Artificial Algae-Optimized Support Vector Machine for Sentiment Analysis of Network Public Opinion

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This research is aimed at analyzing the user behaviour of network public opinion using a novel sentiment analysis algorithm. Although social network platforms like Twitter have distinct features, including tweet size, misspellings, and unusual characters, sentiment evaluation on these platforms is essential, yet existing categorization techniques mostly target textual content. So, in this research, an artificial algae-optimized adaptable support vector machine (AAO-ASVM) approach is proposed. The AAO method is applied to enhance the performance of the ASVM regarding effective sentiment analysis. Initially, we gather social network data samples, like Twitter, from a public source to train the proposed method. The gathered data samples are pre-processed for preparing and filtering textual data. This is followed by the presentation of the feature extraction technique known as term frequency-inverse document frequency (TF-IDF). From the extracted features, the proposed method is applied in sentiment analysis to analyze user behaviour in network public opinion. This research is developed on the Python platform to analyze the proposed method's performance regarding sentiment analysis. From the experimented outcomes, it can be concluded that the AAO-ASVM approach achieves the maximum performance in sentiment analysis compared to other existing studies. Consequently, the suggested approach AAO-ASVM achieves 92.54% precision, 90.4% recall, and 89.94% F1 score. Regarding user behavior and public opinion on the network, our suggested method outperforms the current one with accuracy as 94.50%.

Povzetek: Razvili so algoritem AAO-ASVM, optimiziran s pomočjo metode umetnih alg, ki združuje podporne vektorske stroje za analizo sentimenta javnega mnenja v omrežjih.

1 Introduction

Statements that make sense in light of people's prior opinions are more likely to be believed. In addition, people gravitate towards others who share their opinions. Confirmation bias and selective exposure are two methods that can produce homogeneous and polarized opinion clusters, known as echo chambers. Echo-chamber effects can potentially radicalize those with extreme beliefs by preventing them from being exposed to facts or viewpoints that contradict them [1]. Social hot topics and emergencies will attract attention in an open network environment, and it may be easier to sway public opinion online. Consequently, the establishment and progression of research perspectives can facilitate the examination and comprehension of various elements implicated in the shaping of public opinion. The core of comparable ideas provides a major explanation for public opinion behavior in macro groups that arise from the rules of micro individuals' evolution [2]. Social media data is being used by journalists to infer public opinion, which influences future reporting, gives policy development priority, and aids citizens in conceptualizing and feeling a part of their community. There is a recursive cycle in public opinion where citizens' attitudes are shaped by public opinion reporting [3].The media and other transformations in online public opinion providers have brought about a time of head-down reading in Chinese culture. Activities serve as the primary means for the majority of hackers to express, share, and engage with other's perspectives the network functions as the foundation upon which online public opinion is constructed[4]. An empirical collection of individual opinions, goals, and ideas among the adult population was defined as public opinion. The idea has been applied to discuss how society is impacted by the collective ideas of individuals along with the organic complex of opinions that people understand collectively rather than separately [5]. New media is gradually taking the place of traditional media as the main means of Information dissemination considering the Internet's rapid development. Users of the internet are typically individuals who voice their ideas and leave comments on subjects that interest them. Additionally, big data-driven collaborative filtering and recommendation algorithms meet the diverse needs of users for news topics, allowing users to engage with one another on online platforms [6].

Using online social networks (OSNs) allows users to be quickly informed about local and international news and events along with facilitating communication with friends and family. These data might contain opinions of those people who possess the key to further analysis, namely, opinion leaders and networks of these leaders [7]. Challenges that are inherent when using the behavior for network public opinion are; privacy issues when engaging in data collection, issues of a biased nature in gathered information, and finally, issues of analyzing the variety of sentiments. They may bring down the validity of the scope gained by the sentiment analysis, which poses a threat to its application in comprehending such dynamics of public opinion. To overcome these limitations, we propose an artificial algae-optimized adaptable support vector machine (AAO-ASVM) approach for analyzing the user behavior of network public opinion.

The work is categorized into related work in section 2, the methodology could be explained in section 3, section 4 explains the experimental results, and section 5 provides the conclusion.

2 Related work

Table 1: Summary of related works

Reference	Performance result	Merits	Limitations
[8]	SIRS Epidemic model is proposed and BA, FCN, SW models are compared with parameters and BA Model shows highest accuracy	This study enhances communication and interaction by introducing the SIRS epidemic model, connection strength variables from the J-A model, and employing the BA network model as the agent adjacency model.	this paper are not straightly applied to the empirical scene now This Author did not straightly applied to the empirical scene.
[9]	This Author chosen to confirm the applicability of ADDHM in terms of classification accuracy on the four experimental data sets, which are 96.68%, 88.86%, 89.64%, and 92.72%, respectively. It also has the best ROC curve performance.	In order to create a dual-channel model for emotion feature extraction, the model uses CNN and BiLSTM. To improve the attention to words associated to emotions, an attention mechanism is applied to every channel.	It is challenging to accurately identify word ambiguity and capture text sentiment elements.
[10]	The study utilized simulations to analyze the impact of game parameters on stability and improve the public opinion network's atmosphere and oversight effectiveness.	The study uses an evolutionary game model and ESS for constrained rationality to investigate public opinion monitoring as a game involving marketing accounts, web users, and platforms.	The public opinion and behavior strategies of network subjects are influenced by various elements, with the selection of relevant parameters being subjective.
[11]	Our proposed model outperforms existing rumor detection methods after extensive experiments on a large-scale real dataset.	This paper introduces a dynamic graph learning method that integrates network structure, context semantics, and sequential information to simplify the computational complexity of social network evolution.	Lack of detailed explanation of the performance metrics in network structures

[12]	The survey report evaluates sentiment analysis methods and emphasizes the role of researchers in predicting election outcomes using social media material.	This report reviews previous research on social media users' political leanings and highlights unresolved issues in sentiment analysis and election outcome prediction research concerns.	Predicting the outcome of elections appears to be an unexpected field that requires further development for accurate prediction.
[13]	This paper has two Bi-LSTM network layers, the prediction model trained using Tanh's activation function performs better than sentiment classification in terms of accuracy and F1-measure.	The objectives of this research were to create a military sentiment dictionary, create a sentiment analysis framework for social media, and evaluate the effectiveness of several deep learning models with various parameter calibration setups.	Lack of large dataset and actual model explanation
[14]	Netizens and the media are impacted by government regulation and oversight. The media is more affected by stronger oversight and instruction, which improves the government's capacity to direct the network.	It analyzed interactions between three groups in space and time. Ultimately, netizens' ability to manage their public attitude online, participate in cooperative decision-making and receive consistent attention was enhanced by their trust in the government and media.	Improvements are needed to the temporal evolution model, which assumes linear parameters, and the weak data in the 75-person research on the spatial structure of public mood evolution.
[15]	They examined that public opinion evolved, finally in the ultimate agreement of public opinion through structural whole spanners in joint communities and regular agents in a community using FJ model.	A unique structural-hole-based public opinion management strategy in social networks was the Social Hyper graph Community Public Opinion (SHCPO) technique in study has enhanced with FJ model	Lack of clear data sources and metrics the author used for the accuracy.
[16]	The proposed method f1_score of 98.5% and public opinion classification accuracy rate of 98.72% demonstrate that this method can perform well on the network public opinion sentiment analysis.	In order to obtain the query vector, key vector, and value vector, this approach maps the input text sequence to the three spaces of Query, Key, and Value.	There is not enough prediction value to explain.

3 Methodology

In this study, we obtained data from Twitter and pre-processed the raw data such as replacing emotions, reversing repeated words, replacing network words and eliminating links, numerals, punctuations, and stop words. Feature extraction utilized Term Frequency-Inverse Document Frequency (TF-IDF). An artificial algae-optimized adaptable support vector machine (AAO-ASVM) approach is proposed used for user behaviour of network public opinion using sentiment analysis. Figure 1 shows an overall flow.

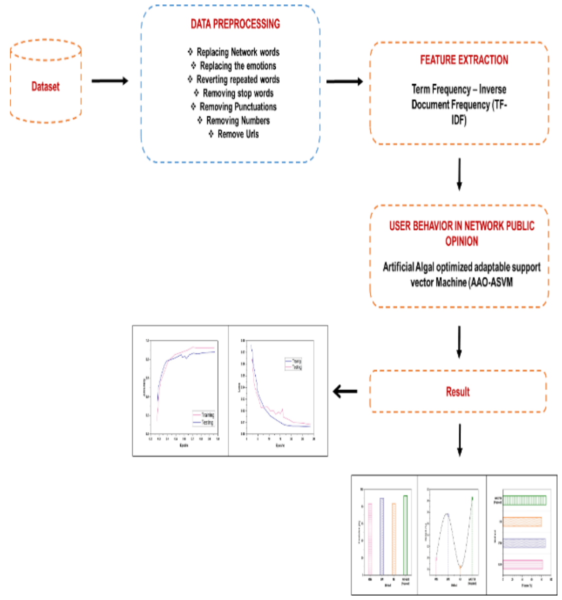

Figure 1: Overall flow

3.1 Dataset

This study gathered the data from Twitter, which is a well-liked academic research source due to its large global user base and availability of high-quality raw data. This research gathered the 7,253,928 tweets and Airline tweets(5,140,523). The feature that sets this dataset apart is the 140-character limit on the gathered texts. Twitter trims characters beyond this limit when it sends out the data. One of its features is the large number of answered tweets.

3.2 Data pre-processing

In this section, the raw data as text were pre-processed using seven different types of processing operations such as revealing repeated words, punctuations, replacing emotions, replacing network words, and eliminating links, numerals, and stop words.

- **Replacing network words**

Network terms are used extensively and frequently in Chinese. The accuracy of categorization will undoubtedly suffer if we ignore the network words because that word typically does not convey the meanings. Hence, the original meaning of the network word must be used in its place.

- **Replacing the emotions**

In Pinyin, "丿 (→→)︿"If pre-processing is not applied, this emoji will be interpreted as punctuation. It conveys a cheerful message. Since Happy is a positive word that will affect the classification's result, which is incorrect. We collected commonly used emotions and their associated meanings for this study. Additionally, we used the query method to replace the emotion queries with their associated meanings.

- **Reverting repeated words**

People on the network frequently use the same words. As an illustration, consider "我午伀伀伀伀伀伀伀心心开龍." Individuals frequently convey their emotions in this manner, in this instance, words or characters were utilized a lot. But this will have an impact on the effect of other steps.

- **Removing stop words**

Compared to providing helpful for sentiment analysis tasks, such as "吧" and "啊" and other stop words, this information will negatively impact the outcomes of the emotional analysis. The stop words in the text must be eliminated to lessen this effect.

Stop words are those that are often eliminated prior to processing natural language. These words, which include conjunctions, articles, prepositions, pronouns, and others, are actually the most often used in all languages and don't really add anything to the text. In English, some examples of stop words are "the," "a," "an," "so," and "what."

- **Removing punctuations**

Similar to stop words, punctuation such as commas and periods won't provide valuable data for sentiment analysis; rather, they will also negatively impact the accuracy. We must eliminate the punctuation from the text to lessen this effect.

- **Removing numbers**

The numbers also need to be eliminated because, generally speaking, they won't include any relevant information for the sentiment analysis task.

- **Remove URLs**

Numerous jumbled pieces of information, including numbers and symbols, can be found in the link. Furthermore, to mitigate this detrimental effect, these data are typically meaningless therefore it was used to remove the URLs.

3.3 Feature extraction

In this section using TF-IDF for feature extraction, user behaviour in network public opinion helps to identify and analyze sentiment dynamics across digital platforms by highlighting key phrases and patterns in user-generated material.

3.3.1 TF-IDF

A common method for figuring out a word's significance in a text is TF-IDF. The term frequency (t) for a given word is obtained by dividing its total number of occurrences in a document by its number of appearances. We can utilize IDF to determine important phrases. Certain terms, such as "is," "an," "and," and so on are frequently employed but have no real significance. $IDF\ (t)\ =\ log\ (N/DF)$, The formula for computing $IDF$is$N\ +\ DF$, where N is the number of documents and DF is the number of documents that contain word t. It is more efficient to use $TF - IDF$ when converting a textual information representation into a Vector Space Model (VSM).

In a text document, for instance, frequently occurring terms could be "Good," "Bad," "Happy," or "Sad." The recognition and usage of these terms might be extremely important in the process of opinion research. Frequency of Term (TF) is the quantity of instances of a phrase in a certain document and can be computed using the equation that follows:

$$w_f(t) = TD(t, d) \quad (1)$$

In a given document d, where TD is the frequency of word t, TF-IDF holds the inverted document frequency (IDF), which reverses the increased occurance for uncommon situations.
preserving a lower frequency for common ailments. IDF can be calculated with the following equation:

$$IDF_t = \log\left(\frac{d}{d_t}\right) \quad (2)$$

where d stands for both the number of terms and the number of frequency network. The results are computed using the following formula when the TF and IDF parameters are both set to true the equation that follows:

$$W_t = TF(t, d) \cdot IDF_t \quad (3)$$

3.4 Sentiment analysis of user behaviour in network public opinion

To analysis the Sentiment analysis of user behaviour in network public opinion using the artificial algae-optimized adaptable support vector machine (AAO-ASVM) which integrates the artificial algae optimization (AAO) and adaptable support vector machine (ASVM). Sentiment analysis of user behaviour in network public opinion involve analyzing the attitudes, emotions, and opinions articulated by users betweena variety of online platform and networks.Sentiment analysis of user behaviour in network public opinion is atechnique that utilizes computational approaches to examine the emotional tones that people express in online forums and social media.Thesentiment analysis categorizethe opinions as neutral, positive or negative by through processing method. It creates possible to comprehend how public opinion change over time and amongvaried groups, impacting communication tactics and decisions across a range of organization.

3.4.1 Artificial Algae Optimization (AAO)

AAO dynamically adjusts to user behaviour trends, developing network public opinion analysisthe characteristics and living behaviour of microalgae serve as the motivation for the AAO, an meta-heuristic optimization technique. An algae colony is a collection of algae that live together. Each colony is an example of a potential fix. Algal colonies make up the population, which is represented as follows:

$$Population = \begin{bmatrix} w_{1,1,} & w_{1,2,} & \cdots & w_{1,C} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,C} \\ \vdots & \vdots & \cdots & \vdots \\ w_{OM,1} & w_{OM,2} & \cdots & w_{OM,C} \end{bmatrix} \quad (4)$$

$$j^{th} algalcolony(W_j) = [w_{j,1}, w_{j,2}, \dots, w_{j,C}] \quad (5)$$

Where C denotes the dimensions of the algal colonies, PN is the number of algal colonies in the population, and $W_j$represents the algal cell in the j^{th} dimension of thej^{th} algal colony. A collection tweets datathat are thought to have solution dimensions make up an algal colony. The algal colony travels in unison in the direction of a suitable habitat that provides nutrients. The analysis moves, changes, and grows in an attempt to get into a greater place. When the colony is positioned optimally, the best positive user behaviour outcome is achieved public opinion. Every algal colony develops by the light and nutrients it gets throughout the search process. For all algal colonies, the initial size (greatness-G) is one. Eqs. (6) and (7) are used to compute the algal colony's growth for tweets data with public opinion (l).

$$\mu_j^s = \frac{\mu_{max}^s \times T^s}{L_t^s + T^s} \quad (6)$$

$$H_t^{s+1} = H_t^s + \mu_j^s H_j^s \quad (7)$$

Where H_j^s is the size of the j^{th} algal colony at time s, L_t^s is the substrate saturation constant at time$s$ (understood to be half of H at time s), and μ_{max}^s is the highest specific growth rate at the time in user tweet analysis. The three primary components of AAO are adaptability, helical movement, and the evolutionary process.

3.4.2 Adaptable support vector machine

The adaptable support vector machine learns from user behaviour patterns to optimize network public opinion analysis. The most effective learning technique for classifying text documents is Adaptable Support Vector

Machines (ASVM). The sentiment analysis theory's structural danger minimization concept serve as its foundation. The public opinion concept is to found the theoretical values with the least rate of mistake. In this examine endeavor, the classifier can use the linear kernel as the threshold function. This classifier requires both positive and negative training sets for analysis of tweets in network public opinion. These training sets are utilized to search for an option surface, which distinguish positive from the negative tweets and the negative tweets from the positive tweetsin the multidimensional space characteristics for public opinion, which is represented by a hyperplane. A "support vector" is a document representative that is closest to the decision surface.

$$G_1 \rightarrow \omega^S w_j + a = 1\ for\ z_j = 1 \quad (8)$$

$$G_2 \rightarrow \omega^S w_j + a = -1\ for\ z_j = -1 \quad (9)$$

Let bj be the desired output andaj the training documents. The separating hyperplane, which divides the positive and negative texts with the greatest margin, is examined by this algorithm.

The two hyperplanes, G_1 andG_2, separating the example documents in sentiment analysis for user behaviournetwork public opinion. Documents are not separated byG_1, but documents are separated byG_2using the smallest possible margins. In terms of performance, the ASVM method is superior to other classification algorithms. The feature selection function is used by this method to exclude undesired characteristics from public opinion with a high-dimensional feature space. This classifier's main drawback is the amount of time and memory it takes to train and classify documents' high-dimensional features. The following defines how the hyperplanes G_1 and G_2 are constructed:

$$z_j\left(\omega^S w_j + a\right) - 1 \geq 0 \forall_j = 1,2,\ldots,M \quad (10)$$

$M$is the total number of papers in this case. Equation (12) defines the sentiment investigation for public opinion that need to twitter data be maximized as follows:

$$min \frac{1}{2}\|\omega\|^2 \mathrm{b}$$

$$Subjectto z_j\left(\omega^S w_j + a\right) - 1 \geq 0 \forall_j = 1,2,\ldots,M$$

$$(11)$$

This formula is transformed into the Lagrange formula by connecting the restrictions and the objective function. This is described as:

$$\min K_o = \frac{\|\omega\|^2}{2} - \sum_j \alpha_j\left(z_j\left(\omega^S w_j + a\right) - 1\right)$$

$$\frac{\|\omega\|^2}{2} - \sum_j \alpha_j\left(z_j\left(\omega^S w_j + a\right) - 1\right) + \sum_{j=1}^{M} \alpha_j$$

$$(12)$$

$$\alpha_j \geq 0\ andj = 1,2,\ldots,M$$

The kernel matrix computation is carried over into the ASVM for text classification. Let domains and M be the total number of user network public opinion. Next, the term vector is expressed $SU_j \in \underline{Q}^m$ where n is the dimension and I stands for $\{1,2,\ldots M\}$. This can be changed to enhance the classification performance. The feature matrix $EN_j = SU_j$is created by the term vector SU_j. The kernel matrix $LN = EN_j.EN_j$follows. Using the original ASVM for the model computation could need a significant amount of storage space. The model computation will require less memory to the method for analyzing sentiment regarding public opinion through tweets. When $i = 1,2,\ldots M$, the term vector SU_jwill have the new term vector new SU_j with components of (value, location) when the values don't match the equation (9). The updated SU_jvector includes the new feature matrix new FM.

3.4.3 AAO-ASVM

Sentiment analysis of user behaviour in network public opinion analysis in tweetoffers important insights into the general emotional reaction to particular subjects or occurrences. Through the analysis of sentiment patterns shared on multiple platforms for user behaviour in network public opinion in some tweets, including social media and forums, researchers can determine popular perceptions and important narratives. This approach highlights the main forces underlying changes in public opinion and aids in understanding that network public opinions develop and propagate throughout online communities. In the end, applying sentiment research helps public and private sectors anticipate trends, develop communication strategies, and promote well-informed decision-making.

Prior to classifying the input data (test set), the algorithm must first be trained using pre-classified data (training set) in order to generate classification rules. Pre-classified data is supplied as test data for any AAO-ASVM algorithm's performance analysis, allowing the algorithm's output to be contrasted with the pre-labeled data. The suggested grid search technique's performance is examined in this investigation using the same methodology. One source of pre-labeled datasets is social forums is Twitter.

4 Result

4.1 Experimental setup

Using Python 3.10.1 software and the Tensor Flow/Keras or scikit learn technique, a Windows 10 laptop with an Intel i7 core CPU and 8GB of RAM was modeled.In this section proposed approach AAO-ASVM is contrasted to existing methods such as Support Vector Machines, K-Nearest Neighbors, and Random Naïve Bayes (SVM, KNN, and NB) [17]. The following specifications are used: F1 score, recall, and precision.Loss measurements the error or discrepancyacrosspredict and definite sentiment analysis, which is important for assess the effectiveness of sentiment analysis techniques in accurately capturing user opinions. Accuracy process the accuracy of sentiment prediction in user behaviouranalysis, indicating how well the model predicts sentiments compare to actual data. Figure 2 shows accuracy and loss. The two dataset parameters are analysed in Figure 2 (c,d) tweets shows highest accuracy as compared with Airline tweets dataset in sentiment analysis in network public opinion.

Table 2: Outcome value of training and testing set.

Dataset	Training set (75%)	Testing set (25%)	Accuracy (%)
tweets(7,253,928)	5,440,446	1,813,482	94.50
Airline tweets(5,140,523)	3,855,392	1,285,131	89.05

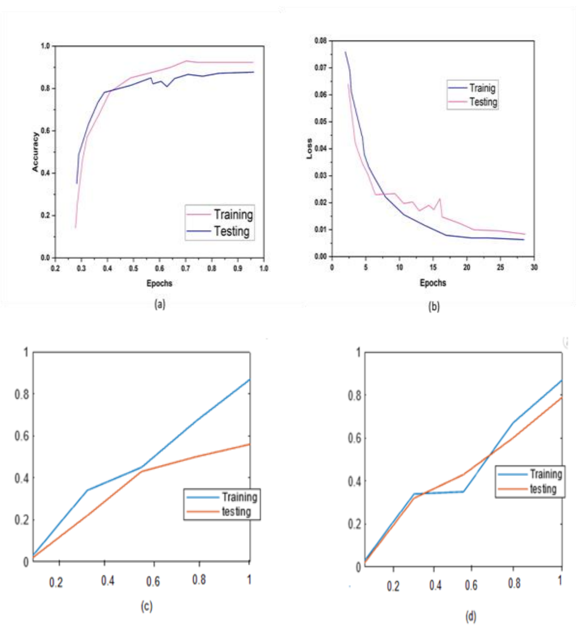

Figure 2: Accuracy and Loss

Recognition and categorization of feelings expressed in user-generated content are critical components of precision sentiment analysis of user behaviour. It gauges the accuracy of sentiment forecasts, which is important for comprehending the dynamics of public opinion.

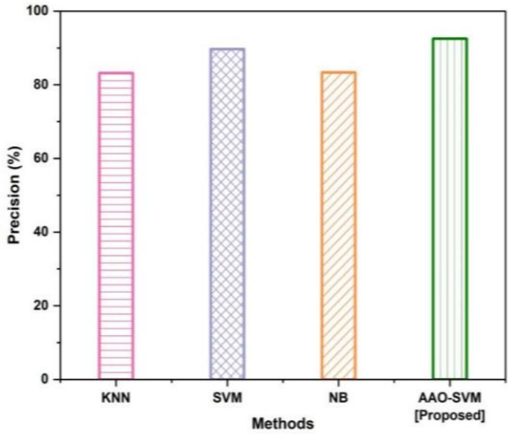

Figure 3: Precision performance

Figure 3 displays the precision performance. The proposed AAO-ASVM precision value is 92.54%, outperforming the existing systems, KNN, SVM, and NB which have the precision of 83.2%, 89.7%, and 83.33% respectively. Our proposed method is effective in analyzing the behaviour of network public opinion using sentiment.

Recall measures how well the model recognizes every pertinent sentiment conveyed in user-generated content when it comes to sentiment analysis for user behaviour.

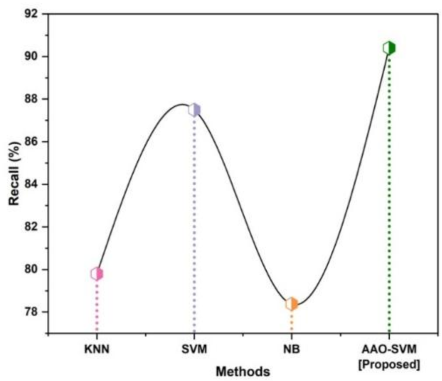

Figure 4: Recall performance

Figure 4 display the recall performance. The proposed AAO-ASVM recall value is 90.4 %, outperforming the existing systems, KNN, SVM, and NB which have the recall of 79.8%, 87.5%, and 78.38% respectively. Our recommended method is superior in analyzing the behaviour of network public opinion using sentiment.

The combination of recall and precision in one metric, the F1 score offers a fair assessment of a model's performance in detecting pertinent sentiments while analyzing user behaviour through sentiment analysis. The evaluation of sentiment analysis performance on a variety of user-generated information is very helpful as it provides an understanding of the model captures the accuracy and comprehensiveness of sentiment predictions.

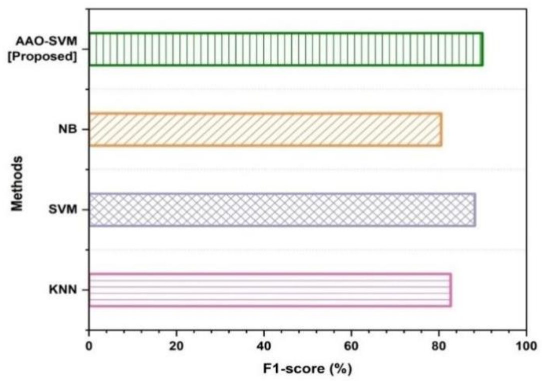

Figure 5: F1- score performance

Figure 5 displays the F1 performance. The proposed AAO-ASVM F1 value is 89.94%, outperforming the existing systems, KNN, SVM, and NB which have the F1 score of 82.7%, 88.2%, and 80.52% respectively. Our suggested method is better in analysing the behaviour of network public opinion using sentiment. Table 3 displays the values of Precision, recall, and F1-score.

Table 3: Outcome values of F1score, recall, and precision

Methods	Precision (%)	Recall (%)	F1score (%)
KNN	83.2	79.8	82.7
SVM	89.7	87.5	88.2
NB	83.33	78.38	80.52
AAO-SVM [Proposed]	92.54	90.4	89.94

4 Discussion

Applying standard machine learning algorithms to sentiment analysis tasks, particularly on social media platforms, like SVM, KNN, and NB, often results in several limitations. In large datasets, for instance, KNN becomes computationally costly and ineffective due to its relevance to similarity computations for every data point. Despite its disadvantages, SVM requires extensive parameter change and not scalable when handling large volumes of data. Naïve Bayes relies on feature independence which is rarely applicable on text data derived from real world sources and it can produce lower sentiment predictions. To avoid these difficulties, the AAO-ASVM that stands for artificial algae optimization adaptable support vector machine was proposed. As a result, this method improves the SVMs and their flexibility, by dynamically optimizing the SVM parameters using the artificial algae optimization methodology. The proposed AAO-ASVM approach is useful in addressing the scalability issue, handling non-linearity and interpretability of sentiment data and augmenting the precision of sentiment analysis. Unlike normal KNN, SVM and NB algorithms, the AAO-ASVM technique optimize the SVM parameters in real-time and handles voluminous noisy data characteristic of SMCPs well. This makes more reliable and accurate as an approach towards undertaking sentiment analysis effectively. To confirm the impact of AAO-ASVM on sentiment classification, a comparative experiment is planned. The ideal hyperparameter combination is chosen by selecting appropriate evaluation indexes and adjusting the hyperparameters. Two sets of public opinion data are chosen for experimentation, and the outcomes are analyzed with accuracy rate of 94.50%.

5 Conclusion

In network public opinion user behaviour, a novel sentiment analysis algorithm is applied. This research proposes the artificial algae-optimized adaptable support vector machine (AAO-ASVM) approach. The AAO technique is applied to increase the ASVM's effectiveness in sentiment analysis. The python tool is used to stimulate the proposed method. As a result, the performance of the proposed method attains precision - 92.54%, recall-90.4%, and F1- score-89.94%. In terms of user behaviour and public opinion on the network, our proposed method is better than the existing approach. Future developments in Artificial Algae Optimization-Adapted Support Vector Machine (AAO-ASVM) user behaviour analysis in network public opinion involve improving sentiment analysis accuracy using sophisticated optimization approaches. Complementing big data analytics with deep learning helps improve comprehension of intricate user behaviour. However, issues like computational complexity, scalability of the model and the requirement for reliable data pre-processing exist. It will be imperative to address these to properly use AAO-ASVM in real-world settings, guarantee trustworthy insights into the dynamics of public opinion across various digital platforms, and enhance sentiment analysis-based decision-making processes. Future research is being conducted to identify issues and opportunities related to e-learning in light of public opinion. Subsequent investigations will examine advanced techniques for extracting opinion and product features, along with novel classification models that can tackle the ordered labels property in rating inference. It's also anticipated that in the near future, applications leveraging sentiment analysis data will become available.

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References

[1] Wang, X., Sirianni, A.D., Tang, S., Zheng, Z. and Fu, F., 2020. Public discourse and social network echo chambers driven by socio-cognitive biases. *Physical Review X*, *10*(4), p.041042.https://doi.org/10.1103/physrevx.10.041042

[2] Liu, S., Tian, Y. and Chai, J., 2020, December. Group Opinion Evolution Model and Analysis Based on Heterogeneous Individuals. In *2020 IEEE 6th International Conference on Computer and Communications (ICCC)* (pp. 2186-2190). IEEE. https://doi.org/10.1109/iccc51575.2020.9345007

[3] Dubois, E., Gruzd, A. and Jacobson, J., 2020. Journalists' use of social media to infer public opinion: The citizens' perspective. *Social science computer review*, *38*(1), pp.57-74.https://doi.org/10.1177/0894439318791527

[4] Bai, H., 2022. Social public opinion communication and network legal management based on artificial intelligence cognitive wireless network. *Mobile Information Systems*, *2022*(1), p.1127931.https://doi.org/10.1155/2022/1127931

[5] Zhang, Y., Su, Y., Zhao, G. and Guo, X., 2023. Research on Network Public Opinion Propagation Model of Major Epidemics Under Cross-infection of Double Emotions. *Journal of System Simulation*, *35*(12), pp.2582-2593.

[6] Yuan, J., Shi, J., Wang, J. and Liu, W., 2022. Modeling network public opinion polarization based on the SIR model considering dynamic network structure. *Alexandria Engineering Journal*, *61*(6), pp.4557-4571. https://doi.org/10.1016/j.aej.2021.10.014

[7] Rehman, A.U., Jiang, A., Rehman, A., Paul, A., Din, S. and Sadiq, M.T., 2020. Identification and role of opinion leaders in information diffusion for online discussion network. *Journal of Ambient Intelligence and Humanized Computing*, pp.1-13. https://doi.org/10.1007/s12652-019-01623-5

[8] Chen, T., Shi, J., Yang, J., Cong, G. and Li, G., 2020. Modeling public opinion polarization in group behaviour by integrating SIRS-based information diffusion process. *Complexity*, *2020*(1), p.4791527. https://doi.org/10.1155/2020/4791527

[9] C. Yan, J. Liu, W. Liu, and X. Liu, "Research on public opinion sentiment classification based on attention parallel dual-channel deep learning hybrid model," *Engineering Applications of Artificial Intelligence*, vol. 116, p. 105448, Nov. 2022, doi: https://doi.org/10.1016/j.engappai.2022.105448.

[10] Jin, C., Zhai, X. and Ma, Y., 2023. Research on Optimization of Public Opinion Supervision Model of Social Network Platform Based on Evolutionary Game. *Information*, *14*(3), p.151. https://doi.org/10.3390/info14030151

[11] Wang, Y., Liu, Z., Jiang, C., Chen, C. and Xia, C., 2022, May. A real-time monitoring method of public opinion evolution based on dynamic social network. In *International Conference on Electronic Information Engineering, Big Data, and Computer Technology (EIBDCT 2022)* (Vol. 12256, pp. 585-590). SPIE. https://doi.org/10.1117/12.2635786

[12] Chauhan, P., Sharma, N. and Sikka, G., 2021. The emergence of social media data and sentiment analysis in election prediction. *Journal of Ambient Intelligence and Humanized Computing*, *12*, pp.2601-2627. https://doi.org/10.1007/s12652-020-02423-y

[13] Chen, L.C., Lee, C.M. and Chen, M.Y., 2020. Exploration of social media for sentiment analysis using deep learning. *Soft Computing*, *24*(11), pp.8187-8197. https://doi.org/10.1007/s00500-019-04402-8

[14] Li, S., Liu, Z. and Li, Y., 2020. Temporal and spatial evolution of online public sentiment on emergencies. *Information processing & management*, *57*(2), p.102177. https://doi.org/10.1016/j.ipm.2019.102177

[15] Gong, C., Du, Y., Li, X., Chen, X., Li, X., Wang, Y. and Zhou, Q., 2020. Structural hole-based approach to control public opinion in a social network. *Engineering Applications of Artificial Intelligence*, *93*, p.103690. https://doi.org/10.1016/j.engappai.2020.103690

[16] Q. Dong, T. Sun, Y. Xu, X. Xu, M. Zhong, and K. Yan, "Network Public Opinion Sentiment Analysis based on Bert Model," *2022 IEEE 10th International Conference on Information, Communication and Networks (ICICN)*, Aug. 2022, doi: https://doi.org/10.1109/icicn56848.2022.10006589. https://doi.org/10.1109/icicn56848.2022.10006589

[17] Lin, H. and Bu, N., 2022. A CNN-based framework for predicting public emotion and multi-level behaviours based on network public opinion. *Frontiers in Psychology*, *13*, p.909439. https://doi.org/10.3389/fpsyg.2022.909439