Firefly with Levy Based Feature Selection with Multilayer Perceptron for Sentiment Analysis

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***Abstract*—Sentimental Analysis (SA) has recently received a lot of attention in decision-making because it can extract and analyze sentiments from web-based reviews made by customers. In this case, SA has been used as a Sentiment Classification (SC) problem, in which reviews are typically labeled as positive or negative depending upon online reviews. By combining FS (Feature Selection) and categorization, this work proposes an effective SA method for internet reviews. FireFly (FF) and Levy Flights (FFL) algorithms have been used for extracting features of web-based reviews, and also the Multilayer Perceptron (MLP) framework has been used to categorize the emotions. A standard DVD database displayed the efficacy of the FF-MLP model on the testing. The outcome shows that the suggested FF-MLP system accomplishes enhanced performance with maximum sensitivity of 98.97%, specificity of 93.67%, accuracy of 97.97%, F-score of 98.75, and kappa of 93.32%.**

***Keywords*—sentiment classification, data mining, firefly algorithm, feature selection, multilayer perceptron**

I. Introduction

Overall, Sentimental Analysis (SA) was generally thought to be an essential research tool in the decision-making process for extracting and classifying feelings from online reviews. It finds relevant sectors such as economics, academics and internet shopping, among others [1]. SA seems to be primarily concerned with conducting a thorough study of internet reviews and establishing rankings about all sentiments. It was also known as the Sentiment Classification (SC) issue because it divides online product reviews into negative and positive expressions based on online words that arise in sentiment [2]. For example, a few words such as super, wonderful and brilliant depict a positive score while words such as waste, valueless and harmful denote a negative score. In terms of user reviews, internet products can be classified as either the finest or worst. However, after reading customer reviews, a significant fraction of users has decided to purchase products in recent years [3]. Reviews are used in various businesses to improve the quality of the product and identify customer satisfaction. For instance, when a person needs to buy clothing, the customer could read the Textile shop's reviews and purchase the item. The presence of many reviews makes it difficult to see all of them in real-time uses. As a result, it is critical to implement a technique for ranking products based on customer feedback. Consequently, the dataset used in SA seems to be more critical.

Data collection for SA has been proposed using a variety of ways. A large amount of information is gathered from both the user's and reviewer's websites. It develops a model that can be used in financial markets, publications, public discussions and other situations [4]. The attitude of people towards election candidates can be discovered in detail during political meetings. As the users distribute feature data, social media blogs and sites are generally regarded as the primary data sources. The classification of SA rules is complicated due to many datasets. As a result, increasing the number of datasets reduces computing a classifier technique. The Feature Selection (FS) procedure, which has the purpose of selecting critical elements from the database is being used to enhance the classifier's results. Therefore, the removal of unnecessary features helps to improve the overall simulation result of the classification phase.

The FS process is likely to be an optimization problem, and meta-heuristic methods may be utilized to solve the issue. Because of the efficient search approach, such models have been used. Basari *et al.* [5] introduced the Particle Swarm Optimization (PSO) and Support Vector Machine (SVM) technique to categorize movies as watchable or unwatchable. A PSO-Ascent approach has also been created to analyze and calculate SA, used in the PSO system. In SA, the feature extraction method seems more crucial because it removes undesirable characteristics to provide the best outcome. As a result, the precision of the PSO approach is generally computed using feature count in the reduced set. An effective Cuckoo Search (CS) and a K-means clustering technique called CSK are developed to classify problems better. Therefore, a collection of two similar methods is implemented to get a positive outcome.

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Bravo-Marquez *et al.* [6] created a practical SA approach by merging Twitter data's robustness, sentiments, and polarity. Kontopoulos *et al.* [7] was using an ontology-based SA for tweets that schedule sentiment ranking across all tweet services. On the other hand, Mohammad *et al.* [8] used a supervised artificial classifier to assess US president election-related tweets and identify the emotional state, stimulation, and significant theme of data. Coletta *et al.* [9] presents the benefits of SVM classification using cluster ensemble that aids in tweet classification refining. The SVM method is implemented to classify the data, and also the C3E-SL strategy is exploited to improve the SVM. Agarwal *et al.* [10] identified an appropriate SA by combining broad sense and content information collected from a ConceptNet-based ontology. It can also be used to discover application based concepts which is added to achieve domain oriented basic features. The authors established a successful SA model based on logic and context knowledge derived from ConceptNet-related ontology. It can be used to identify domain-oriented concepts and obtain domain-specific main characteristics. Saif *et al.* [11] presented the SentiCircle approach, which assigns the sentiment orientation for words based on their context.

The SentiCircle method was thus described for dynamically updating the sentiment strengths for different phrases. Kranjc *et al.* [12] utilize active learning upon the stream of data. A web-based tool based on SVM was provided to develop and maintain SA techniques. A workflow feature that uses web services is described for attaining the user interface for labeling tweets and a successful active learning SA system. Using document-level SA, Xia *et al.* [13] proposed a cascade strategy to address with polarity shift problem. In addition to that, for such perception lexicon development and goal extraction issue, Qiu *et al.* [14] created the double propagation system based on a semi-supervised technique. Moreover, a combination comprising three domain-independent emotion lexical features like SentislangNet, SenticNet and Senti-WordNet. Pandarachalil *et al.* [15] proposed an unsupervised and distributed framework to SA. Fernández-Gavilanes *et al.* [16] had created an unsupervised framework for sentiment prediction using informal writing based on a linguistic sentiment propagation technique. It does not require any training because of its unsupervised behavior, and it uses language content for SA.

The lexicon-based sentiment categorization algorithm was developed for social media types based on textual neighborhood activity with text classification [17]. In contrast, Appel *et al.* [18] developed an integrated model for detecting semantic polarity and intensity of posts using fuzzy sets and Natural Language Processing (NLP). Cambria [19] also discussed the benefits and limitations of several SA approaches including hybrid, statistical and knowledge-based statistical. Shah *et al.* [20] created the multimedia summarizing approach to studying online User Generated Contents (UGC) in multiple modalities.

SA could be handled like an SC issue in which the online reviews experience categorization into negative and positive aspects based upon words present as in online reviews.

The contribution of the paper is given as follows. This research proposes an efficient SA framework for online product reviews by incorporating feature extraction and categorization. The FireFly (FF) method extracts features in online product reviews followed by the Multilayer Perceptron (MLP) algorithm for sentiment categorization. The dataset is used in the research and the outcomes have been evaluated using several evaluation metrics. According to the acquired results, the provided FF-MLP algorithm obtains the best performance of the classifier on all of the used datasets across a variety of performance metrics.

A. Sentiment Analysis

An automatic and computer analysis of people's emotions, attitudes and feelings towards a specific objective is SA and OM [21]. OM takes and evaluates people's view on a subject, whereas SA recognizes and analyses the emotions expressed in such a text. SA tries to simplify the process of identifying opinions, recognizing the sentiments people portray and categorize their SA.

On various fields, people's perceptions act as an essential role to make decisions. If a person decides to buy a thing, they might also want to understand what others have to say about it before making a purchase. Businesses and organizations seek customer feedback on services and goods in the real world. SA applications have grown across numerous sectors including trend prediction, Ad placements and recommendation systems to politics and healthcare. Social media (such as postings, comments, forums, reviews, and blogs on social networking websites) has exploded in popularity on the internet has increased. The majority of businesses rely on them to build judgments. Because of the vast amount of open access data, organizations are no longer reliant on polling results, interviews or focus group discussions due to the requirement for verifying each website. A human reader would have difficulty in identifying relevant websites and extracting views. As a result, automatic SA is essential.

For SA and OM, two methods are commonly used: which is based on Lexicon and Machine Learning (ML). To recognize sentiments, the ML-based technique employs a variety of supervised or unsupervised classification algorithms. Lexicon-based approaches use a lexicon dictionary comprising sentiment words connected to a particular domain for sentiment classification. Each word's polarity, or whether it is negative or positive, is listed in a dictionary. The polarity of the words in a sentence could be determined by comparing them to the words in the dictionary. Lexicon-based and ML approaches were merged by certain researchers [22].

B. Multi-layer Perceptron

A multilayer perceptron was a very well-known and widely utilized neural network type. Signals were typically transferred over one way inside the network: between inputs and outputs. There seems to be no loop because each neuron's result does not affect the neuron overall. Feedforward architecture is the name for this design.

Hidden layers were those which were not directly connected to the surroundings. There has been some debate in reference literature on whether the initial layer (its input layer) should be regarded as an independent layer in the network. The sole purpose of it is to carry the input signals towards upper strata without pre-processing. We will identify the layers with stand-alone neurons in the following, noting that inputs were clustered within the input layer. Also, feedback networks could transfer signals in both ways due to response links as in-networks. Such networks were tremendously strong, but they may also be highly complex. The networks remain dynamic, constantly altering their state till the network meets the state of equilibrium. At that point, the new balance searching begins again with every input alteration. The necessity to expand the difficulty of decision areas prompted the addition of additional layers. A perceptron having a single layer with one input produces decisions area-like of semi planes, as described in the prior paragraph. When adding a layer, every neuron works like a typical perceptron for outputs of neurons within the preceding layer, allowing the network's output to calculate convex decision areas formed by the intersection of neurons' semi planes. On the other hand, the three-layer perceptron could produce arbitrary decision regions. Whenever it comes to the activation function of the neurons, it must have been discovered that multilayer networks cannot provide a significant improvement in processing capacity, particularly compared to single-layer networks [23].

Non-linear activation functions are the one that provides power to the multilayer perceptron. Except for polynomial functions, almost any non-linear function could be employed for this. A single-pole (and logistic) sigmoid has been the most often utilized function nowadays, as seen in Fig. 1 and Eq. (1).

$$f(s) = \frac{1}{1+e^{-s}} \tag{1}$$

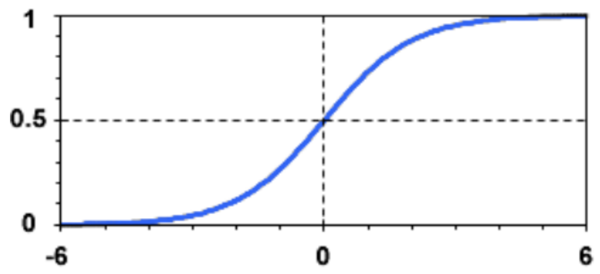

Figure 1. Single-pole Sigmoid activation function.

A bipolar sigmoid (i.e., hyperbolic tangent) process with $a = 2$ is given in Eq. (2):

$$f(s) = \frac{1-e^{-a.s}}{1+e^{-a.s}} \tag{2}$$

It's important to note that sigmoid functions behave almost linearly for low actual values of input and thus are saturated for large actual values of the input, thus taking on the role of the threshold. A network (potentially infinite) including one hidden layer has been proven to measure every continuous function [24].

II. The Proposed FFL-MLP Technique

In this work, we have introduced a new FFL-MLP model for sentiment classification. The proposed model follows a series of subprocesses as given as follows: Preprocessing of internet reviews that reduce redundant information, feature extraction, FF-L based on FS, and MLP categorizing system.

A. Pre-processing

The unwanted noise areas such as URLs, hashtags, and many gaps had been deleted before the feature extraction procedure and the normal expression mapping will be used to eliminate URL linkages in this instance. The punctuation marks like as /, _,\ and white spaces have been removed from the hashtag (#), whereas white spaces were replaced by white space. However, only a few words were transformed into lowercase for product reviews and stopping terms such as on, an, the, a, and is that do not begin with an alphabet were rejected. The acronyms and stop word dictionaries can be exploited to improve the accurateness of the input data.

B. Feature Extraction

The preprocessed web reviews were converted to feature vectors by generating ten features from the application dataset. The following are a few of the retrieved features out from the dataset:

- Neutral Words
- Negative Words
- Positive Words
- Negation
- Negative Exclamation
- Positive Exclamation
- Neutral Emojis
- Negative Emoji's
- Positive Emojis
- Character value

C. Firefly Algorithm

1) Behavior of fireflies

In temperate and tropical climates, the flashing light of the fireflies seems to be a big attraction as in the summer sky. There seem to be over 2000 various types of fireflies and also the majority of them generate brief, rhythmic lights. Its flash patterns were frequently distinctive to species. A Bioluminescence creates flashing light and also, actual roles of the specific communication systems were being disputed. Yet, the two primary functions of certain flashes seem to attract potential prey and attract potential mates (conversation).

Moreover, flashing can be used as a safety alert system. The signal system that pulls the sexes closer comprises a rhythmic flash, flashing rate, and duration. The Females react toward a male's distinctive flashing patterns of the same kind. Still, female fireflies in some species like photos could replicate the mating flashing pattern of certain other species to attract and consume male fireflies who could misinterpret the flashes as an acceptable prospective partner. This flashing light could be designed to be linked to the optimization objective function, allowing to the creation of innovative optimization techniques. The remainder of this work would outline the basic definition of Firefly Algorithm (FA) before execution and evaluation [25].

2) Feature selection based on FFL

The FF method has been used to choose the best attributes out of a higher dimension subset of features in SA. It was an essential method to the FF methodology because it uses pertinent data on the lighting of nearby FFs to analyze them uniquely. Based on the foundation of the distance process, each FF represents the interest over-highlighted neighbors. As in the standard FF approach, the searching procedure is based on control factors that possess both absorption and arbitrariness. A degree the best defined as determining the perfect mandatory acceptable route for the FS issue. The method incorporates several flashing FF elements to create an approach inspired by FFs. Apply the following three model ideas to demonstrate the flexibility of the Firefly Algorithm (FFA): 1) Each firefly was unisex. Thus, one FF will be engaged with the other fireflies regardless of sex. 2) Brightness seems proportional to clarity. Therefore, two flashing FFs should go to the appealing one. While no appealing one exists in comparison to a particular FF, it must be moved randomly. 3) It's the illumination of FF gets controlled by the goal function's site. The appeal becomes simple to contrast towards the objective function value while maximizing the issue. In the same way, another form of brightness was described as the fitness functions for GAs and Bacterial Foraging Algorithms (BFA).

The change in light intensity and the brightness formation are two significant issues in FA. It is simply stated that the brightness of FF was associated with attraction, which would be linked by encoding its goal function. Overall, FF attractiveness at a particular position gets chosen as $IT(p) \propto f(p)$ in the simplest case towards maximizing optimal issues. However, its brightness β seems relative, which should be evaluated and forecasted utilizing various FFFs Consequently, it varies depending on the r_{uv} Distance between FF u and FF v. Furthermore, as light intensity decreases and the distance from the light source is absorbed by media, we should allow the brightness that varies depending upon the absorption degree. Its light intensity $IT(d)$ varies according to the inverse square law $IT(d) = \frac{IT_s}{d^2}$, in which IT_s seem to be the source intensity.

Its illumination IT varies over distanced to produce an average light absorption coefficients γ collection. It appears as in Eq. (3),

$$IT = IT_O e^{-\gamma d} \tag{3}$$

IT_O represents the actual illumination. As the brightness of FF has been comparable towards the light intensity observed as nearest FFs, it explains an FF's brightness β in Eq. (4).

$$\beta = \beta_o e^{-\gamma d^2} \tag{4}$$

in which, β_o represents the brightness when d = 0.

3) Lévy- Flight FF techniques

During implementation, the brightness function $\beta(d)$ in Eq. (5) takes on its original form, a monotonically lowering function like the simpler version.

$$\beta(d) = \beta_o e^{-\gamma d^m}, (m \geq 1) \tag{5}$$

The feature-length to a set γ occurs as $\Gamma = \gamma^{\frac{-1}{m}} \to 1$ as $m \to \infty$. Parameter γ has been used as a distinctive main principle as in optimized issue that gives length scale Γ. It is $\gamma = \frac{1}{\Gamma^m}$. The Cartesian distance between two fireflies of u and v at p_u and p_v, respectively, is given in Eq. (6).

$$d_{uv} = ||p_u - p_v|| = \sqrt{\sum_{k=1}^{r} \left(p_{u,k} - p_{v,k}\right)^2} \tag{6}$$

wherein $p_{u,k}$ seems to be the k^{th} component of i^{th} FF's spatial control of p_u.

The distance involves time stoppage, and suitable appearances are other applications. The FF u progression to a more appealing FF v gets produced in Eq. (7).

$$p_u = p_u + \beta e^{-\gamma_{uv}^{d^2}} (p_u - p_v) + \alpha \; sign\left[rand - \frac{1}{2}\right] \oplus Levy \tag{7}$$

The second term would be due to brightness, while the third term is randomized utilizing Lévy flights, it will be as randomized parameter α. The output ⊕ denotes entry-by-entry multiplication. Even as arbitrary stage duration was created, the Lévy distribution as in Eq. (8), $sign\left[rand - \frac{1}{2}\right]$ With rand ∈ [0,1], provides a random symbol and orientation.

$$Levy \sim i = t^{-\lambda}, (1 < \lambda \leq 3) \tag{8}$$

Through an infinite mean, everything does have a limitless variation. The FF motion phase has become an arbitrary walk approach based on a solid tail power-law step division length.

4) MLP based classification

MLP is an FFNN method that assists in converting such a set of inputs toward an output power. It is expected that Logistic Regression (LR) classifier can transform the primary input using the acquired non-linear transform. Fig. 2 depicts the MLP architectural network. MLP discriminates non-linear transformations with unique hidden layers.

$$j = f_\theta(i) = \sigma(1 + B.\sigma(A + A.i)) \tag{9}$$

where A, B signify two matrices implying a set of two vectors, whereas sigmoid functions become (...). Its reduction functions were made up of j components as in Eq. (9), each improved using SGD (Stochastic Gradient Descent) and regular classification data. The objective function is denoted by C(θ). An effective SGD method simulates more tasks that have been needed. Several local minima generally restrict the function f_θ . The Local minima are investigated using several challenges such as Parity, Spiral and XOR that train the smaller NN.

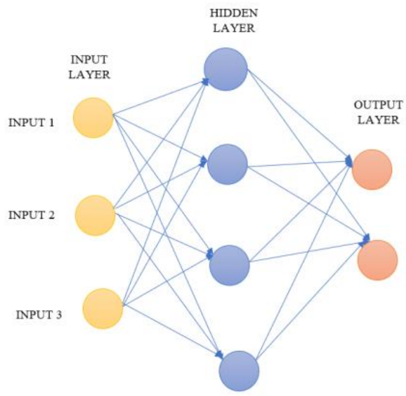

Figure 2. Design network of MLP.

Despite the occurrences of local minima, additional attempts have been made for training. Every local minimum as in parameter vector exhibits a considerable number of local minima because of f_θ symmetry. C(θ) may retain the basic hierarchy comprehensively across several scales. Various models have been used to train NN. Among a similar model with repeated annealing, the momentum becomes required to be shaped out from the local minima. The learning rate program has possibly been equipped with a minima hierarchy in multiple scales.

According to MLPs connection monitoring with varied load setups, comparable outcomes have been achieved in the weight area. It is also combined with the high MLP dimensional weight space search. As in the context of MLP, it seems to be necessary to figure out how the SGD optimization approach operates. A variety of origins can represent optimization monitoring. The necessary vectors are assessed and validated using the test sample of $\{\xi_1, \ldots, \xi_N\}$ as in equation 10, collected irrespective of θ factors.

$$\tau(\theta) = (f_\theta(\xi_1), \ldots\ldots, f_\theta(\xi_N)) \tag{10}$$

It would be necessary for using $(\theta) \approx \tau\,(\theta')$ to θ and 0 considering as two weight vectors. The usual evaluation becomes precise in the situation of NN-SGD optimization, and under predictions might well be stated as accurate whether there are numerous local minima.

SGD optimization tracks a learning rate until it reaches a significantly greater standard. At this point, it departs from the random process as in basin, which is concerned primarily with local minima. Each parameter space θ is divided into areas based on the learning rate in concern, and that everyone rises beyond the learning rate's local minima. It is possible to find multiple beginning points in the parameter space that combined to create the basin just above the actual scale of local minima [26].

III. Performance Validation

The proposed model is simulated using Python 3.6.5 tool on PC i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, 250GB SSD, and 1TB HDD. The DVD dataset was used to validate the performance of provided FF-MLP algorithm. There are 839 examples in the DVD dataset with 684 cases as in positive class and 155 cases as in negative class. The details of dataset are listed in Table I.

Table II shows a collection of extracted features from every dataset which contains both negative and positive words. Table III lists several examples of elements, each with a detailed description [27].

Fig. 3 and Fig. 4 have various measures. Table IV shows the comparison of results provided by model of FFL-MLP over the other comparable approaches.

TABLE I. Description of Dataset

Dataset	No. of instance	No. of classes	Positive	Negative
DVD	839	2	684	155

TABLE II. DVD Dataset - Extracted Features

S. No	Feature Name	DVD	
		Mean	**Standard Deviation**
1	Total Characters	59.098	58.098
2	Positive Emoji	0	0
3	Negative Emoji	0	0
4	Neutral Emoji	0	0
5	Positive Exclamation	0.023	0.023
6	Negative Exclamation	0	0
7	Negation	0	0
8	Positive words	0.886	0.886
9	Negative words	1.031	1.031
10	Neutral words	0.027	0.027

TABLE III. Samples of Different Features

Feature Name	Descriptions
Stopwords	Ah, can't, cause, etc, isn't
Positive Emoji	:-),:-),:-3,:),:],:3,:>,8),:),:->,8-)
Negative Emoji	:-(,:(,:-c,:c,:-<,:<,:-[,:[,:-‖,>:[,:{
Neutral Emoji	:-/,:/,:-.,>:/,:\,=/,=\,:L,=L,:S
Positive Exclamation	Ah, Oh, Oof, Phew, Whew, Aha, Boo-yab, H0-ho
Negative Exclamation	Ack, Bah, Ew, Gak, Ick, Ugh, Yuck, yech
Negation	No, Not, None, No one, Nobody, Nothing, Neither
Positive words	Accomplished, accurately, adaptable, beautiful
Negative words	Abnormal, abort, abuse, anxious, ashamed
Neutral words	Okay, fine, adequate, family, rarely

TABLE IV. Comparison of Existing and Proposed Method Using DVD Dataset

S. No	Dataset	Classifier	Sensitivity	Specificity	Accuracy	F-Score	Kappa
1	**DVD**	**FFL-MLP**	98.97	93.67	97.97	98.75	93.32
2		**FF-MLP**	98.52	91.19	97.14	98.24	90.59
3		**ACO-K**	98.23	89.93	96.66	97.94	89.03
4		**ACO**	97.92	86.50	95.70	97.35	86.03
5		**PSO**	96.57	79.69	92.61	95.23	78.76
6		**CSK**	96.27	72.85	90.10	93.48	73.05
7		**SVM**	96.93	74.88	91.18	94.20	75.85
8		**NN**	93.93	71.61	87.84	91.82	68.15

Various performance metrics, including overall F1 score, recall, precision, and accuracy are used to measure the sentiment analysis methods performance. The confusion matrix Table V is used to calculate the values of different measures.

TABLE V. CONFUSION MATRIX

	Predicted Positives	Predicted Negatives
Examples of Actual Positive	Examples of Total True Positive (TP)	Examples of Total False Negative (FN)
Examples of Actual Negative	Examples of Total False Positive (FP)	Examples of Total True Negative (TN)

The overall accuracy in Eq. (11) is measured to analyze the sentiment classification effectiveness.

$$\text{Overall Accuracy}=\frac{TP+TN}{TP+FP+TN+FN} \quad (11)$$

A prominent measure for evaluation has been:

The ratio of relevant records obtained to an overall number of unnecessary and relevant records returned is PRECISION, as shown in Eq. (12). In every case, it is expressed in percentage.

$$\text{Precision}=\frac{TP}{TP+FN} \quad (12)$$

The number of significant records extracted divided by an absolute number of substantial records in the database is known as RECALL, as given in Eq. (13). It is also represented as a percentage.

$$\text{Recall}=\frac{TP}{TP+FP} \quad (13)$$

When evaluating the classifier's performance in terms of sensitivity, this is discovered that the NN model performs ineffectively for producing improved results with the lowest sensitivity score of 93.93. The SVM, CSK and PSO models that uses average sensitivity ratings of 96.93, 96.27 and 96.57 correspondingly, produce relatively improved and nearly identical results. An ACO method, which has a sensitivity score of 97.92, delivers a tolerable classifier result. In addition, an ACO-K method achieves a high sensitivity score of 98.23, demonstrated even more efficient classifier outcomes. On the other hand, FF-MLP does have a competitive classifier result having a sensitivity score of 98.97. However, the FFL-MLP approach produces successful outcomes, having the highest sensitivity score of 98.97.

While evaluating the classifier's performance in terms of specificity, it is discovered that the NN model performs useless in producing improved results, with the lowest specificity score of 71.61. On the other hand, it's PSO, CSK and SVM algorithms produce relatively improved and nearly identical outcomes having moderate specificity scores of 79.69, 72.85 and 74.88 correspondingly. An ACO algorithm with a specificity score of 86.50 delivers an acceptable classifier result. In contrast, an ACO-K method achieves a high specificity score of 89.93, demonstrating much more efficient classifier outcomes. The FF-MLP provides highly comparable classifier results, including a better specificity score of 91.19. However, the FFL-MLP approach produces practical evaluation, with the highest specificity score of 93.67 [27].

While evaluating the classifier's accuracy, it is discovered that the NN model was ineffective in producing improved results, with the lowest accuracy score of 87.84.

The PSO, CSK, and SVM methods, on the other hand, provide relatively improved with nearly identical results, having average accuracy scores of 92.61, 90.10, 91.18, correspondingly. Consequently, the ACO model delivers a good classifier result with a 95.70 accuracy value. In addition, the ACO-K method achieves the highest accuracy score of 96.66, demonstrating much more efficient classifier outcomes. The FF-MLP has a comparable classifier result, including a higher accuracy score of 97.14. However, the FFL-MLP system produces significant results, with the highest accuracy score of 97.97 [27].

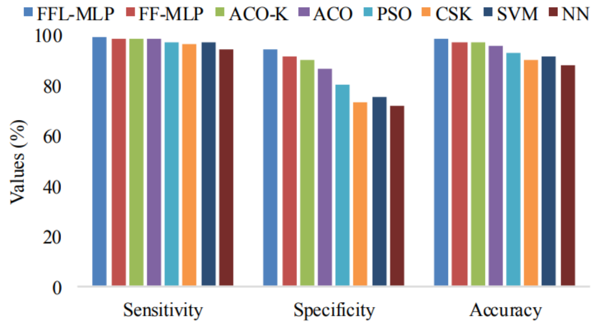

Figure 3. Performance measures of Sensitivity, Specificity and Accuracy classifiers.

While evaluating the classifier's performance in terms of F-score, it is evident that the NN algorithm performs ineffectively for producing better results, including a minimum F-score of 91.82. The PSO, CSK, and SVM algorithms, on the other hand, provide relatively improved and nearly equal results, having a moderate F-score of 95.23, 93.48, 94.20 correspondingly.

Accordingly, the ACO method offers a good classifier result with an F-score of 97.35. In addition, the ACO-K model achieves the highest F-score of 97.94, demonstrating much more efficient classifier outcomes. Similarly, the FF-MLP has a better F-score of 98.24, indicating a comparable classifier result. However, the FFL-MLP approach provides significant results, with the highest F-score of 98.75.

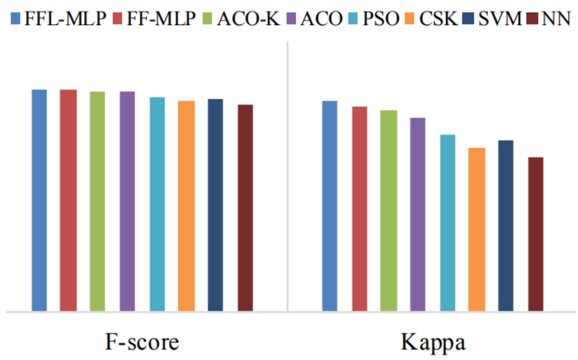

Figure 4. Performance measures of F-score and Kappa classifiers.

While evaluating the classifier's performance in terms of Kappa, it is evident that the NN algorithm performs ineffectively at producing improved results with a minimum Kappa score of 68.15. The PSO, CSK, and SVM algorithms on the other hand, provide significantly improved and nearly identical results with average Kappa scores of 78.76, 73.05, and 75.85 correspondingly. The ACO method, which has a Kappa score of 86.03, provides a good classifier result. Furthermore, the ACOK method achieves a high Kappa score of 89.03, demonstrating more efficient classifier outcomes. FF-MLP, on the other hand, does have a comparable classifier performance with such a highest Kappa score of 90.59. However, the provided FFL-MLP model produces significant results, having a Kappa score of 93.32 [27].

Finally, Table V reports a comparative computation time (CT) analysis of the proposed model with existing models. The experimental values indicate that the CSK, SVM, and NN model achieves higher CT values whereas the FF-MLP, ACO-K, ACO, and PSO models accomplish moderate CT values. But the FFL-MLP model results in effective performance with least CT of 11.24s.

TABLE V. COMPARISON OF EXISTING AND PROPOSED METHOD IN TERMS OF COMPUTATION TIME

S. No	Dataset	Classifier	Computation Time (s)
1	**DVD**	**FFL-MLP**	11.24
2		**FF-MLP**	16.23
3		**ACO-K**	17.46
4		**ACO**	26.21
5		**PSO**	32.23
6		**CSK**	63.48
7		**SVM**	54.69
8		**NN**	67.63

IV. CONCLUSION

SA is primarily concerned with conducting a thorough study of internet reviews and establishing values, including all sentiments. It is known as the SC issue since it classifies online product reviews as negative and positive aspects based on emotion-based online phrases. This research has proposed an effective SA method regarding online reviews by combining FS and categorization. The FFL method has been utilized to extract features from web-based reviews and also feelings are classified using MLP. A standard DVD database thus shows the proposed method's performance that has been used for testing. The outcome indicates that the suggested FF-MLP approach can easily classify data from any database by attaining maximum sensitivity of 98.97%, specificity of 93.67%, accuracy of 97.97%, F-score of 98.75, and kappa of 93.32%. In future, the performance of the proposed model can be improved by outlier detection and data clustering techniques. In addition, deep learning classifiers can be designed to improve the SA performance of the proposed model.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization: D. Elangovan and V. Subedha; methodology: D. Elangovan; software: D. Elangovan; validation: V. Subedha; formal analysis: D. Elangovan; investigation: V. Subedha; resources, writing—original draft preparation: D. Elangovan; writing—review and editing: D. Elangovan; visualization: D. Elangovan; supervision: V. Subedha; project administration: V. Subedha; all authors had approved the final version.

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