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Integrating swarm intelligence with deep learning for enhanced social media sentiment analysis

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ABSTRACT

Understanding user views on social media in the advent of internet content demands sentiment analysis. This study introduces a novel approach called particle swarm-accelerated model (PSAM), that integrates deep learning with long short-term memory (LSTM) with two hyper-parameters and swarm intelligence through particle swarm optimization (PSO). In the sentiment classification of YouTube movie reviews for "Pushpa 2," the recommended approach classifies opinions as "positive," "negative," or "neutral," with an accuracy score of 95.3%. The process involved utilizing YouTube API to collect user-genearted comments, followed by advanced preprocessing steps such as punctuation removal, stopword filtering, slang normalization, and emoji handling. PSO performs feature selection to boost the efficiency of classification systems. The PSAM model reaches superior outcome results compared to support vector machines (SVM), Naive Bayes, CNN, and random forest classifiers when evaluated based on F1-score and accuracy metrics. The proposed hybrid model demonstrates its ability to boost sentiment analysis in different social media platforms according to research findings.

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1. INTRODUCTION

Rising content creation on social platforms such as "Facebook", "Twitter" and "YouTube" require improved sentiment analysis algorithms that perform at high levels. This occurs because users express their emotions with high intensity and volatility across these platforms. Sentiment analysis functions as a "natural language processing" subfield which identifies textual subjectivity to extract wider perception data involving emotions and customer preferences [1], [2]. The sentiment analysis ability is essential a cross-marketing domains as well as policy development and content generation because businesses need audience feedback to modify their strategies effectively [3]. Due to the failure to handle context, sarcasm, and ambiguous language, traditional sentiment analysis methods such as Random Forest, support vector machines (SVM), and Naïve Bayes can misclassify. Such methods face difficulties understanding delicate language elements that include sarcastic statements and ambiguous expressions along with proper situational comprehension [4], [5].

Deep-Learning models, especially long short-term memory (LSTM), helps overcome many of these challeges. LSTMs are effective at understanding long-term relationships in data, making them ideal for sentiment analysis, where word connection in long texts matter [6], [7]. However, choosing the right feature greatly affects LSTM performance. The goal is to select the most importnat features to reduce data size and improve accuracy [8]. Swarm intelligence approaches, including particle swarm optimization (PSO), offers a potential method for feature selection. By optimizing feature subsets using a fitness function, PSO performs in combination with LSTM to boost the effectiveness and accuracy of classification of sentiment while assuring that only the most relevant features are retained [9], [10]. The benefits of LSTM and PSO are merged in the novel particle swarm-accelerated model (PSAM) model. The sentiment classification is performed is by LSTM, and the feature selection is refined by PSO. By integrating the advantages of both approaches, this integration bypasses the limitations of both “traditional machine learning” and standalone “deep learning models”.

The PSAM model's performance is evidenced by applying it to YouTube comments about the film Pushpa-2. The model's way to spot sentiments as neutral, negative, or positive is incredibly accurate [11], [12]. These outcomes showed how successfully the PSAM model could be applied to identify sentiment throughout all multiple platforms and retrieve data from user-generated content.

1. A innovative PSAM approach incorporates feature extraction and sentiment classification by implementing deep learning and swarm intelligence techniques.
2. A improved sentiment analysis process utilizes PSO to improve feature subsets, which increases classification accuracy.
3. Whether through sentiment analysis of YouTube comments on "Pushpa 2," the PSAM performance is tested, trying to demonstrate its correctness in categorizing sentiments as neutral, negative, or positive. demonstrating that it produces noticeably better outcomes than conventional techniques.

The theoretical background as well as relevant studies on sentiment analysis and feature selection are examined in Section 2; the proposed PSAM model, which combines LSTM and PSO, is explained in Section 3 in addition to its application to sentiment analysis tasks; and a thorough analysis of the experimental results is offered in Section 4.

2. LITERATURE REVIEW

Sentiment analysis (SA) has improved dramatically with the rise of deep learning and advanced feature extraction. Existing approaches such as “lexicon-based approaches” and machine learning techniques like Naive bayes and SVM proceed effort to learn being used widely in the diversity of human language. These methodologies are far less accurate in real world situations so even though they face challenges with delicate aspects like sarcasm, ambiguity, and contextual nuances [13], [14]. As according to recent research, deep learning models-LSTM have the benefit of being able to acquire complicated contextual relationships in text data and outperforming conventional methods in sentiment analysis tasks [15], [16].

PSO is a swarm intelligence algorithm which has gained popularity as a trustable feature selection method. It is motivated by the group behavior of fish and birds. PSO iteratively refines feature subsets by adjusting particle placements to accommodate both individual experiences and the overall optimization process. In order to enhance the effectiveness of classifiers such as SVM and neural networks, this iterative process aims to identify the most relevant features while also reducing dimensionality [17], [18]. Some many studies have already shown that well PSO works to enhance classifier accuracy through optimized feature selection [19], [20].

Even though LSTM models excel at sentiment analysis, little is recognized about how they can be merged with PSO for feature selection. This research proposes a technique to close taking the strengths gap by of PSO for accurate feature selection and LSTM for sentiment classification [21], [22]. Correlations with extremely effective models, such as SVM, Naïve Bayes and random forest, verify the superiority of the our hybrid model’s, trying to suggest that it has the attempt to optimize SA in a range of applications [23], [24].

3. PROPOSED HYBRID MODEL

The suggested PSAM model combines LSTM networks for ‘sentiment classification’ with PSO for feature selection shown in Figure 1. To get the input data ready, the process starts with text preprocessing, which includes tokenization and cleaning. To boost sentiment prediction, the method makes use of the complementary advantages of lexicon-based and deep learning methods. By trying to identify the most essential variables, minimizing dimensionality, and increasing the effectiveness the of the LSTM network, PSO aims at maximizing feature selection. The LSTM model after which uses the enhance features to categorize sentiments as neutral, negative, or positive even while taking account for contextual dependencies in the text. A comprehensive sentiment analysis solutions are offered by this hybrid approach, that also cleverly merges sophisticated deep learning and feature optimization.

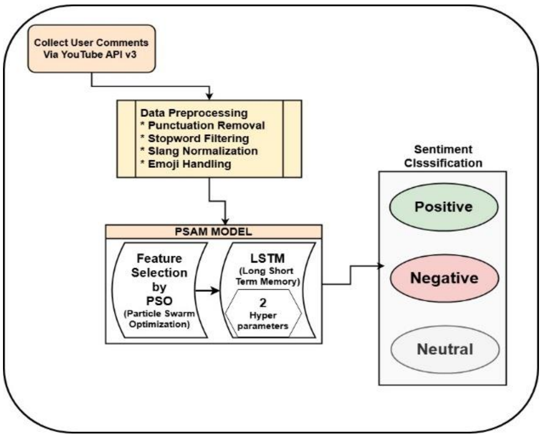

Figure 1. Architecture of the proposed PSAM model, combining PSO for feature selection and LSTM

3.1. Methodological framework

In this research the complete methodological Framework follow some steps which are as under:

3.1.1. Data collection

The YouTube data API that was also used to collect user comments related to Pushpa-2. Using the search.list API, relevant videos such as trailers, reviews and discussions were identified. The Figure 2 illustrates the YoutTube Data API request and response, showing how user comments were then retrieved via the commentThreads.list API, extracting text, user ID, timestamp, like count, and replies. Neutral, Negative, and Positive points of view that represent a variety of emotions of and points of view are among the many distinct emotional viewer sentiments that are represented in it. Since these comments offer great opportunities casual yet significant dataset full of complexities like slang terms, casual language, misspellings, and sarcasm, they for sentiment analysis [25], [26].

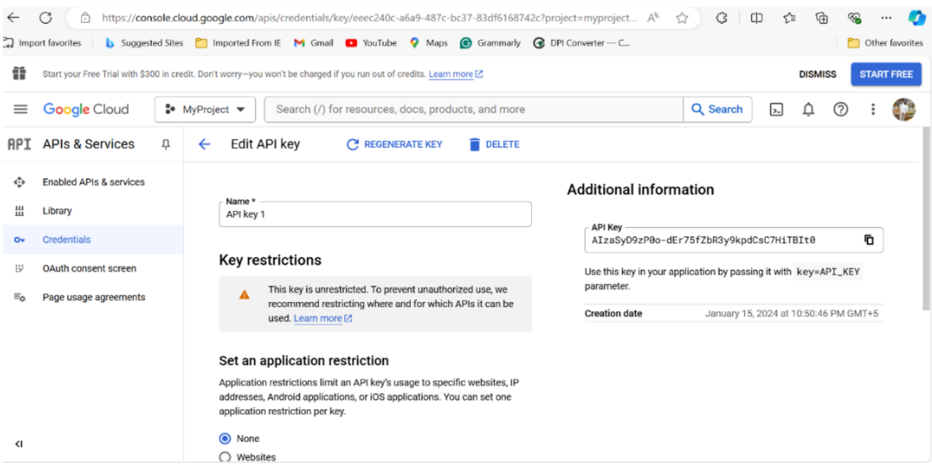

Figure 2. Console.cloud.google.com for API

3.1.2. Data preprocessing

By carefully cleaning the text using methods like input standardization and tokenization, the initial phase's primary goal is to enhance the data's quality. To maintain consistency and reduce on extraneous distractions, input standardization includes extracting URLs, emoticons, and special characters using regular expressions (RegEx). SpaCy's tokenizer was applied for tokenization after which splits the text into distinct words as according spaces, enabling for independent word analysis. Stopword removal was applied using the NLTK stopwards corpus so that common stop words including such \the\ and \and\ are then eliminated because they have little analytical significance [27]. Lemmatization using Wordnetlemmatizer standardizes words by converting them to their base forms, reducing redundancy and improving sentiment classification accuracy. Table 1 provides a clear understanding of the terms used to express emotions by showcasing important words and their frequencies chosen to take from movie reviews. This table plays a pivotal role in training sentiment analysis models by quantifying essential word occurrences, enabling the models to effectively recognize sentiment within the reviews.

Table 1. Word count frequency

Word	Count
Allu	890
puspa	400
arjun	240
wild	125
fire	110
super	91
fight	82
bad	15
boring	6
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3.1.3. Feature extraction

By enhancing feature subsets, the PSO algorithm is being used to enhance classification accuracy. As can be shown by Figure 3, each particle in the algorithm represents a potential subset of features, and its fitness is established based on the classification performance. The following formula-1 were used to adjust particle position and velocity.

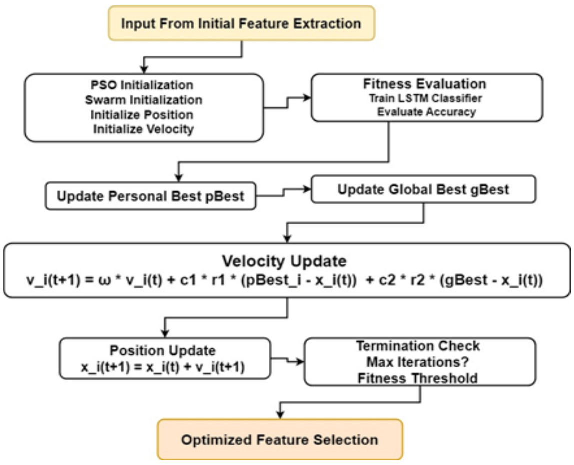

Figure 3. Architecture of feature selection based on PSO swarm

In the PSO feature selection technique, the correctness of each particle feature is evaluated by training an LSTM classifier and evaluating its performance on a validation set. If a particle improves its classification accuracy, its "personal best position (pBest)" is updated. Similary, when a particle's fitness surpasses the global best solution, the "global best position (gBest)" is modified [9], [19]. As the particles move through the search space, they balance individual learning (pBest) and global optimization (gBest) to refine feature selection, ensuring higher classification accuracy and reduced dimensionality.

Formula -1 is the velocity update formula:

$$\mathrm{v_i}(t+1) = \omega.\mathrm{v_i}(t) + c1.r1(\mathrm{pBest_i} - \mathrm{x_i}(t)) + c2.r2\,(\mathrm{gBest_i} - \mathrm{x_i}(t))) \quad (1)$$

in which:
- The velocity of particle I at iteration t is denoted by vi(t).
- The inertia weight is denoted by ω.
- The cognitive and social coefficients are denoted by c1 and c2; and the random integers r1 and r2 range from 0 to 1.

– Particle I's position at iteration t is denoted as xi(t), where pBesti is its personal best position and gBest is its global best position among all particles.

To investigate new possible feature subsets, particles adjust their positions based on their updated velocities using the formula - 2:

$$\mathrm{x_i}(t+1) = \mathrm{x_i}(t) + \mathrm{m_i}(t+1) \quad (2)$$

The graphical representation of the feature selection process using PSO algorithm appears in Figure 4. The protocol shows how particles adjust their positions through the x-axis numbers from 0 to 300 during the time cycles. The fitness score measured through classification accuracy resides on the y-axis which ranges from 0.0 to 1.0. Each evaluation cycle examines different features starting from Feature 0 to Feature 4 through which particles determine their positions using their personal best (pBest) values together with global best (gBest) positions. The algorithm performs repetition to lead particles towards the best possible feature subset which combines selectivity with minimal feature duplication.

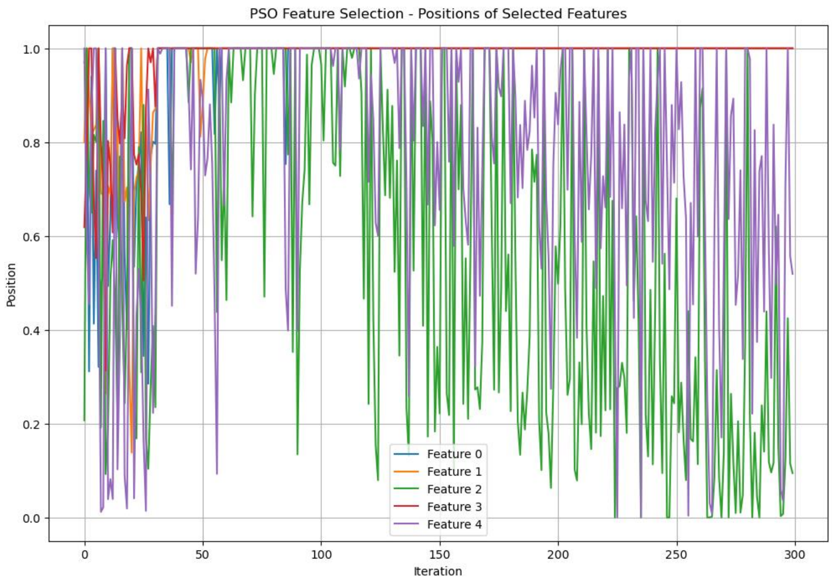

Figure 4. Feature selection by PSO

3.1.4. LSTM classifier

The LSTM classifier proved suitable for sentiment classification due to its ability to detect long dependencies in text alongside its solution to the vanishing graduent problem. LSTM processed the features selected with PSO through an architecture that included an embedding layer followed by LSTM layers then dropout then fully connected layers that produced sentiment predictions as “positive” or “negative” or “neutral”.

A novel contribution of this research involves the optimization of two hyper-parameters (hidden unit size and learning rate) to boost prediction outcomes. The hidden unit size improves the model’s complex contextual relationship retention, and the learning rate maintains balanced weight updates for avoiding slow convergence. The optimized parameters deliver better performance results than standard LSTM systems. The model achieved better accuracy performance together with precision and recall metrics as well as F1-score metrics (Formula-3) [6], [15] after training with Adam optimizer and categorical cross-entropy loss.

$$F1 = 2\,X\,\frac{\text{Precision X Recall}}{\text{Precision+Recall}} \quad (3)$$

3.1.5. Model evaluation

Analysis of the model to validate accuracy while making sure the model can identify intricacies in YouTube videos, metrics such as “precision”, “recall” and “F1-score” have been combined with separate experimental data. Patterns in YouTube material are displayed in the comment clustering graph Figure 5, which was generated using K-means clustering and shown with PCA. Different groups can be identified by different shades:

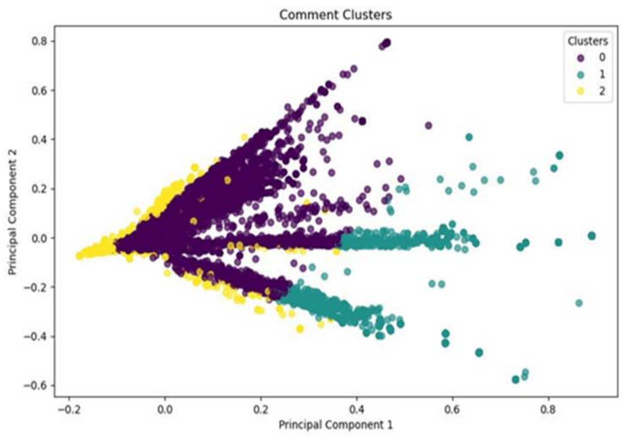

Figure 5. Comment clusters

4. RESULTS AND DISCUSSION

An examination of YouTube comments uses graphical representations, as shown in Figure 6, such as pie charts (Figure 6(a) and word clouds (Figure 6(b), to illustrate the categorization of emotions. The word clouds display words in varying sizes depending on their frequency of occurrence, emphasizing dominant emotions such as "amazing," "love," "awesome," and mentions of personalities like Allu Arjun. Figure 6(b) displays these common terms, offering a glimpse into the emotional mood conveyed in the comments.

(a) (b)

Figure 6. Examining YouTube comments using graphical representations; (a) distribution of user sentiment, pie chart representation and (b) word cloud of frequently used terms

The pie chart Figure 6(a) illustrates the distribution of attitudes, revealing that 70.2% of individuals hold positive attitudes, 10.3% exhibit negative attitudes, and 19.5% remain neutral. Once taken together, these visual elements provide a thorough understanding of the ideas presented in YouTube comments, providing qualitative as well as quantitative data about user viewpoints. Furthermore, the effectiveness of the proposed methodology is demonstrated thorough a comparative study table with an amazing 95.3% accuracy. Compared to more traditional processes like random forest, SVM and Naive Bayes, this result shows how well our model is able in accurately classifying attitudes. Our proposed sentiment analysis technique achieves better effectiveness and reliability in sentiment analysis through the comparison data presented in Table 2.

Table 2. MPRAF-model’s precetion, recall, accuracy, F1-score comparison with traditional algorithms

“Model”	“Precision”	“Recall”	“Accuracy/Result”	“F1-Score”
“Naive Bayes”	82.0	81.5	84.1%	0.79
“SVM”	89.0	88.5	90.4%	0.81
“CNN”	84.7	84.2	85.3%	0.85
“Proposed Model”	94.8	94.5	95.3%	0.93

5. CONCLUSION

The proposed research introduced PSAM as a hybrid model which combines PSO for feature selection and LSTM for sentiment classification tasks. The system achieves enhanced sentiment analysis capabilities by improving feature selection optimization with basic LSTM hyper-parameter adjustments regarding hidden unit dimensions and learning speed. According to model performance measurements the PSAM reached accuracy surpassing traditional classification techniques including Naive Bayes, SVM along with CNN by attaining 95.3%. PSO achieves dimension reduction of features which enhances both system performance and accuracy levels. The model's robust performance accross different evaluation metrics ('accuracy', 'precision', 'recall', & 'F1-score') confirms its effectiveness in handling social media sentiment analysis. Future work can explore real-time sentiment analysis, multimodal sentiment integration (text, audio, video), and further deep learning enhancements to improve generalizability across datasets.

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Parminder Singh	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓
Saurabh Dhyani		✓								✓	✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no known financial, personal, or professional conflicts of interest. There are no competing interests that could have influenced this research.

DATA AVAILABILITY

The data that supports the findings of this study are available from the corresponding author, Parminder Singh, upon reasonable request. Due to privacy and ethical considerations, the dataset is not publicly accessible but can be shared with qualified researchers for academic purposes.

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