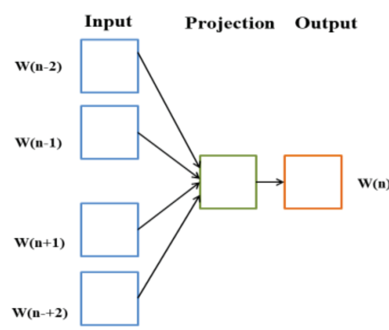

Fig. 2. CBOW method

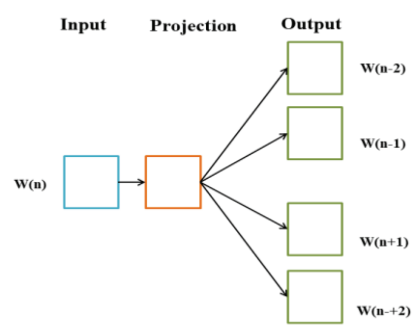

Fig. 3. SG method

It basically works on two different architectures [12], in Figure 2Continuous bag-of-words (CBOW) and Figure

3Skip Gram (SG). SG method takes the target words as input and recommends the surrounding words for the target word. It is calculated as:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-k<l<k,l\neq 0 i=1}^{t} logp(w_{n+1}|w_n) \tag{3}$$

On the contrary, CBOW forecasts the target words by acquiring the content of each input word. It is calculated as:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-k<l<k,l\neq 0 i=1}^{t} logp(w_t|w_{t+l}) \tag{4}$$

This is the most popular method in which the entire corpus is scanned, and the semantic closeness of the words is calculated.

D. Glove

Glove word is derived from two different terms, Global and Vectors. It is a global vectorization method based on Word2Vec for text word embedding. The probability ratio between the two words is calculated as:

$$F(w_x.w_y, w_z) = \frac{P_{xz}}{P_{yz}} \tag{5}$$

The idea of this matrix is to identify the relationships of the words using statistics [13].

III. Deep Learning based Sentiment Analysis

With the incremental growth of neural network models in the past few years, deep learning techniques acquired vast success in multiple applications [14-16]. These techniques have more potential to solve NLP-related problems. Various layers of deep neural models can deeply handle the complexity of a text for sentiment polarity detection.

A. CNN

CNN's are the special neural models with a known grid-type topology. These are continuously applicable for different types of applications such as time series forecasting and classification types of data with a 1D grid and for image processing data with a 2D grid pixel. CNN's have a linear sequence of layers, where the previous layer transfers one volume of activation to the next layer. CNN's have become a popular model for image sentiment classification [17].

Figure 4 presents the central architecture of CNN. CNN holds the input, convolutional filters, convolutional, and max-pooling layers. Unlike the image processing corpus, the NLP input is usually a sentence where each row indicates the word and each word indicates the vector.

B. RNN

RNN is a network in which the output of the preceding layer is inserted into the succeeding layer as an input. Therefore, RNN has become more popular for solving NLP-related problems. RNNs hold the memory that can store arbitrary long sequences and help to predict the next word. Figure 5 presents the working procedure of RNN where x_t depicts the input of t time, s_t is the hidden state of time t, and o_t depicts the output of t time. Unfolding means building a network for the full sequence. U transfers the xt input to the S_t, state. W transfers the previous S_{t-1} state to the S_t, current state, and V is used to map the s_t state to the o_t output [18].

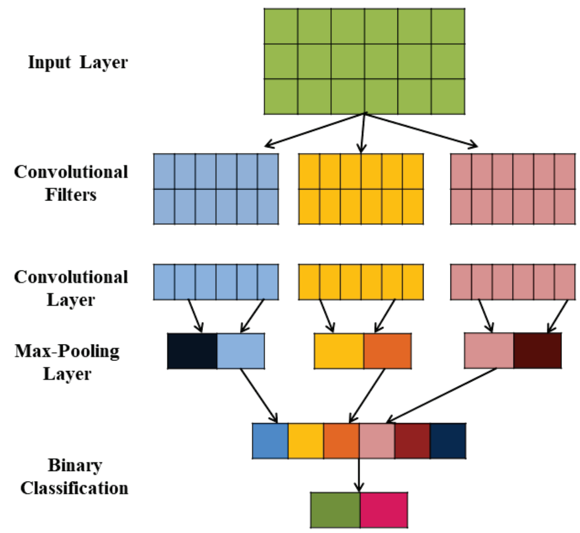

Fig. 4. Fundamental Architecture of the CNN Model

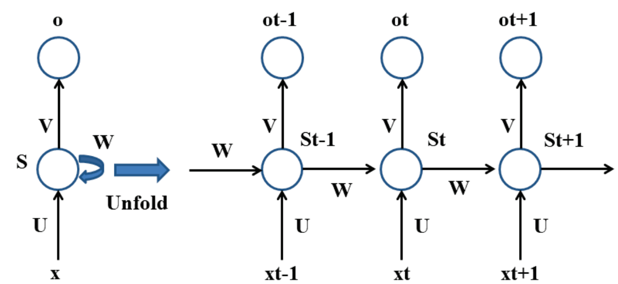

Fig. 5. RNN Working Architecture

1) LSTM

LSTM is the special variant of the RNN model. It has the capability to learn long-distance dependencies. They are widely adopted in various kinds of applications.

$$i_n = \sigma(w_i[H_{n-1}, x_n] + b_i) \tag{6}$$

$$f_n = \sigma(w_f[H_{n-1}, x_n] + b_f) \tag{7}$$

$$o_n = \sigma(w_o[H_{n-1}, x_n] + b_o) \tag{8}$$

$$\hat{c} = \tanh(w_c[H_{n-1}, x_n] + b_c) \tag{9}$$

$$c_n = f_n * c_{n-1} + i_n * \hat{c}n \tag{10}$$

$$H_n = o_n * \tanh(c^n) \tag{11}$$

Here, i_n represents the input gate, f_n represents forget gate, o_n represents output gate, w_x is the weight for related gate (x), $H_{n-1}$is the output of preceding state, s_n indicates input in current timestamp, b_x shows the biases for related gate (x), and c_n is the cell state at n timestamp [19].

2) GRU

GRU is similar to LSTM as it has gates to manage the information flow but introduced little advancement over

LSTM. Unlike LSTM, GRU does not hold separate memory cells. Instead, it keeps only the hidden state to make the process simpler and faster. GRU has only two gates, namely Update Gate and Reset Gate.

- **Reset Gate:** holds the information for short-term memory timestamp.
- **Update Gate:** holds the information long-term memory time stamp.

At every timestamp, the GRU cell takes an input (X_t) and hidden state (H_{t-1}) from the previous timestamp (t-1). After that, it produces output (H_t) for the next timestamp.

$$R_t = \sigma(X_t * U_t + H_{t-1} * W_t) \tag{12}$$

$$U_t = \sigma(X_t * U_u + H_{t-1} * W_u) \tag{13}$$

$$H_t = \tanh(X_t * U_g + (r_t . H_{t-1}) * W_g) \tag{14}$$

$$H_t = U_t . H_{t-1} + (1 - U_t) . H_t \tag{15}$$

where, $R_t$represents to the reset gate, $U_t$represents the update gate, H_t represents candidate hidden state and H_t shows the hidden state [20].

C. RecNN

RecNN is an adaptive model based on deep tree complex inherent chains [21].

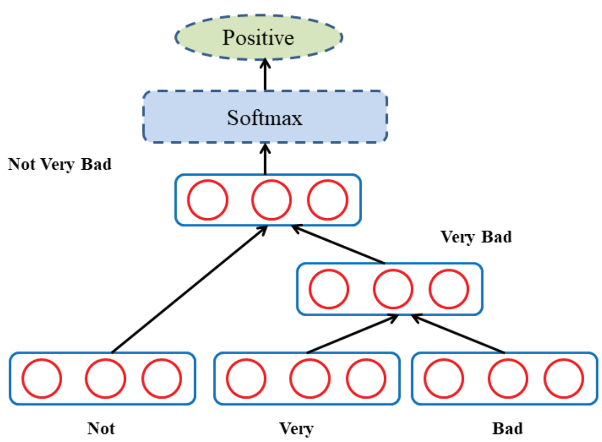

Fig. 6. RecNN Composition Architecture

Figure 6 presents the composition process of RecNN. It represents the phrases in dimensional vectors and follows the method of binary trees for composition. Where it obtains the composition based on the bottom-up approach [22].

D. MN

The architecture of the MN neural model contains the memory m with four major components, namely Input Feature Map (I), Generalisation (G), Output Feature Map (O), and Response (R).MN works like a CPU attached with memory. It is used to process a large amount of data, such as for knowledge base questions and answering tasks [23].

IV. Results and Discussion

Deep neural networks have the potential to deal with the complexities of linguistic content. Therefore, it is widely adopted by researchers to perform sentiment analysis tasks on different domain datasets.

A. Popular Datasets

This section presents the popularly adopted different domains datasets for the sentiment analysis tasks.

- **Stanford Sentiment Tree Bank (SST):** is a sentence dataset categorised into binary and fine-grained versions. The binary version (SST2) has been labelled as positive and negative and holds 18,000 records.
- **Yelp Challenge:** contains restaurant-related reviews extracted from Yelp.com. It has three subsets namely yelp-13 stores 335,015 reviews, yelp-14 stores 1,125,457 reviews, and yelp-15 stores 1,569,264 reviews. It is labelled as five categories of review rating.
- **IMDB:** is a popular movie reviews dataset that contains 50,000 movie reviews equally divided into 25,000 positive and 25,000 negative classes.
- **Customer Reviews:** is a benchmark dataset, extracted from the Amazon shopping website, that holds 3,775 customer reviews labelled as positive and negative.
- **Semantic Evaluation (SemEval):** is an aspect-based sentiment analysis dataset labelled as positive, negative, and neutral polarity. It contains 3845 different domain and languages reviews.
- **Vietnamese Student Feedback (UIT-VSFC):** contains 16,175 student feedback records. It is a freely available dataset categorised into positive, neutral, and negative feedback.
- **Kindle:** is an Amazon product reviews dataset containing 982619 reviews records with positive and negative polarity.
- **Sentiment140:** is a Twitter dataset introduced by Stanford University graduate students. It holds 1,600,000 tweets automatically distributed into positive and negative polarity.
- **Political Party Tweets:** This Twitter dataset holds 1,00,000 reviews about the various political parties categorised into positive and negative sentiments.
- **Trip Advisor:** holds the 1851 user reviews about London and New York cities. The average length of reviews is 73 words that polarised as positive and negative sentiments.

B. Existing Deep Learning Research Results

As mentioned above, the deep learning approach is widely adopted by researchers for various NLP-related tasks. This section presents the various state-of-the-art existing research results in a comparative manner. Table I presents the chronological results of the existing deep learning-based sentiment analysis models.

TABLE I. CHRONOLOGICAL SUMMARY OF RESULTS OF EXISTING DEEP LEARNING BASED SENTIMENT ANALYSIS MODELS.

Study	Technique	Result (Accuracy)
Ouyang et al. [24] (2015)	Proposed a framework for sentiment analysis with the combination of Word2Vec and CNN.	45.4%
Naguyen et al. [25] (2015)	Perform an aspect-based sentiment analysis using RecNN.	66.20%
Stojanovski et al. [26] (2016)	Proposed a novel model by adjusting the CNN model's weights to optimize the sentiment results.	64.59%
Poria et al. [27] (2016)	Proposed a 7-layer CNN model for aspect extraction in opinion mining.	86.20%
Baly et al. [28] (2017)	For sentiment analysis, utilize the deep learning advancement, namely Recursive Neural Tensor Network (RNTN).	81%
Dou et al. [29] (2017)	Proposed a Deep MN for document-based sentiment analysis.	61.30%
Chen et al. [30] (2018)	Proposed a new scheme LSTM with extra attention on emojis for sentiment analysis.	90%
Ma et al. [31] (2018)	Proposed a Sentic-LSTM hybrid model for aspect-based sentiment analysis.	66.19%
Rehman et al. [32] (2019)	Proposed CNN-LSTM based hybrid model for movie reviews sentiment analysis.	91%
Edara et al. [33] (2019)	Proposed a distributed framework using LSTM neural network for medical records sentiment analysis.	82.18%
Yang et al. [34] (2020)	Proposed a novel model with the combination of CNN and BiGRU for E-commerce product reviews for Chinese language sentiment analysis.	93.5%
Murthy et al. [35] (2020)	Perform a sentiment analysis on IMDB movie reviews dataset using LSTM.	99.56%
Pathak et al. [36] (2021)	Proposed a Topic-level sentiment analysis model using LSTM neural network	87.9%
Li et al. [37] (2022)	Proposed a bi-directional emotional RNN for conversational sentiment analysis	65.93%

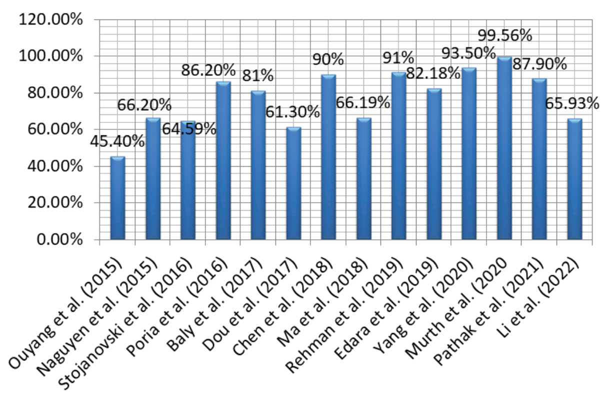

Fig. 7. Comparative Results of existing Sentiment Analysis Model based on Deep Learning

Figure 7 presents the comparative results of deep learning models for the sentiment analysis task. It is observed that most of the researchers applied LSTM neural model for the sentiment analysis task, as it has the memory to store long-term dependencies of text content.

V. CONCLUSION

Deep learning is a powerful mechanism for analysing the sentiments from texts, images, and videos dataset. Therefore, huge research has been done in this field by experimenting with the different feature engineering and optimization techniques. Hence, this survey presented profound knowledge regarding various deep learning-based feature engineering and classification techniques. Additionally, the state-of-the-art research in sentiment analysis using deep learning models is discussed with their comparative results and applied neural networks. It is observed that researchers frequently use the LSTM model for text sentiment classification. Moreover, LSTM and the combination of LSTM with CNN achieve better accuracy than other neural models for sentiment analysis tasks. According to the existing research and feature engineering techniques, it has seen that no manual features are required for deep learning models, and an end-to-end network model can directly calculate the sentiment polarity. Furthermore, ten benchmark datasets are also presented that are frequently used by the researchers for experimenting the text classification-related research. It is to be expected that this in-depth knowledge regarding sentiment analysis and deep learning techniques will be contributed to further research in this field.

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