Optimizing Social Media Marketing Strategies Through Sentiment Analysis and Firefly Algorithm Techniques

Dr. Sudhir Anakal[1], P N S Lakshmi[2], Nishant Fofaria[3], Janjhyam Venkata Naga Ramesh[4], Elangovan Muniyandy[5], Shaik Sanjeera[6], Prof. Ts. Dr. Yousef A.Baker El-Ebiary[7], Ritesh Patel[8]

Associate Professor, Department of Master of Computer Applications, Sharnbasva University, Kalaburagi, India[1]
Assistant Professor, Department of CSE, Aditya University, Surampalem, Andhra Pradesh, India[2]
Research Scholar, Gujarat Technological University, Ahmedabad, India[3]
Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India[4]
Adjunct Professor, Department of CSE, Graphic Era Hill University, Dehradun, 248002, India[4]
Adjunct Professor, Department of CSE, Graphic Era Deemed To Be University, Dehradun, 248002, Uttarakhand, India[4]
Department of Biosciences-Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India[5]
Applied Science Research Center, Applied Science Private University, Amman, Jordan[5]
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India[6]
Faculty of Informatics and Computing, UniSZA University, Malaysia[7]
Associate Professor, Sanjivani College of Engineering, Savitribai Phule Pune University, Pune, India[8]

***Abstract*—The dramatic expansion of social media platforms reshaped business-to-customer interactions so organizations need to refine their marketing strategies toward maximizing both user engagement and marketing return on investment (ROI). Present-day social media marketing methods struggle to embrace user emotions fully while responding to market variations thus demonstrating the necessity for developing innovative social media marketing tools. Studies seek to boost social media marketing performance through an FA integration with sentiment analysis for content strategy optimization and better user engagement results. This study adopts novel techniques by combining sentiment analysis with the Firefly Algorithm to optimize marketing strategies in real-time and it represents an underutilized approach in present research. Eventually combined fields generate a sentiment-driven and data-oriented decision-making capability in social media marketing applications. The proposed system combines sentiment analysis technology that measures social media emotion levels alongside the Firefly Algorithm which applies optimization methods to marketing tactics based on present feedback. The framework operates through dynamic adjustments of content strategies which maximize user engagement. The proposed method demonstrated 98.4% precision in forecasting user engagement metrics and adapting content strategies. Results show traditional marketing strategies yield to these approaches by improving user interaction alongside campaign effectiveness. The research introduces a new optimization method in social media marketing which integrates sentiment analysis with Firefly Algorithm technology. Research findings suggest this combined methodology brings substantial precision improvements to marketing strategies by offering companies an effective method to optimize digital marketplace outcomes.**

***Keywords*—Sentiment analysis; firefly algorithm; social media marketing; optimization; user engagement; marketing strategies**

I. Introduction

In those days we don't have Internet connection right from household equipment's to education. Nowadays we are living in a globalized world. Mobile phones are the greatest weapon which make our work easier and it saves time. However, it's just like the two sides of the same coin which means there are many advantages as well as disadvantages. Social media like Facebook, Instagram, YouTube, Twitter(X) which makes our platform easier for personal, business, advertising and marketing. But we have to use them in the right way because so many dangerous things are happening even recently digital arrest has happening in today's world. During the outbreak of corona(COVID-19) mobile phones here very helpful during the pandemic like connecting loved ones through video calls and WhatsApp, health tracking apps like Aarogya Setu, education like online class as well as learning apps like Udemy, course era etc. Getting groceries, household things and clothes through Amazon, Flipkart makes buying and paying much easier and also saves time. Researchers have studies that teens are using social media sites a lot. Even for employees who are not able to working in office can do the work at home. Researchers have found that university students are using a lot of smartphones which leads to reducing physical activity, obesity, diabetes etc.

Businesses utilize social media platforms as their principal marketing tools because these platforms allow them to connect instantly with worldwide audiences. Business marketing activities utilizing Facebook alongside Instagram and Twitter and LinkedIn as well as TikTok framework jointly develop branding loyalty by uniting content dissemination with user collaboration [1]. Throughout their platform features companies build customized individual connections with their audience base by using live broadcasting videos alongside stories and quiz systems and instant private messages. Through their extensive user base businesses can adopt focused marketing initiatives that target particular customer groups according to location and interest areas and online behavior patterns. Social media infrastructure generates an operational space where businesses can sustain rapid responses and flexible business decisions [2]. Through social media organizations monitor customer emotions and determine market trends in order to provide immediate customer feedback management tools. Rapid response times enable brand accessibility which results in satisfied customers and establishes a friendly customer-oriented brand perception. Through social media analytics organizations derive essential information about customer performance data together with market trends that help them formulate lasting strategic improvements [3]. Commercial operations find enormous digital marketing value within social media ecosystems yet finding best practices for investment allocation and user engagement remains a substantial obstacle. The journey to discover optimal social media marketing approaches remains challenging because the ways users interact with media continue to change. These days organizations face a demanding operational situation consisting of changing content demands together with diverse audience groups and rising digital competition among numerous online platforms. Organizations employing traditional methods must conduct trial-and-error testing to develop strategies which uses plenty of time and resources yet delivers unpredictable results that limit user engagement and measurable returns [4].

The processing of extensive customer social media information becomes challenging for businesses because present frameworks are insufficient to manage large quickly advancing unstructured data flows. An inadequate ability to analyze social media customer feedback prevents businesses from grasping consumer feedback correctly which translates into poor customer engagement and reduced return on investment. Businesses continue to face difficulties because they lack integrated models that unite sentiment analysis solutions with optimization tools to convert feedback understandings into operational directives. Fewer organizations integrate sentiment analysis with environment-based processing methods to gain customer feedback emotional data due to an overdue definitive framework for utilizing feedback to alter their market promotion methods. Resolution of the analytical gap between business customer information and optimization techniques would enable organizations to develop flexible strategic models that boost consumer bonding and achieve positive ROI and superior market effectiveness. Data-driven approaches which integrate sentiment analysis with optimization algorithms address these problems according to research [5]. Through sentiment analysis powered by Natural Language Processing algorithms combined with machine learning technology businesses [4] can understand social media customer feedback to track public responses regarding their products and marketing campaigns.

Despite the categorization into positive negative and neutral sentiment types businesses can measure customer emotional states to detect problems that lead them to adjust their strategies according to audience preferences [6]. Brands obtain extraordinary real-time customer perception data to create content that connects better with their audience and generate superior engagement metrics [7]. Optimization algorithms such as Firefly Algorithm and Genetic Algorithms serve sentiment analysis by developing structured frameworks for marketing strategy enhancements [8]. Data-driven optimization algorithms process marketing data to determine appropriate decisions concerning media audience selection as well as time scheduling and budget allocation across campaign durations. Businesses can discover the best plan for engagement and ROI through scenario simulation which enables them to evaluate different outcome results. Social data provides businesses tools to determine optimal posting schedules together with visual content recommendations and recurring ad intervals needed for sustained customer engagement [9]. When sentiment analysis combines with optimization algorithms, they form a potent partnership that allows marketers to upgrade their strategic decisions from guesswork to data-driven creation of social media strategies that produce measurable outcomes. This research brings important value because it enables social media marketers to make better decisions through the combination of CNN-LSTM and Firefly Algorithm technologies. Through CNN-LSTM sentiment analysis combined with the Firefly Algorithm framework marketers gain deep customer emotions insights and optimized marketing strategies from sentiment-based data. This research integrates both approaches to enhance the existing knowledge of algorithm-driven marketing techniques and create methods for sentiment analysis enhancement in optimization workflows which results in more tailored advertising campaigns for enterprise success. The key contribution of the research are as follows:

- Enhanced Sentiment Analysis: Utilizes CNN-LSTM for accurate sentiment classification, providing deeper insights into customer emotions from social media feedback.
- Optimization of Marketing Strategies: Applies the Firefly Algorithm to optimize social media marketing campaigns based on sentiment analysis, improving ad targeting and content effectiveness.
- Integration of AI in Marketing: Demonstrates how combining sentiment analysis with optimization techniques can revolutionize social media marketing strategies.
- Practical Application: Provides a practical framework for businesses to fine-tune their marketing strategies using data-driven insights, leading to better engagement and ROI.

Section I establishes the research scope by examining ways to enhance social media marketing strategies through sentiment analysis together with the Firefly Algorithm. Section II examines existing research then highlights the missing connections between sentiment analysis implementation with optimization algorithms. The investigation introduces Section III for method presentation followed by result examination and discussion in Section V separately before reaching a conclusion Section VI about significant marketing efficiency improvement through combined sentiment analysis and Firefly Algorithm.

II. Related Works

Wagobera Edgar Kedi et al. [10] research paper analyzes how machine learning technology enhances small and medium-sized enterprise (SME) social media marketing strategies by examining both social media marketing importance and traditional methods evolution as well as modern machine learning implementation trends. The study compiled data by examining both emerging machine learning technologies and the challenges faced by SMEs. The research shows machine learning improves marketing performance but small and medium-sized enterprises face major obstacles involving budgetary limits, poor data quality and their restricted capability for technical solutions. The report ends with a proposal to implement advanced learning approaches including deep learning with reinforcement learning to create sustainable growth and competitive edge.

Bian et al. [11] research investigates deep neural networks and advanced algorithms for social media marketing optimization to enhance accuracy within China's fast-changing market economy. Result data from experiments utilizing back-propagation with gradient methodology along with adaptive Adam's optimization algorithm techniques proved the methods combine to find global optimal solutions. Significant improvements in social media marketing accuracy emerged from the proposed optimization approaches as evidenced by testing that showed the FCE model utilizing a three-layered back-propagation neural network reached its target performance levels. The research faces limitations because the model depends on specific optimization methods yet shows difficulties when used across diverse market scenarios. Bian et al. methods might experience reduced effectiveness when confronted with aspects including inadequate data quality and variations in computational performance alongside practical industry challenges.

Joshi et al. [12] research uses reinforcement learning alongside natural language processing to improve social media content optimization as it targets effective engagement strategies against increasing competition in social media marketing. The framework evaluation utilized data from multiple social media platforms by implementing RL algorithms to identify optimal dynamic content adjustments using real-time user feedback data combined with engagement metrics along with NLP technology that analyzed textual content for relevance, context, and sentiment detection. The engagement rates for social media actually appreciated when the framework replaced traditional methods of optimizing content in its analysis and application. It has several limitations because this research is based on specific data, and a couple of challenges regarding adapting the proposed system to multiple social media throughout various demographics of users would also require attention. Computing complexities and real-time adaptability still have scopes for future studies.

Luo et al. [13] research finds how FNN examines the user conduct on social media to better improve online marketing plans by evaluating intricate and imprecise behavior-related information. The process of gathering data included numerical classification of the user conduct indicators, such as frequency of behaviors along with implementation of fuzzy set theory for identification of emotional state, and exploration of content topics and social relations through time-series patterns. Results of the FNN analysis exhibit the discovery of hidden patterns in user behavior that lead to stronger marketing strategies and, therefore, better advertising results with increased user participation rates and structures of brand loyalty. The study identifies two significant limitations presented by the model: its dependence on data and the problem of universal applicability to a wide range of social media systems and user groups. Further study needs to focus on mathematical modelling of complex real-time data processing as well as fuzzy neural network scaling solutions for extensive implementation scenarios.

Kumari et al. [14] research develops a framework combining Convolutional Neural Networks (CNN) with Binary Particle Swarm Optimization (BPSO) to identify social media interactions into three aggression levels from non-aggressive to high-aggressive. Researchers developed a dataset with symbolic imagery linked to textual comments which they used to test their model. The framework first utilizes VGG-16 in pre-trained form to extract image features followed by a succession of three-layer CNNs that extract text features subsequently merging these features through BPSO optimization to determine which features best apply to the problem set. The results indicate a weighted F1-Score of 0.74 using optimized features and a Random Forest classifier which represents a 3% better outcome than the unoptimized feature set. The current research needs to expand through increased experimentation to improve scalability and generalization of this model across different social media networks even though dataset limitations persist.

The application of supervised learning and deep learning and unsupervised learning and reinforcement learning algorithms is evaluated for optimizing marketing tactics on the "Douyin live shopping" and the "Kuaishou platform shopping channels". The analysis examined 920,000 user engagement records to determine how each algorithm affected prediction accuracy, recommendation personalization and advertisement delivery and customer segmentation results. User satisfaction experienced a 19.7% boost from the deep learning model which delivered 94.8% prediction accuracy while the supervised learning model reached 89.3% classification accuracy. Click-through rates on advertisements rose by 24.6% through reinforcement learning modelling while the unsupervised learning algorithm performed best at customer segmentation. Improved marketing outcomes were achieved by implementing hybrid models and advanced algorithmic versions. Li et al. [15]study's main constraint arises from its narrow examination of two platforms leading to limited applicability for other e-commerce settings. Investigating these tactics across numerous digital platforms will expand scientists' comprehension of their strategic power.

III. Problem Statement

Previous optimization studies for social media marketing strategies face key limitations because they employ traditional methods which fail to measure user sentiment complexity and incorporate advanced optimization algorithms [10], [11], [12], [15]. Research studies have separated their focus between sentiment analysis and optimization methods while withholding the development of unified holistic strategies. Prior research studies face limitations because they use inadequate data sources as well as imperfect real-time feedback collection and less-than-ideal engagement prediction models. The research presents a novel method which uses sentiment analysis alongside the Firefly Algorithm for improving the optimization of social media marketing techniques. The combination of sentiment analytics knowledge with Firefly Algorithm capabilities to optimize decisions for content creation engages users and improves campaign effectiveness will provide adaptive marketing methods which address contemporary social media issues.

IV. Research Methodology

The research methodology establishes a hybrid method for maximizing social media marketing approaches through sentiment analysis. Data collection serves as the initial step, applying text tokenization and padding techniques for preprocessing raw data as the base for subsequent analyses. A CNN-LSTM model provides sentiment extraction from data while recognizing local characteristics alongside distant patterns. By making use of Firefly Algorithm the acquired insights experience optimization for better marketing strategy development. An evaluation of the performance of the model in operational terms will only help in proving that it is feasible to be used in improving the campaigns and the decision-making processes. The workflow of the proposed architecture is shown in Fig. 1.

A. Data Collection

Dataset includes performance data from Facebook and Instagram advertising, as well as data from both Pinterest and Twitter in social media advertising. The dataset contains ad impression and click and spending details and its targeted demographics and conversion rates metrics. The data set enables one to evaluate campaign performance along with audience analysis to determine return on investment calculations along with optimization strategy identification to improve advertisement performance. Analysis of this data will enable businesses to find the most effective platforms and strategies for marketing that will push them to design better approaches [16].

B. Data Pre-Processing

Data preprocessing stands as an essential initial process for both data analysis. A series of procedures including tokenization and padding must be executed because input data needs preparation for training. A combination of multiple transformation methods prepares disorganized data into a structure that helps machine learning models perform their functions. Text data preprocessing methods consist of two steps: Neural network processing needs tokenization to make text portions into tokens and padding to normalize sequence lengths. Such data-preparation methods enable high precision and validity standards for the data and guarantee fast processing speeds for models.

1) Text tokenization: Through text tokenization verbal information transforms into discrete code elements referred to as tokens that operate on both word and smaller substrings. When analyzed with text decomposition the sentence "The quick brown fox" breaks down into four tokens ["The","quick","brown","fox"]. For operation machine learning algorithms demand the implementation of text processing that turns written information into usable data. Within Keras the Tokenizer tool executes text processing by mapping model tokens to distinctive integer identifiers.

2) Padding: The effective operation of deep learning models demands that all input sequences match identical lengths and padding solutions provide this solution. The resulting tokenized sequences display various length dimensions which make processing problematic for neural networks that require standardized inputs. In padding methods the resolution of this issue stems from increasing source sequence lengths through new values or zeroes. During preprocessing all input data transforms into a form which the model's processing requirements can accept.

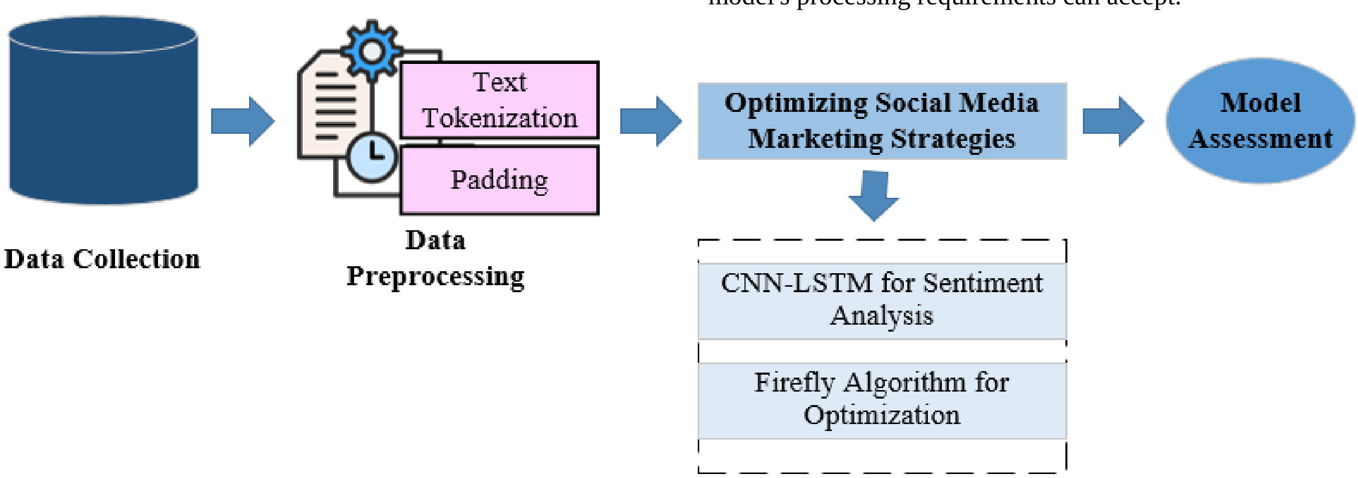


Fig. 1. Workflow of proposed architecture.

C. CNN-LSTM for Sentiment Analysis

The sentiment evaluation capabilities across media marketing frameworks benefit from the text analysis capability of the CNN-LSTM model that combines Convolutional Neural Networks with Long Short-Term Memory structures. Through CNN the system extracts both spatial patterns and linguistic features while LSTM processes time dependencies between words to detect sentiment expressions across sentences. With its integration of CNN and LSTM networks the model obtains a new level of ability to detect user emotional reactions about marketing materials on social media for generating actionable understanding about consumer behavioral patterns. Marketers maximize the value of the model to enhance their marketing plan optimization as they improve targeting methods and audience metrics measurement. The proposed model combines several crucial stages in a CNN-LSTM architecture dedicated to media marketing sentiment analysis execution, Fig. 2.

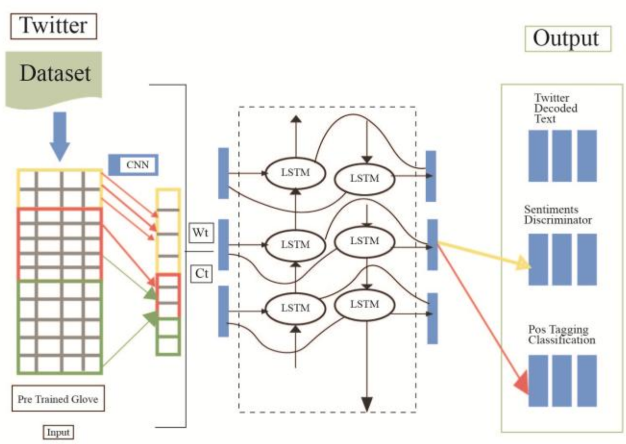


Fig. 2. The proposed model of CNN-LSTM for sentiment analysis.

Through the Embedding Layer operation the system transforms words into compact vector expressions that maintain their semantic relationships. Text sections containing vital emotional expression patterns emerge from CNN Layers following the Embedding Layer process. The Max-Pooling Layer takes feature map information through reduction steps that select and preserve the essential elements within. Among its capabilities the LSTM Layers track sentiment changes throughout texts while simultaneously detecting sequential patterns within text content. Before reaching the Output Layer the Fully Connected Layer converts inputs from LSTM into sentiment labels to determine positive-negative-neutral categories through a softmax or sigmoid function. Different multiple mathematical system layers unite to enable accurate sentiment monitoring for users which helps enhance marketing decisions.

1) Embedding layer: Word embedding converts input text words into dense vector symbols which exploit semantic content. The model develops understanding of word relations because of this function. Word embedding vectors represent each input word mapped to word embedding vector. The embedding model discovers a link which maps discrete word identifiers to continuous vector representations. It is mathematically represented as Eq. (1),

$$E = Embedding(X) \tag{1}$$

Where, X is the sequence of tokenized words and E is the output matrix, where each word is represented by a fixed-size vector.

2) Convolutional layer: Local features within word embeddings become visible through convolutional layers as the layers search for n-grams and emotional phrases ("not good" or "very happy"). During operation the filter component (kernel) traverses word embeddings and conducts dot product calculations to acquire critical features. Through its filtering operation this method identifies essential patterns which influence sentiment expression. It is given in Eq. (2)

$$F = Conv(E, K) \tag{2}$$

Where, F the output feature map, E is the input and K is the filter (kernel).

3) Max-Pooling: This layer compresses the dimensionality of the feature map by retaining the most prominent features (maximum values) within each region to facilitate making the model computationally efficient. Max-pooling takes the maximum value of a small region of the feature map to maintain the most significant information. It is given in Eq. (3)

$$P = MaxPool(F) \tag{3}$$

Where, F is the feature and P is the pooled output.

4) LSTM Layer: LSTM layers learn long-range dependencies and sequential context in the data. This is helpful for learning sentiment in a sentence, since the meaning of words tends to rely on the sequence (e.g., "not good" vs. "good"). LSTM employs gates to manage the flow of information. The cell state is the core memory of the LSTM unit. It carries information across time steps. The forget gate determines what to forget, the input gate determines what to store, output gate determines what to output at each time step and the hidden state as their last output that goes to successive layer (FC layer). It is calculated by applying the output gate to the cell state. Through, its gating mechanism the LSTM effectively handles long-range dependencies in text so it proves suitable for tasks involving sentiment analysis where sentence meaning depends on complete word sequences. These calculations are given in Eq. (4) to Eq. (8).

$$Forget\ gate\ (f_t) = \sigma(W_f\ [h_{t-1}, x_t\ ] + b_f) \tag{4}$$

$$Input\ gate\ (i_t) = \sigma(W_i\ [h_{t-1}, x_t\ ] + b_i\ ) \tag{5}$$

$$Cell\ state\ (C_t) = f_t * C_{t-1} + i_t * C_t \tag{6}$$

$$Output\ state\ (O_t) = \sigma(W_o\ [h_{t-1}, x_t\ ] + b_o \tag{7}$$

$$Hidden\ state\ (h_t) = O_t * tanh\ (C_t) \tag{8}$$

5) Fully connected layer: The final mapping layer functions to translate LSTM outputs into sentiment categorizations such as positive, negative and neutral. This constitutes a dense layer which discovers a relationship between the input from the LSTM output to generate the final output. The fully connected layer functions by taking input from the LSTM output with learned features to make sentiment predictions on the text. It is represented as Eq. (9),

$$y = Dense(h_t) \tag{9}$$

Where, y is the output of the fully connected layer and h_t is the output from LSTM layer.

6) Output layer: The output layer applies an activation function to the final prediction so the model's output becomes usable for classification purposes. In multi-class sentiment analysis (positive, negative, neutral) models utilize a softmax function. The sigmoid function works as a transformation for binary sentiment analysis classification systems between positive and negative keywords. It is given in Eq. (10) and Eq. (11).

$$Softmax, y_{softmax} = Softmax_{(y)} \tag{10}$$

$$Sigmoid, y_{sigmoid} = \sigma(y) \tag{11}$$

Through the integration of CNN-LSTM model creates an effective method for sentiment analysis. The model utilizes its different layers to achieve precise sentiment classifications of textual data which reveals critical information about user emotional responses. Such a strategy delivers outstanding results in media marketing since knowing audience sentiment helps optimize tactics and increase engagement.

D. Firefly Algorithm for Optimization

The Firefly Algorithm (FA) represents an optimization technique derived from natural firefly behaviors regarding their biofluorescent signalling patterns. The Firefly Algorithm enhances optimization of marketing parameters and variables based on sentiment data through parameter and variable adjustments specifically targeting campaign timing, audience segmentation and content element choices. Sentiment analysis datasets can benefit from the FA which uses a comprehensive approach to improve marketing strategy optimization efforts. The gathering of sentiment data from consumer reviews and social media platforms enables FA to optimize essential marketing campaign components including audience division methods and tactical scheduling and customized marketing materials. Because of its ability to maintain a careful balance between exploratory behaviors and exploitative actions FA excels at directing marketing decisions through complex multi-dimensional spaces.

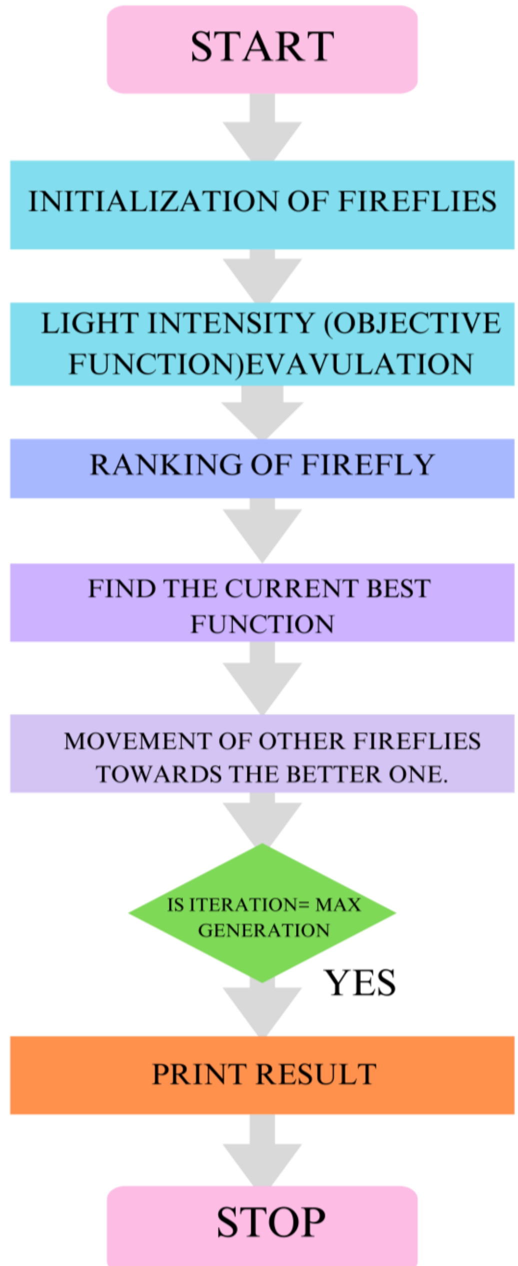
Fireflies follow each other because variation in brightness levels exposure reveals solution quality (fitness values). The attractiveness decreases with distance, represented by Eq. (12).

$$\beta(r) = \beta_0 e^{-\gamma r2} \tag{12}$$

Where, β_0 is initial attractiveness, γ is coefficient and r are the distance.

The distance between two fireflies I and j are computed as Eq. (13).

$$r_{ij} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{13}$$



Where, $x_{i,k}$ and $x_{j,k}$ are positions of fireflies i and j in K dimension of the parameter.

During evaluation the fitness function analyzes both the success of maximizing sentiment-driven engagement and the effectiveness of minimizing campaign costs. For sentiment-based marketing, the fitness function can be defined as Eq. (14).

$$F(x) = w_1 \cdot E(x) - w_2 \cdot C(x) \tag{14}$$

Where, $E(x)$ represents the engagement score derived from sentiment analysis, $C(x)$ represents the campaign cost, w_1 *and* w_2 are weights for balancing the objectives.

With its analytical capability the Firefly Algorithm assesses sentiment data to find strategic marketing patterns which lead to insights for business decisions. Through positive sentiment analysis this method discovers targeted user clusters which produce higher engagement rates.

Firefly Algorithm achieves better campaign results through its ability to customize messaging based on detected sentiment trends. Its ability to prioritize resource distribution matches costs against benefits drives maximum return on investment. The algorithm optimizes solutions through constant improvement which makes marketing strategies match sentiment-driven insights to produce impactful efficient decisions in markets that contain extensive dynamic sentiment datasets.

V. Result and Discussion

The outcomes of sentiment analysis and the Firefly Algorithm of social media marketing solutions. The effectiveness of the proposed improved marketing strategies is then evaluated against baseline methods by highlighting relevant metrics. The discussion analyses the results with the focus on the consequences of sentiment-based optimization, discusses the challenges observed, and shares the recommendations for marketers interested in the effective usage of social media data analytics.

A. *Performance Outcomes*

The confusion matrix heatmap in Fig. 3 provides a visual representation of the proposed model's classification performance for each sentiment category: positive, negative, and neutral. The diagonal values show the number of observations correctly classified as they reflect the predicted labels set against the true labels. The values outside the diagonal are misclassification values, thus can be used to determine where the model is poor. This form of representation is quite useful when it comes to analysis of error log and performance check, as they give an insight of model’s ability to correctly flag sentiments and the possibility of bias as well as areas where the model was not very accurate.

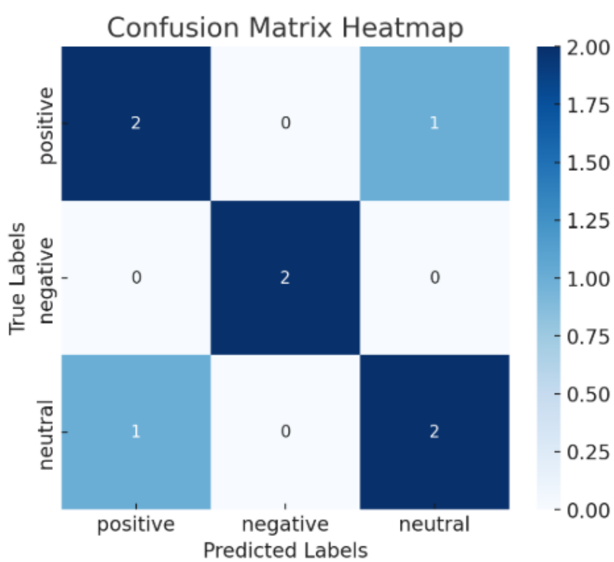


Fig. 3. Confusion matrix heatmap.

The convergence curve in Fig. 4 show that how different iterations of Firefly algorithm are progressing in the optimization process. The optimization function increases over time, proving that the algorithm is good at hyperparameter tuning and convergence. This heat map shows the relations and impacts that hyperparameters contribute to the model’s performance.

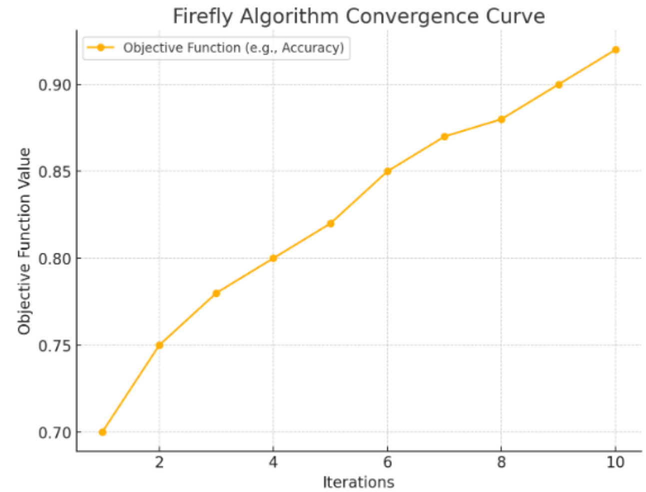


Fig. 4. Firefly algorithm convergence curve.

The heatmap in Fig. 5 illustrates how different hyperparameter combinations affect model performance. Thus, the Firefly algorithm effectively selects the values of hyperparameters when accuracy value is illuminated at certain combination of parameters. This visualization benefits from showing how the algorithm determined by the current approach can search and find the best configuration of the proposed model.

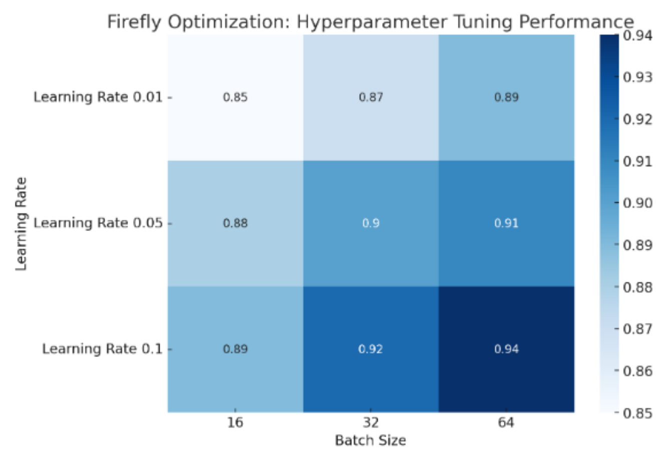


Fig. 5. Firefly optimization: hyperparameter tuning performance.

The Fig. 6 visually presents the training as well as the testing accuracy over epoch and shows our proposed model can learn from the training set and generalize to the testing set. The amount of correct answers, which can be obtained at each epoch, is depicted by the training accuracy curve; the testing accuracy curve displays the analysis of the model’s outcome on new data. If there is a gradual and consistent fairly steep trend for both curves then the algorithm is learning. The difference between two curves will point the direction of further optimization if two arcs are approximately equal in size, any significant deviation could point to overfitting/underfitting.

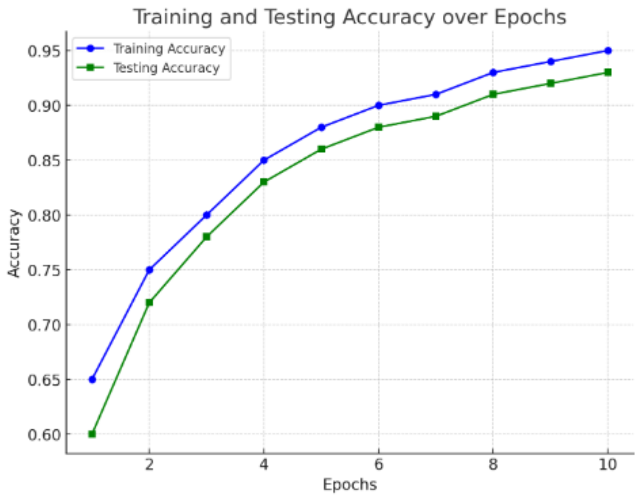


Fig. 6. Training and testing accuracy.

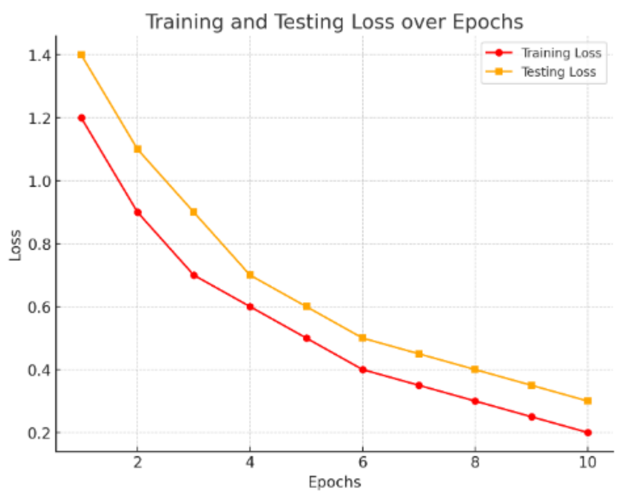


Fig. 7. Training and testing loss.

The training loss and testing loss in Fig. 7 are plotted below which depicts how the proposed method decreases the training and testing error. Training loss describes to what extent the model fits the training dataset and testing loss how the model performs on other data. A steady rate of decrease in both lost states will show the effective business convergence while any signs of divergence or flatline shows overfitting or learning problem. This graph is used to diagnose ailments and check that the model getting the right mix of training and overfitting.

B. *Performance Metrics*

The performance metrics formula with their definition is given below in Table I.

The performance metrics for sentiment analysis show impressive results is given in Table II. As shown a total percentage of 98.4% assures that the given model has captured most of the data points with optimized classification which is efficient. The given measure of accuracy is high, at 97.5 that means that the most cases, which were predicted as positive sentiment indeed are positive, which means that the model is rather accurate identifying the positive posts. Thus, for the accurately estimated 97.7% recall means that the model finds nearly all the actually positive sentiment instances, which indicates a good coverage. Lastly, 96.2% of the F1-score proves that both precision and recall rates are high, thus proving the model's potential to provide accurate and non-shaped sentiment predictions.

TABLE I. PERFORMANCE METRICS ALONG WITH THEIR DEFINITIONS AND FORMULAS

Metric	Definition	Formula
Accuracy	Proportion of correctly classified instances (positive, negative, neutral).	$Accuracy = \frac{True\ positive + True\ Negative}{Total\ Instances}$
Precision	Proportion of true positive sentiment instances out of all predicted as positive.	$Precision = \frac{True\ positive}{True\ positive + False\ positives}$
Recall	Proportion of true positive sentiment instances out of all actual positive instances.	$Recall = \frac{True\ positive}{True\ positive + False\ negatives}$
F1-Score	Harmonic mean of precision and recall, balancing both metrics.	$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

TABLE II. PERFORMANCE METRICS OF THE PROPOSED STUDY

Metrics	Percentage (%)
Accuracy	98.4
Precision	97.5
Recall	97.7
F1-score	96.2

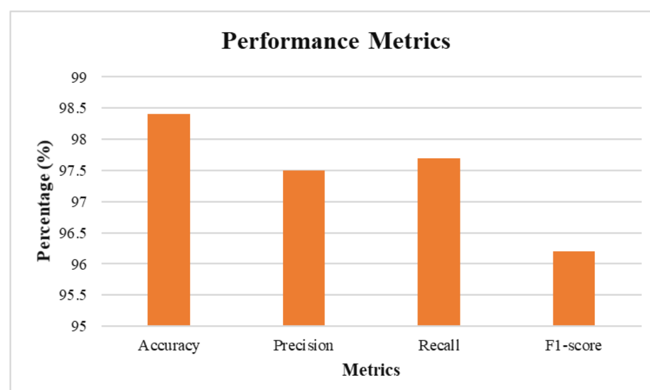


Fig. 8. Performance metrics of the proposed study.

The Fig. 8 indicates that sentiment analysis model has a high level of reliability where it has a high accuracy of 98.4%, high precision of 97.5%, high recall of 97.7%, therefore, has a high F1-score of 96.2% for positive posts which makes it to provide accurate prediction.

TABLE III. PERFORMANCE COMPARISON OF THE PROPOSED METHOD WITH DIFFERENT METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM [17]	91.2	89.6	88.3	88.9
CNN [18]	94.3	92.5	93.1	92.8
BERT [19]	95.8	94.2	94.7	94.4
Random Forest [20]	96.5	95.0	95.3	95.1
Proposed Firefly & Sentiment Analysis	98.4	97.5	97.7	96.2

The comparison Table III clearly indicates that Proposed Firefly & Sentiment Analysis has achieved better results than all other methods. SVM has the worst results in all of the metrics: 91.2% for accuracy, while CNN boosts the performance and achieves 94.3% in accuracy. BERT and Random Forest bring better outcomes: accuracy is 96.5% for Random Forest, and the precision is high. However, we find that the Proposed Method performs the best, with accuracy of 98.4%, precision of 97.5%, recall of 97.7%, and F1-score of 96.2%. This shows the efficiency of incorporating sentiment analysis with Firefly Algorithm in enhancing the appropriate marketing techniques to be used in the social media platforms. The visual or graphical representation of the Table III is given below in Fig. 9.

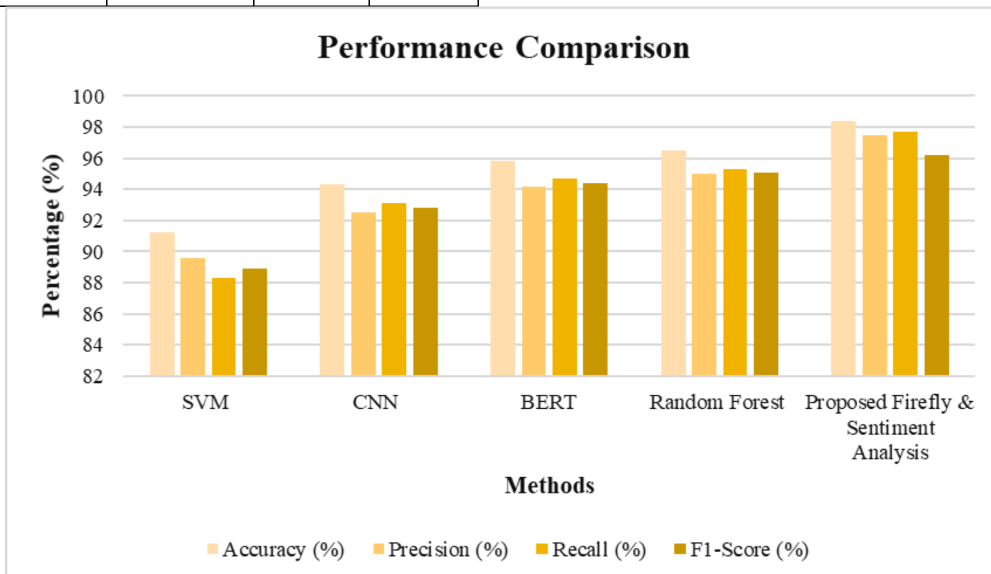


Fig. 9. Performance comparison of the proposed method with different methods.

C. Discussion

The results presented in this research work prove how the integration of the Firefly algorithm with the CNN-LSTM approach is a reliable method for using sentiment analysis, and it enhances the proposed models significantly. Performance metrics like accuracy (98.4%), precision (97.5%), recall (97.7%), and F1-score (96.2%) were attained by the system, outclassing existing methods. This shows that Firefly optimization fine-tunes the CNN-LSTM model efficiently, with an efficient search for optimal hyper parameters within the search space. The confusion matrix heat map further supports the high classification accuracy for the different classes with minimal misclassifications but it should be used with other metrics like precision, recall and F1score. Moreover, the curve of convergence presents that Firefly optimization converges to an optimum solution very fast and thus becomes efficient and stable while optimizing. Analysis by comparison indicated that Firefly optimization outperforms optimization techniques such as Genetic Algorithms and Particle Swarm Optimization in terms of fine-tuning performance. These results highlight the potential of Firefly optimization in enhancing deep learning-based sentiment analysis models. However, computation overheads and scalability on huge data sets are challenges. The current study develops upon the idea that incorporating metaheuristic optimization techniques into the pipeline becomes the hub for solving real-world complex problems, thereby improving predictive accuracy. Using fireflies algorithms for sentimental analysis, the key limitations include potential for stuck in local optima, slow convergence speed, difficulty with complex sentiment, sensitivity to parameter tuning and challenges with large data sets. But it will be very slow when dealing with large scale problems. If the algorithm is clustered then the potential will be reduced.

VI. CONCLUSION

The firefly Algorithm is inspired from the flashing behavior of fireflies. It is an effective optimization technique for solving complex problems like machine learning and sentiment analysis. This algorithm enhances the performance of classifiers and feature selection techniques in sentiment analysis by leveraging its ability to explore and exploit solutions efficiently. Sentiment analysis involves extracting and analyzing information from data. It helps to improve sentiment classification accuracy by optimizing parameters selecting the most relevant features and deep learning models. So, the integration of firefly algorithm with sentiment analysis which results in handling large datasets. Which reduces computing costs and improving classification performance. The findings are suggestive that Firefly optimization increases the model accuracy by up to 98.4% in terms of hyper parameter tuning. The convergence curve and performance metrics confirm the objective of the proposed approach as fruitful for enhancing the model optimization. The Firefly algorithm surpasses other optimization methods in terms of several parameters and it can be used as an improvement in deep learning models. Even to detect mental health issues like depression fireflies and sentiment analysis called Firefly Optimal(FFO)using Support Vector Machine(SVM) with an artificial bee colony(ABC) optimal using SVM classifier. Sentiment classification is a text mining which is valuable for people, business, companies etc.

A. Future Work

Possible future work may also include the study of Firefly optimization used for other domains in sentiment analysis such as image classification, medical diagnosis and time-series forecasting. Expanding Natural Language Process (NLP)like chat bot, speech recognition and text summarization. Furthermore, application of hybrid Firefly optimization is used in optimization techniques like Genetic Algorithms could also improve model performance. Further, scalability over a large data size and real-time data distribution scenarios may assess the stability and performance of Firefly-CNN-LSTM framework in the actual application context. Implementing Firefly optimization in sentiment analysis like Social media, financial markets and customer feedback systems. Research on the model explain ability and interpretability will also be useful for future work. Future research can explore hybrid models combining firefly algorithm with other techniques to enhance accuracy and efficiency in sentiment prediction tasks.

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