Advances and Applications in Mathematical Sciences
Volume 21, Issue 5, March 2022, Pages 2565-2580

EMOTIONAL ANALYSIS OF TWITTER SOCIAL MEDIA DATA WITH AN EFFICIENT DEEP LEARNING MODEL

S. SANTHOSH BABOO and M. AMIRTHAPRIYA

Principal and Research Supervisor
P. G. and Research
Department of Computer Science
D. G. Vaishnav College, Arumbakkam
Chennai-600106, India

Research Scholar
P. G. and Research
Department of Computer Science
D. G. Vaishnav College, Arumbakkam
Chennai-600106, India

Abstract

Individuals are encouraged by the modern age to communicate their emotions through web-centered media locales namely Facebook, Instagram, Twitter, etc. A well-known microblogging service is Twitter in which status messages (named "tweets") are created by users. Sometimes, opinions are expressed by these tweets regarding disparate topics. For the emotion identification of Twitter data, an effective Deep Learning (DL) algorithm, namely Enhanced Long Short Term Memory (ELSTM) is created by this paper. From data collection, the research method is started. From the openly accessible database, the data for the existing work is gathered. The gathered data is preprocessed after data collection. From the preprocessed data, the extraction of features namely emoticon and non-emoticon features are done. Afterward, for the extracted features, score values are allotted along with fed into the classifier for emotion prediction. For examining the proposed work's performance efficiency, experiments are performed. The results illustrate that better accuracy is attained by the proposed ELSTM when contrasted to existent classifiers.

2020 Mathematics Subject Classification: 46.
Keywords: Emotion analysis, Twitter, Deep learning, Term weighting, Long Short Term Memory.
Received October 15, 2021; Accepted December 24, 2021

1. Introduction

A major part of the globe is Social media (SM) [1]. For communicating with one another without worrying about differences in morals along with social values, huge opportunities are created by social networking websites, namely Twitter and Facebook for a user [2, 3]. Views, opinions, along with emotions are expressed by numerous people regarding a specific thing via social networks. An outstanding opportunity is offered by the researchers for analyzing the emotions of social networking users' activities [4]. For sharing information and expressing their opinion through tweets, Twitter is a microblogging website that is extensively utilized by the public [5]. When contrasted to several other SM platforms, a media platform is offered by Twitter which allows sharing opinions easily utilizing different content forms comprising text, images, and links [6]. Among all, one among the most favored SM platforms or channels is deemed as Twitter [7] from which an enormous quantity of rich records could be extracted in the opinion mining (OM) field [8].

Different opinions are distinguished by OM in favor or against any product, service, policy, issue, event, etc [9]. A strong feeling regarding a human's situation or relation with others is called emotion [10].

The multi-class classification of text into disparate emotion classes is called Emotion Mining. For the emotion's extraction, a hugely complex and difficult task is to investigate the textual postings on account of the complicated and informal language style along with semantics [11]. Fortunately, numerous Machine Learning (ML) methods are applied by researchers for uncovering the emotional pieces of information. However, continuous research efforts are still needed for the proposed method's accuracy. Besides, a common disadvantage of labeling huge training data is suffered. Utilizing computational methods along with techniques, the method of extracting high-quality information as of a huge amount of unstructured text is called Text Mining (TM) [12, 13]. For extracting the data, only a specific alphabet is required by this method. Further, it is then converted into disparate recommendations and expectations. The entire automatic Natural Language Processing (NLP) is encompassed by TM [14]. A similar analysis of NLP is allowed by TM utilizing the existent information which is available online. Therefore, new knowledge is discovered by the method via examining and detecting the pertinent information as of vast amounts of currently existent unstructured data [15]. For identifying the emotions of the Twitter data, this paper proposes a DL algorithm like ELSTM as a TM model. For obtaining more precise results, effective pre-processing and feature extraction processes are performed by the proposed work.

This paper is systematized as: Section 2 proffers the related work. Section 3 offers the proposed work. Section 4 illustrates the attained outcomes of the existent work. Section 5 provides the conclusion.

2. Related Work

Suboh M. Alkhushayni et al. [16] gathered a tweets dataset that was specified at least one of '7' fundamental emotions. A collection of 42,000 tweets was encompassed by the dataset with a balanced existence of every emotion. A lexicon of about 40,000 words was created from this collection; each of them was related to a weighted vector equivalent to one of the emotions. Then, in these cleaned tweets, disparate techniques of detecting emotion were executed and assessed. Lexically-centered classification along with supervised ML-centered classification was incorporated by these techniques. Lastly, the assessment of an ensemble technique was done which comprised numerous multi-class classifiers that were trained on the lexicon's unigram features. This evaluation illustrated that every other tested method was outperformed by the ensemble method when tested on existent datasets along with the dataset formed for this study.

Fereshteh Ghanbari-Adiv and Mohammad Mosleh [17] introduced an ensemble classifier that comprised '1500' of Multilayer Perceptron, k-Nearest Neighbor, along with Decision Tree classifiers. It was capable of systematically distinguishing disparate fine-grained emotions among regular along with irregular sentences with appropriate accuracy. Furthermore, for tuning the basic classifier's parameters, Tree-structured Parzen Estimator was utilized. For calculating the method, "3" disparate sets of ISEAR, OANC, along with Crowd Flower were employed that comprised regular along with irregular sentences. In the recognition of regular along with irregular sentences, the ensemble classifier's accuracies were 99.49 as well as 88.49%, correspondingly as exhibited by the results.

Maryam Hasan et al. [18] created and assessed a supervised ML system for automatically classifying emotion in text streams. '2' major tasks were incorporated by the approach such as an offline training task along with an online categorization task. For categorizing emotion throughout the 1st task, a system named Emotex was formed to generate models. For classifying live streams of tweets for real-time emotion tracking, a 2-stage framework named Emotex Stream was created in the 2nd task. Experiments revealed that emotion in 90% of text messages was accurately categorized by the created models.

Jitendra Kumar Rout et al. [19] employed unsupervised along with supervised algorithms for sentiment classification (SC) of unstructured Twitter data. For classification, a lexicon was produced and utilized. For determining the score for every term utilizing point-wise mutual information, a Google search engine was utilized by the model. A specific challenge was addressed in sentiment analysis that was, sudden variation as of positive to negative polarity. For the sentiment's detection in disparate datasets, ML algorithms were implemented. It was discovered that when contrasted to the other features utilized, the sentence-level classification with features namely unigram presence and POS were most precise.

Kashfia Sailunaz and Reda Alhajj [20] identified and examined sentiment along with emotion articulated by people as of the text in their Twitter posts. The collection of tweets along with replies on few particular topics was done. Also, a dataset was formed with text, user, sentiment information, emotion, etc. For detecting sentiment along with emotion as of tweets, the dataset was applied. Centered on different user-centered and tweet-centered parameters, the user"s replies and influence scores were estimated. Lastly, for generating generalized along with personalized suggestions for users, the latter information was employed grounded upon their Twitter activity.

For the Twitter emotion's identification, mostly ML classifiers are employed by the above-surveyed methods. A manual job is selecting an algorithm in ML. In every algorithm, the data should be tested. Next, centered on the attained results, only the best algorithm will be chosen. The process is very tedious. Besides, when running the algorithms on the data, it will be almost impossible to eliminate the errors if the data is huge. When analogized to classical ML, DL is more powerful. Here, transferable solutions are created via neural networks that are, layers of neurons/units. Therefore, a DL algorithm is introduced by this paper for executing the Twitter data‟s emotional analysis.

3. Proposed Methodology

For the emotion categorization of Twitter data, an algorithm like ELSTM is proposed as a TM approach in this paper. Initially, as of the publicly accessible dataset, the set of Twitter comments are gathered as an input. After that, by executing tokenization, stop word removal, stemming, along with lemmatization, the preprocessing of collected data is done. Next, the emoticon along with non-emoticon features as of the data is extracted by the feature extraction phase. Next, for the extracted features, the score values are allotted. Lastly, for emotion classification, the score values are offered into classifier ELSTM. '12' disparate classes of data such as happy, sad, anger, disgust, fear, joy, love, optimism, pessimism, trust, surprise along with neutral are encompassed by the ELSTM's output. Figure 1 exhibits the current method's framework.

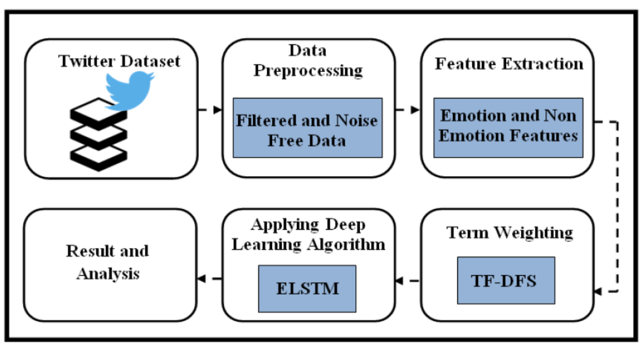

Figure 1. Framework of the research methodology.

3.1 Preprocessing

The tweets are preprocessed after data collection since a lot of noisy data are contained by tweets because of their short length. The subsequent preprocessing operations are executed by the paper.

1. Initially, every Twitter review is split into smaller tokens i.e. the tokenization of whole text document into smaller units, like individual words

or terms was performed.

2. The Twitter notations namely hashtags (#), retweets (RT), along with account Id (@) are removed.

3. URLs, hyperlinks, and punctuations are eliminated.

4. The stop words like “is, am, and, are” etc are removed. The emotions are not affected by stop words; it is simply for compressing the dataset.

5. There are series of repeated characters such as “coooooool”, “wishhhhh”, “happyyyyyy”, et cetera in tweets. These are changed to “cool”, “wish”, “happy”.

6. Stemming and lemmatization is executed. Identifying a general base form of a word by decreasing inflectional forms is the objective of stemming along with lemmatization.

7. Concerning the English expansion, a dictionary full of acronyms and abbreviations was formed. In SM, a few popular acronyms that are regularly utilized were gathered and that will be converted to their abbreviated form.

3.2 Feature Extraction

Here, emoticon (smileys) along with non-emoticon features (texts) are the ‘2’ sorts of features that are extracted.

For both features, a score value is allocated. For the emoticon features, the score value is allotted centered on the subsequent criteria: For the classes (happy, sad, fear, disgust, surprise, and anger), the extracted smiley is initially detected. The score value for the extracted smiley is allocated in the ranges of (0-2), (3-5) along with (6-8) if the identified smiley is in the class of happy, joy, and love. The score is fixed as (-4 to -6) and (-8 to -12) for sad and fear. The scores are allotted as (-2 to -5), (9-12), and (-13 to -15) for disgust, surprise, and anger. The score value is set as (13-15) and (16-18) for optimism and pessimism. The score is allotted in the ranges of (20-25) and (26-30) for trust and neutral. Next, centered on the TF-DFS model, the score value is allocated for non-emoticon features, which is elucidated in the below section.

3.3 Term Weighting

Using the Term Frequency-Distinguishing feature selector (TF-DFS) scheme, a weight is allotted for every term in this phase. Scores are allotted to every term by Distinguishing feature selector (DFS) deeming their distinguishing power and term frequency (TF) is defined as a raw term frequency (number of times a term takes place in a document). The amalgamation of these '2' methods are utilized by the paper, which is specified as

$$W_{TF-DFS} = TF(t_i, d_j) \times \sum_{z=1}^{N} \left(\frac{\left(\frac{t_i c_k}{t_i c_k + t_i \hat{c}_k} \right)}{\left(\frac{\hat{t}_i c_k}{t_i c_k + \hat{t}_i c_k} \right) + \left(\frac{t_i \hat{c}_k}{t_i \hat{c}_k + \bar{t}_i \hat{c}_k} \right) + 1} \right) \quad (1)$$

Wherein, N indicates the number of classes in the gathered data, $TF(t_i, d_k)$ implies the occurrence frequency of term t_i in the document d_j, and the DFS scheme is signified by the 2nd term in the equation. The term $t_i c_k$ denotes that the term t_i is contained by the class c_k, $\hat{t}_i c_k$ implies that the class c_k doesn't comprise the term t_i, $t_i \hat{c}_k$ denotes that the term t_i is not the member of the class c_k, and $\hat{t}_i \hat{c}_z$ indicates the number of sentences that do not comprise the term t_i in other classes. For TM, the score values of emoticon along with non-emoticon features of the single tweet are deemed as a final feature set and offered to the ELSTM classifier.

3.4 Emotion Prediction

A sort of recurrent neural network (RNN) is called LSTM. Here, in the current step, the output as of the last step is provided as input. The issue of RNN's long-term dependencies is tackled where the word saved in the long-term memory could not be predicted by the RNN. However, more precise predictions as of the recent information could be offered. Contrasted with typical RNNs, disparate gates are added by means of the LSTM for controlling the information flow. The LSTM unit's structure is exhibited in Figure 2. A forget gate, an input gate, an output gate, along with various input-output connections controlled by these gates are encompassed by LSTM. The central part of the LSTM is constituted by the '3' gate units. It is ensured that information could be stored and updated by the LSTM.

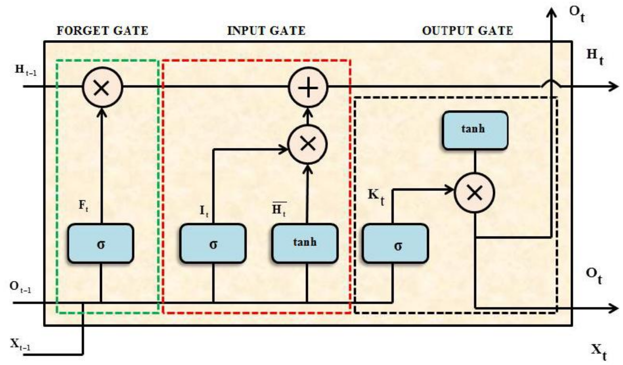

Figure 2. Structure of LSTM.

An input sequence $X = \{X_1, X_2, \ldots, X_T\}$ is mapped to an output sequence $O = \{O_1, O_2, \ldots, O_T\}$ by an LSTM network via assessing the network unit activations utilizing the equations indicated as of (2) to (5). For processing the preceding state O_{t-1}'s output and taking decisions by forgetting unnecessary information, the forget gate is useful. The forget layer with the sigmoid function is indicated in equation (2). New information with suitable scaling is added by the input gate, the values are updated by the sigmoid activation function (AF), and new candidate values (equations (4) and (5)) are formed by the tanh function. The updated new candidate value with appropriate scaling is also presented in equation (4):

$$F_t = \lambda(W_F \cdot [O_{t-1}, X_t] + B_F) \tag{2}$$

$$I_t = \lambda(W_I \cdot [O_{t-1}, X_t] + B_I) \tag{3}$$

$$\overline{H}_t = \tanh(W_I \cdot [O_{t-1}, X_t] + B_I) \tag{4}$$

$$H_t = F_t * H_{t-1} + I_t * \overline{H}_t \tag{5}$$

Lastly, the sigmoid function's appropriate output is signified in the subsequent equations (6) and (7).

$$K_t = \lambda(W_K \cdot [O_{t-1}, X_t] + B_K) \tag{6}$$

$$H_t = K_t * \tanh(H_t) \tag{7}$$

Wherein, I, F, and K implies the input, forget along with the output gate layer, H_t indicates the memory cell state, $\overline{H}_t$ denotes the candidate vector, and W and B in each equation signifies the weight and bias values of the specific layer.

The output layer is the LSTM's final layer that is utilized for the prediction of the emotion. For the prediction, only the AF is encompassed by the output layer, and the soft max AF is utilized in this case. But, an issue of "vanishing gradients" is caused by the usage of sigmoid activation. Therefore, rather than conventional sigmoid functions, an improved sigmoid AF is utilized. Improved sigmoid function together with its derivative are mathematically presented by (8) and (9),

$$f(X) = \begin{cases} \varepsilon(X - a) + s(a) & X \geq a \\ s(x) & -a < X < a \\ \varepsilon(X - a) + s(a) & X \leq -a \end{cases} \tag{8}$$

$$f'(X) = \begin{cases} \varepsilon & |X| \geq a \\ sigmiod'(x) & |X| < a \end{cases} \tag{9}$$

Hence, with the improved sigmoid AF, the equations that employ sigmoid may be substituted. For categorizing diverse issues, the LSTM networks' performances are promising; these networks are trained as other neural networks that rely deeply upon a set of hyper-parameters (weights together with biases), which define numerous algorithm behavior's aspects. Consequently, it is significant to ameliorate the LSTM hyper-parameters for attaining an effective performance in emotion categorization. To enhance LSTM, the BMCSO is employed in this paper. For the presented categorization system, the term ELSTM is given regarding this performance enhancement type in LSTM utilizing improved sigmoid activation together with its optimization. The optimization algorithm's comprehensive elucidation is provided below.

3.4.1 Cockroach Swarm Optimization

The cockroach's behavior of searching food, namely scattering, moving in swarms, or escaping from light, inspires the cockroach swarm optimization (CSO) algorithm. To resolve diverse optimization issues, namely dispersing, chase-swarming, together with ruthless behavior, at every iteration, '3' processes are engaged in the CSO algorithm. For searching the global optimum, via imitating the cockroach individuals' chase swarming behavior, CSO is primly built. The CSO can fall within local optimum via just executed this behavior; it can exhibit the individuals' diversity utilizing dispersing behavior; simultaneously, it can enhance the outcomes via replicating the ruthless behavior. Nevertheless, occasionally, CSO fails in discovering the global optima with the absence of an efficient balance betwixt exploration and exploitation and has been also confined easily within local optimum. A Brownian movement (BM) centered CSO termed BMCSO is proposed for resolving the premature issue and for enhancing CSO's local searching potential. For creating a candidate solution that is employed for preventing from being confined within local optimum, a modified search equation comprising extra helpful information as of the search experiences is implied in the proposed algorithm utilizing the BM. The steps are:

Step 1. Create the population of n individuals together with the algorithm's parameters as,

$$P_i = \{P_1, P_2, \ldots, P_n, S_{size}, V_S, S_D, C_S\} \tag{10}$$

Wherein, S_{size} implies the step size; V_{sc} signifies the visual scope; D signifies the space dimension; S_{cr} symbolizes the stopping criteria.

Step 2. Look for B_i (inside the i^{th} individual's visual scope) along with G_{bp}.

Step 3. Apply the chase-swarming behavior and then update G_{bp} at the last; the algorithm's chase swarming behavior is equated as:

$$P_{i,\, b+1} = \begin{Bmatrix} P_{i,\, b} + S_{size} * r_1(B_{i,\, b} - P_{i,\, b}),\ P_{i,\, b} \neq B_{i,\, b} \\ P_{i,\, b} + S_{size} * r_2(G_{bp,\, b} - P_{i,\, b}),\ P_{i,\, b} = B_{i,\, b} \end{Bmatrix} \tag{11}$$

Wherein, $P_{i,\, b}$ signifies the cockroach present position at the b^{th} generation; S_{size} implies a constant value; r_1 and r_2 signifies the random numbers $\in [0, 1]$. B_i symbolizes $P_{i,\, b}$'s finest position that is enumerated via the subsequent Equation (12) as,

$$B_i = Opt_j\{P_j |\ P_i - P_j\ | M_P\} \tag{12}$$

Wherein, M_p signifies the perception constant; $G_{bp,\, b}$ symbolizes the global best position at the b^{th} iteration. The algorithm utilizes the [0, 1] range for random number selection. Consequently, for random number selection, the BM is employed by the proposed methodology as an alternative of executing this. Herein, for acquiring a BM value, the BM is implemented into the random sequences as an alternative of selecting random numbers in the [0, 1] range. BM is amidst the physical phenomena type wherein a quantity constantly passes via small, random fluctuations. In the context of the minimal values in the benchmark functions, sure success is attained whilst BM is employed. The BM equation is,

$$B_m = g * rand(\cdot) * W_P \tag{13}$$

$$g = \sqrt{\frac{M_T}{G}} \tag{14}$$

$$G = 100* < M_T \tag{15}$$

$$W_P = \frac{1}{g\sqrt{2\pi}} \exp\left(-\frac{(D - cookroaches)^2}{2g^2}\right) \tag{16}$$

Wherein, M_T signifies the motion time duration in seconds of cockroaches; G signifies the number of sudden motions (alteration in the path) for the identical agent in proportion to time; D signifies the search space dimension. Whilst producing a novel solution $P_{i,\, b+1}$ regarding the i^{th} solution P_i via executing BM, the novel candidate $P_{i,\, b+1}$ is equated as:

$$P_{i,\, b+1} = \begin{Bmatrix} P_{i,\, b} + S_{size} * \chi \oplus B_m(\alpha_1)(B_{i,\, b} - P_{i,\, b}),\ P_{i,\, b} \neq B_{i,\, b} \\ P_{i,\, b} + S_{size} * \chi \oplus B_m(\alpha_2)(G_{bp,\, b} - P_{i,\, b}),\ P_{i,\, b} = B_{i,\, b} \end{Bmatrix} \tag{17}$$

Wherein, χ implies the random step size parameter; α_1 and α_2 signify the BM distribution parameter; $\oplus$ symbolizes the entry-wise multiplication.

Step 4. Implement the dispersing behavior and then update G_{pb}. The algorithm's dispersing behavior is equated as,

$$P_i = P_i + R(1,\, D) \tag{18}$$

Wherein, $R(1, D)$ implies a D-dimensional random position, which is fixed inside a specified range.

Step 5. Utilizing the below Equation (19), a ruthless process is applied,

$$P_r = G_{pb} \tag{19}$$

Wherein, r symbolizes a random integer that $\in [1, n]$

Step 6. Till a termination condition is fulfilled, repeat steps 2 to 5 and then output the outcomes. The maximal number of iterations, number of iterations with no enhancement, computational time, acquiring a solution's acceptable error, et cetera, is included in the stopping criterion.

4. Results and Discussion

For emotion classification of Twitter data, the attained outcomes of the proposed ELSTM are proffered. The proposed ELSTM is applied in JAVA, and to examine the presented methodology, the dataset is utilized that is the openly existent Twitter dataset. With the existent algorithms, like Support Vector Machine (SVM), Naive Bayes (NB), along with LSTM, the proposed methodology's outcomes are analogized for assessing the proposed classifier's efficacy. Centered upon '2' classification metrics, like f-measure along with accuracy, the methodologies are analogized. With diverse weighting methodologies, like Word to Vector (W2V), Document to Vector (D2V), TF, DFS, together with proposed TF-DFS, the techniques' *f*-measures and accuracies are analogized; in table-1 and figure 3, this is exhibited.

Table 1. Results of proposed and existing classifiers for emotion detection.

Table 1 (a). F-measure (%).

Techniques	Weighting Schemes				
	W2V	D2V	TF	DFS	TF-DFS
NB	70.14	71.36	74.85	76.23	78.93
SVM	74.25	75.12	76.29	78.64	80.02
LSTM	76.52	75.21	80.36	82.36	87.23

Proposed ELSTM	81.38	83.45	87.45	92.45	94.96

Table 1 (b). Accuracy (%).

Techniques	Weighting Schemes				
	W2V	D2V	TF	DFS	TF-DFS
NB	70.25	72.56	74.69	76.96	78.36
SVM	72.32	75.69	76.76	78.64	80.23
LSTM	78.23	76.32	80.23	84.65	88.32
Proposed ELSTM	82.32	84.98	86.98	90.23	96.38

It was noticed as of the outcomes that the highest accuracy and f-measure are attained by the proposed ELSTM whilst analogized to other algorithms. For the weighting schemes W2V, D2V, TF, DFS, and TFDFS, 82.32, 84.98, 86.98, 90.23, and 96.38 accuracy values and 81.38, 83.45, 87.45, 92.45, and 94.96 f-score values are attained by the proposed one. Analogizing altogether, for all the weighting schemes, the least f-measure and accuracy values are attained by the NB algorithm. For the weighting schemes, namely W2V, D2V, TF, DFS, and TF-DFS, 70.25, 72.56, 74.69, 76.96, and 78.36 accuracy values along with 70.14, 1.36, 74.85, 76.23, and 78.93 f-score are yielded by it. Whilst analogized to all, an average performance level is attained by the SVM. For a proffered weighting scheme, 80.23 accuracy value is yielded by it that is greater analogized to the other weighting schemes. Best performance is attained by all the classifiers whilst applying the TF-DFS scheme, and for the W2V weighting scheme, the least accuracy values are given by the classifiers' performances. Lastly, it was evidently validated as of the outcomes that the Twitter data's emotions are categorized much precisely whilst utilizing the TF-DFS weighting scheme together with ELSTM.

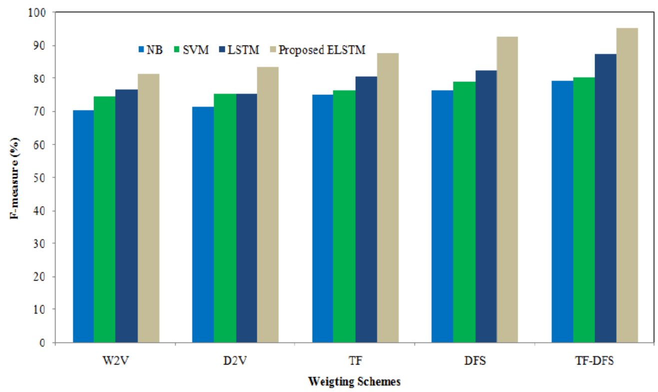

Figure 3 (a).

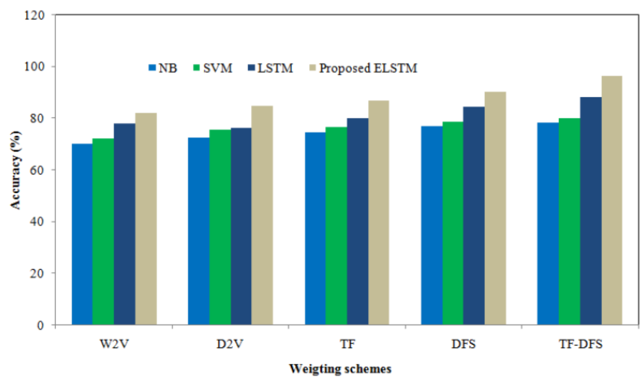

Figure 3 (b).

Figure 3. Results of proposed and existing classifiers.

5. Conclusion

For the SM Twitter data's emotional prediction, an ELSTM classifier, which can envisage the people's opinions for a specific domain, is developed in this paper. Product managers in their marketing campaigns understand customer emotions utilizing the SM data's emotional examination (happy, surprise, joy, disgust, love, fear, sad, trust, pessimism, optimism, anger, and neutral). Whilst it comes to product and brand acknowledgment, customer's satisfaction, customer's loyalty, advertising, and promotion success, together with product's acceptance, it is an essential factor. Whilst analogized to the other existent classifiers, superior outcomes are yielded by the presented

ELSTM; the highest f-score and accuracy levels are yielded by the classifiers whilst utilizing the propounded term weighting scheme (TF-DFS). To execute the textual and visual data's emotional classification, this work can be enhanced by establishing a DL design with an effective feature selection algorithm in the forthcoming future.

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