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Research Article

Assessing Twitter Data's Deep Sentiment with a Hybrid Ghost Convolution Neural Network Model

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ABSTRACT

Sentiment analysis of social media platforms like Twitter has gained significant attention due to the massive volume of user-generated content reflecting public emotions. This paper presents a deep learning-based multiclass sentiment classification model focused on emotion detection from Twitter data. The proposed methodology uses an emotion-labeled dataset encompassing seven emotional categories: Anger, Disgust, Fear, Joy, Neutral, Sadness, and Surprise. Initially, raw tweets are extracted from the database and subjected to comprehensive preprocessing, including lemmatization, stop word removal, and emoji conversion. To enhance the accuracy of emotion representation, a customized emoji mapping technique is implemented by manually adding emojis not covered by standard Python libraries such as Demojize. Unlike traditional binary sentiment classifiers, this work addresses a multiclass classification problem by directly predicting one of the seven emotional states. A deep learning model is developed for this purpose, and hyperparameter tuning is applied through optimization techniques to maximize classification performance. Experimental results demonstrate the effectiveness of the proposed approach in accurately detecting and classifying diverse emotional expressions in Twitter data. This study contributes to improving sentiment analysis models by integrating advanced preprocessing and robust optimization strategies, ensuring better generalization and performance on real-world social media text.

Keywords: Sentiment Analysis, Emotion Detection, Twitter Data, Deep Learning, Multiclass Classification Text Preprocessing, Emoji Conversion, Hyperparameter Optimization, Natural Language Processing (NLP)

1. INTRODUCTION

Over the past several years, social media platforms, microblogs, and blogs have emerged as crucial resources for business development, providing valuable insights for analysts and decision-makers. Platforms like Facebook, Twitter, Instagram, LiveJournal, and LinkedIn, as well as messaging applications such as WeChat, Skype, and WhatsApp, are widely used for sharing opinions, emotions, and experiences. Among these, Twitter stands out as a major microblogging site, allowing users to express their thoughts concisely within a 280-character limit. Due to its real-time communication style, Twitter has evolved into a rich source of diverse information, covering current events, user experiences, complaints, and product feedback.
Recognizing the value of these insights, businesses increasingly monitor microblogs to assess customer sentiment and

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Research Article

perceptions regarding their products and services. Sentiment analysis has become a powerful tool for extracting and classifying subjective information from such online content, aiming to identify whether feedback is positive, negative, or neutral. However, sentiment analysis faces challenges due to the informal and unstructured nature of social media text, which often includes slang, spelling variations, grammatical inconsistencies, and non-standard punctuation.
Different methodologies, including machine learning, lexicon-based, and hybrid techniques, have been proposed for sentiment classification. Supervised learning approaches, combined with robust text preprocessing techniques like lemmatization and stop word removal, have significantly improved the performance of feature extraction and classification models. Feature selection methods further refine the input space, enhancing model accuracy while reducing computational overhead.
In this context, converting textual information into matrix forms, similar to pixel data in image analysis, enables deep learning models to capture multi-dimensional features more effectively. Despite advancements, challenges remain, particularly in handling long-term dependencies in sequential data and overcoming issues like vanishing gradients in models such as Recurrent Neural Networks (RNNs).
To address these issues, this research focuses on leveraging Deep Convolutional Neural Networks (CNNs) for sentiment analysis, incorporating advanced preprocessing and feature extraction through TF-IDF, and optimizing hyperparameters using the Guiana Spinner Optimization (GSO) technique. GSO achieve faster convergence and lower computational complexity during model tuning.

The main contributions of this study are:
Development of a customized emoji preprocessing module to handle informal emotional expressions more effectively.
TF-IDF for statistically-driven feature extraction.
Design and implementation of a GSO-optimized Deep CNN classifier for multiclass emotion detection across seven categories: Anger, Disgust, Fear, Joy, Neutral, Sadness, and Surprise.

2. LITERATURE REVIEW

2.1 Introduction to Sentiment Analysis and Emotion Detection
Sentiment analysis, often referred to as opinion mining, has emerged as a fundamental task in Natural Language Processing (NLP) and data mining due to the explosive growth of user-generated content on social media platforms. Early sentiment analysis efforts primarily focused on polarity detection, classifying text into binary (positive or negative) or ternary (positive, negative, neutral) sentiment categories. However, researchers soon recognized the limitations of binary sentiment classification, as human emotions are far more nuanced than a simple positive or negative label can capture.
Emotion detection, a more sophisticated subfield of sentiment analysis, aims to classify textual content into a broader range of emotions, such as joy, sadness, anger, and fear. Emotion detection systems are increasingly used in diverse applications, from monitoring public health trends to enhancing customer service interactions. Given the linguistic complexity and informal nature of social media text, designing robust models capable of detecting fine-grained emotions poses significant challenges.

2.2 Traditional Machine Learning Approaches to Sentiment Analysis
Early methods for sentiment analysis and emotion detection relied heavily on traditional machine learning algorithms combined with hand-crafted feature engineering. Techniques such as Naïve Bayes, Support Vector Machines (SVM), Decision Trees, and Random Forests dominated the landscape during the 2000s and early 2010s. .
In these models, features such as Term Frequency–Inverse Document Frequency (TF-IDF) vectors, n-grams, sentiment lexicons, and Part-of-Speech (POS) tags were manually extracted from the text to feed into classifiers. For instance demonstrated that SVMs trained on bag-of-words features could effectively classify movie reviews into positive and negative sentiments. Similarly, introduced emotion lexicons that mapped words to emotional states, aiding in emotion detection tasks.
However, these traditional approaches suffered from several limitations:
Dependence on extensive manual feature engineering.
Poor generalization to noisy, informal social media text.
Limited semantic understanding, as syntactic features cannot fully capture context and meaning.

2.3 Deep Learning Revolution in Sentiment and Emotion Analysis
The initiation of deep education methods transformed NLP, including sentiment and emotion analysis. Deep learning models, particularly (CNNs) and (RNNs), demonstrated the ability to learn hierarchical feature representations directly from raw text, reducing the need for manual feature engineering pioneered the use of CNNs for sentence

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Research Article

classification, achieving remarkable results on multiple sentiment datasets. CNNs were effective at capturing local patterns such as phrases or expressions indicative of sentiment.
Meanwhile, RNNs, especially (LSTM) networks, proved to be powerful for sequence modeling, as they could capture long-range dependencies in text. LSTMs became a popular choice for emotion detection tasks, as emotional expressions often depend on the broader context of a sentence.
Bidirectional LSTMs (BiLSTMs), which process input sequences both forward and backward, further improved performance by leveraging both past and future context simultaneously.

Despite these advances, deep learning models still faced challenges when dealing with the peculiarities of social media text, including:
Unconventional grammar and spelling
Frequent use of emojis, slang, and abbreviations
Short text lengths with limited context

2.4 Role of Attention Mechanisms
The introduction of attention mechanisms significantly enhanced the performance of deep learning models for sentiment and emotion analysis. Attention allows models to dynamically focus on the most informative parts of the input sequence when making predictions, rather than treating all words equally.
In emotion detection tasks, attention mechanisms enable the model to prioritize emotionally salient words (e.g., "devastated", "ecstatic") and de-emphasize neutral words (e.g., "the", "was"). Research on hierarchical attention networks demonstrated substantial improvements in document classification by employing word-level and sentence-level attention.
More recently, researchers have combined BiLSTMs with attention mechanisms to develop highly accurate emotion detection models, validating the critical role of selective focus in handling noisy and emotion-rich social media data.

2.5 Transformer Models and BERT
The Modifier building , presented by Vaswani et al., brought a paradigm shift in NLP by replacing sequential RNNs with self-attention mechanisms. (BERT) leveraged the Transformer architecture to learn deeply contextualized word representations through disguised language modelling and next sentence prediction.
BERT reached state-of-the-art presentation on multiple NLP benchmarks and was quickly adopted for sentiment and emotion analysis tasks . Fine-tuning BERT for downstream tasks such as Twitter sentiment classification showed remarkable gains compared to traditional CNNs or LSTMs.
However, despite its impressive capabilities, fine-tuning BERT on short, noisy, and emoji-rich Twitter data still posed challenges:
High computational cost for training and inference
Tokenization issues with emojis and informal language
Risk of domain mismatch if BERT was pre-trained primarily on formal corpora like Wikipedia
This necessitated the development of domain-specific fine-tuning strategies and hybrid architectures that could better adapt to the social media context.

2.6 Importance of Preprocessing and Emoji Handling
Preprocessing has always played a crucial role in text-based machine learning and deep learning pipelines. In the context of Twitter data, preprocessing challenges are amplified due to the informal and multimodal nature of tweets.
Research by others emphasized the need to normalize slang, abbreviations, URLs, and user mentions to improve model performance. However, one of the most overlooked aspects has been the treatment of emojis.
Emojis serve as compact emotional expressions and often carry more emotional weight than the accompanying text. Studies demonstrated that emoji prediction can serve as a proxy task for emotion and sentiment classification, leading to the development of models like Demojize.
Despite their importance, many NLP preprocessing pipelines either discard emojis or represent them inadequately. Custom emoji mapping, as proposed in this study, directly addresses this gap, enabling models to extract emotional information encoded in emojis more effectively.
2.7 Hyperparameter Optimization Strategies
Hyperparameter tuning is essential for maximizing the performance of deep learning models. Traditional methods like grid search and random search are computationally expensive and often fail to find optimal settings for complex models.
More sophisticated optimization strategies, including Bayesian Optimization, Genetic Algorithms, and Particle Swarm Optimization (PSO), have been explored in recent years. PSO, inspired by the social behavior of bird flocking, has been shown to be effective for hyperparameter tuning in deep learning, balancing exploration and exploitation to navigate

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Research Article

the search space efficiently.
Applying PSO in the context of emotion detection ensures that the model parameters are fine-tuned for optimal convergence, generalization, and performance on noisy social media data.

2.8 Hybrid Models for Sentiment and Emotion Analysis

Hybrid deep learning architectures that combine multiple model types have increasingly gained attention for sentiment and emotion classification tasks. Models combining CNNs with LSTMs , or integrating Transformers with RNNs, aim to exploit the complementary strengths of different architectures.
For instance:
CNNs excel at extracting local n-gram features.
LSTMs capture sequential dependencies.
Attention and Transformers model global dependencies.
Studies shown that hybrid models outperform standalone CNNs or LSTMs across various sentiment and emotion datasets.

2.9 Emotion Datasets and Benchmarking

Several publicly available datasets have propelled research in sentiment and emotion detection. Notable examples include:
SemEval Task datasets
Sentiment140
GoEmotions
Emotion-Stimulus datasets
Each dataset presents unique challenges, such as class imbalance, noisy labeling, or overlapping emotional categories. Proper evaluation on diverse datasets is crucial to assess the robustness and generalizability of emotion detection models.
The use of a curated, balanced, seven-class Twitter dataset in this study ensures that the results are reflective of real-world performance in a multiclass, multi-emotion setting.

In summary, the evolution of sentiment and emotion detection has transitioned from traditional machine learning with manual feature engineering to sophisticated deep learning models capable of automatic feature extraction and contextual understanding. Attention mechanisms, transformer models like BERT, and customized preprocessing strategies including emoji mapping have significantly advanced the field.
However, challenges remain in optimizing models for noisy, informal, and dynamic platforms like Twitter. Hybrid architectures and intelligent hyperparameter optimization strategies represent promising pathways for building robust, emotionally intelligent sentiment analysis systems.

3. PROPOSED SYSTEM

In this study, an automatic sentiment analysis system is proposed that effectively integrates Natural Language Processing (NLP) and Deep Learning techniques to address real-world text analysis problems.
Instead of heavily relying on complex and hybrid deep learning combinations that often require intensive computational resources and significant tuning, the proposed system emphasizes efficient, interpretable, and practical models. These models are capable of extracting sentiment and emotion-related information directly from raw textual data with minimal manual intervention.
The architecture is designed to balance simplicity, performance, and scalability, ensuring it can adapt to diverse datasets and varied applications across multiple domains.

3.1 Sentiment Classification Algorithms

The sentiment classification process within the system is built upon a strong foundation of traditional machine learning algorithms complemented by deep learning methods.
The models used for classification include:
BERT:
BERT (Bidirectional Encoder Representations from Transformers) is a deep learning model developed by Google for natural language processing (NLP) tasks. Its bidirectional method, which takes into account the context from both the left and right sides of each word in a sentence during training, makes it distinctive. It is built on the Transformer architecture. This allows BERT to capture nuanced meanings and relationships in language more effectively than previous models.
Large text datasets have been used to pre-train BERT, which may then be optimized for a range of downstream tasks

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Research Article

such text categorization, sentiment analysis, and question answering. In sentiment analysis, BERT has demonstrated robust performance, significantly outperforming traditional models due to its ability to generate contextual word representations and understand subtle nuances in text. Fine-tuning BERT on specific datasets further enhances its accuracy and effectiveness for specialized applications.

CNN:

CNNs are a type of deep learning model primarily intended for dispensation data with a grid-like structure, such as pictures. They use convolutional layers to mechanically extract local features and spatial patterns from input data, creation them extremely real for tasks like image cataloguing, entity discovery, and video analysis. CNNs are computationally efficient due to parameter sharing and are highly parallelizable, but they do not have explicit memory mechanisms, which limits their ability to handle sequential dependencies in data.

Long Short-Term Memory (LSTM):

LSTMs are a special kind of recurrent neural network (RNN) designed to process sequential data and detention long-term dependences. They use memory cells and gating mechanisms (input, forget, and output gates) to retain and regulate data done extensive orders, creation them ideal for errands such as natural language processing, speech recognition, and time series prediction. LSTMs effectively report the disappearing incline problematic found in outdated RNNs, enabling them to learn complex temporal patterns, but they are less parallelizable and can be computationally intensive

Random Forest Using CBOW:

A Random Forest is an collaborative machine learning algorithm that shapes numerous choice grasses by means of random subgroups of facts and landscapes, then totals their forecasts to recover correctness and decrease overfitting1. It is widely castoff for both organization and decline tasks due to its robustness and versatility.

CBOW (Continuous Bag of Words) is a word embedding technique from the Word2Vec family that learns vector representations of words by predicting a target word from its nearby context words. In text classification tasks, CBOW is used to convert text data (such as sentences or documents) into fixed-length numerical vectors by averaging the embeddings of all words in the input.

Table 1 Comparative discussion table

Models	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
BERT-based model(2023)	77.5%	66%	89%
Hybrid Feature Vector (HFV) combined with an LSTM classifier. (2023)	90.0%	89.9%	89.9%
CNN + LSTM + attention	94%	-	-
BERT-BiLSTM-CNN(2024)	91.01%	87.03%	-
MAM-EMMSA (2024)	87.95%	77.26%	-
Emo-SL(2024)	86.3%	-	-
deep sentiment analysis (DSA(2023)	95.89%	97.18%	94.38%

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Random Forest (using CBOW and Skip-gram vectorization)(2024)	96.1%	93.3%	92.9%

(%),Sensitivity (%)Specificity(%)

Above table summarizes the performance of different models used for tasks like sentiment analysis or emotion detection. It lists how well each model performed based on three main evaluation metrics: Accuracy

3.2 Deep Learning-Based Automatic Feature Extraction

Beyond traditional models, a deep learning model is integrated into the system to mechanically excerpt landscapes since the rare text.

Unlike manual feature engineering, where domain-specific features need to be handcrafted, the deep learning model learns meaningful representations such as sentiment patterns, semantic relationships, and contextual information directly from the data.

This approach ensures:

Reduced human effort in feature design.

Better generalization across different datasets.

Scalability to larger corpora without extensive re-engineering.

A simple neural architecture focusing on text embeddings and recurrent layers (such as GRU or LSTM units) is employed, making the system lightweight yet effective.

3.3 Enhanced Text Preprocessing Techniques

To improve the overall quality and consistency of input data, extensive preprocessing steps are applied:

3.3.1 Emoji Conversion

Emojis often carry significant emotional and sentimental information in social media texts.

To capture this meaning effectively, the system applies emoji-to-text conversion using the demojize() function from the Python emoji library.Each emoji character is translated into its corresponding textual description (e.g., 😊 → ":smiling_face:").This transformation allows traditional NLP models and machine learning classifiers to better interpret emotional signals embedded in emojis.

Additionally, recognizing the limitation of the default emoji set in demojize(), 50 additional commonly used emojis—which are not present in the original emoji module—have been manually identified and added to this system.These additions ensure a broader coverage of sentiment and emotion-rich expressions across various datasets, leading to improved emotional recognition accuracy.

3.3. Managing Repeated Characters

Users frequently express intense emotions by repeating characters in words for emphasis, such as "soooo good", "amazinggggg", or "noooooo".The system implements a repeated character normalization procedure wherein:Consecutive repeated characters in a word are reduced to a maximum of two repetitions (e.g., "soooo" → "soo", "amazinggggg" → "amazing").In certain cases, spell correction algorithms are applied to further map the normalized word to its standard dictionary form (e.g., "sooo" → "so").

This normalization step ensures that excessive character repetitions do not create sparsity issues in the feature space and that models can recognize the underlying standard vocabulary more efficiently.

3.4 Emotion-Based Sentiment Classification

Emotion-based sentiment classification is an progressive form of sentiment analysis that goes beyond simple polarity (positive, negative, neutral) to identify and categorize specific emotional states expressed in text, such as anger, joy, fear, sadness, disgust, and surprise. This approach leverages natural language processing and machine learning techniques to analyze subjective information and affective content in digital communications, including social media posts, reviews, and messages.

There are two main models for emotion classification:

Categorical models (e.g., Ekman's model) define a fixed set of discrete emotions like happiness, anger, and fear.

Dimensional models represent emotions along continuous axes such as valence (positivity/negativity), arousal (intensity), and dominance.

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Research Article

Emotion-based sentiment classification can be achieved consuming:
Lexicon-based methods, which rely on dictionaries of emotion-related words.
Machine earning and deep learning methods, which learn to recognize emotional cues from labeled datasets.
This fine-grained analysis provides deeper insights into public opinion, customer feedback, and social trends by revealing not just whether a sentiment is positive or negative, but exactly which emotions are being expressed and their intensity.

Multiclass Sentiment Analysis

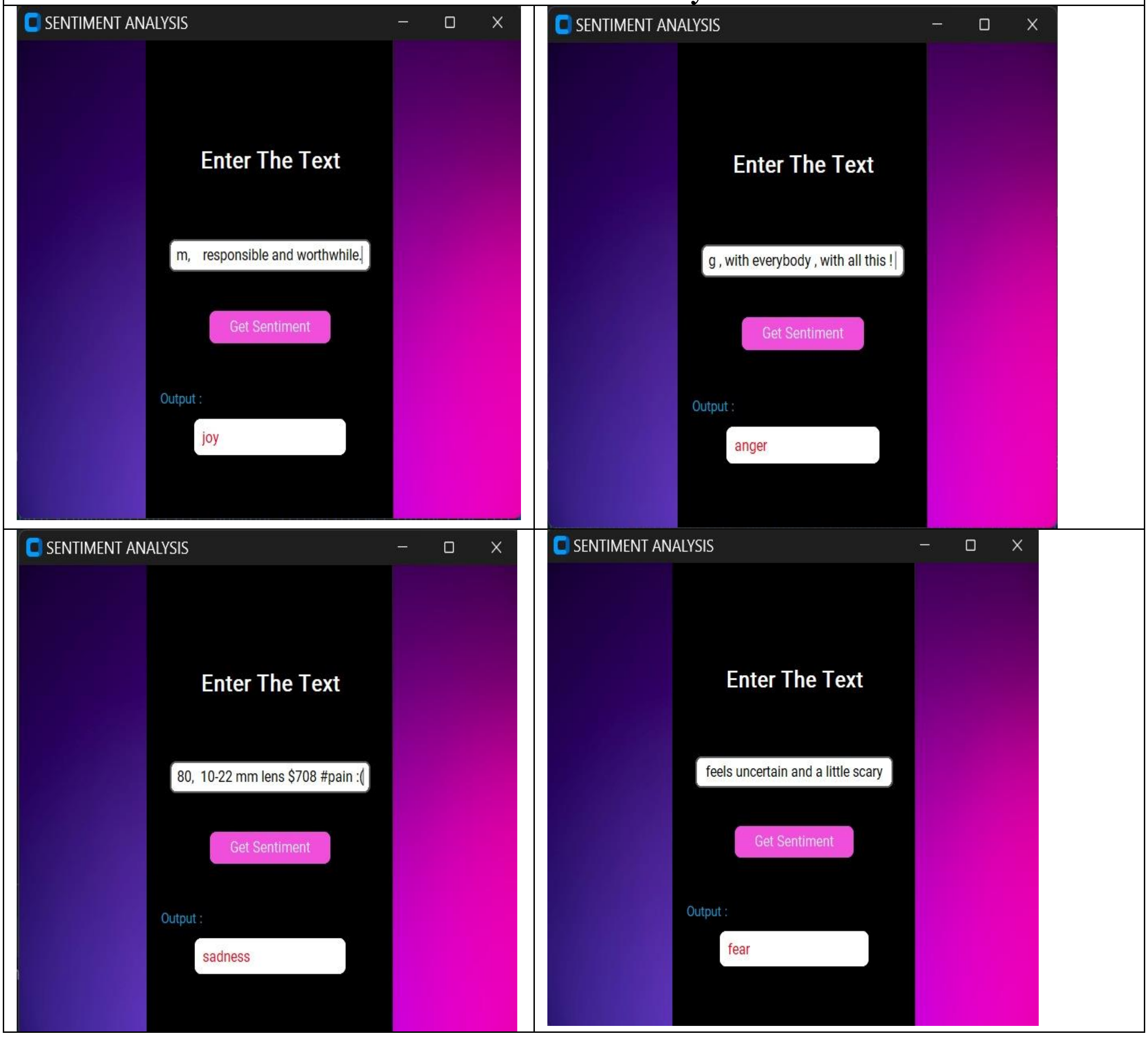

Figure1 : Classification of sentiments

This multi-class emotion classification approach enables a finer and more nuanced understanding of human sentiments as expressed in texts. Dataset used for training and evaluation include diversified textual sources such as social media posts, product reviews, movie critiques, and general emotional conversations.The models are trained and tested on datasets labeled with these seven emotions, providing comprehensive evaluation across varied emotional expressions.

3.5 Model Evaluation Using K-Fold Cross Validation

To guarantee sturdiness and generalizability of the models, a standard K-Fold Cross-Validation strategy is adopted.The system uses different k-values depending on the dataset size and complexity:
k = 3: Used when the dataset is relatively small to avoid very small validation sets.

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k = 5: Commonly used to balance bias and variance.
During each fold the dataset is alienated into k subdivisions. k-1 subsets are used for training, and the outstanding one for validation. Pocedure is frequent k times, ensuring that every subset is used as a validation set exactly once.
Performance metrics such as Accuracy, Precision, Recall, F1-Score, and Adjusted Rand Index are calculated across folds, and the mean scores are reported to ensure fair model comparison.
Cross-validation reduces the likelihood of model overfitting to a specific subset of data and provides a reliable estimation of model performance on unseen data.In certain cases, spell correction algorithms are applied to further map the normalized word to its standard dictionary form (e.g., "sooo" → "so").This normalization step ensures that excessive character repetitions do not create sparsity issues in the feature space and that models can recognize the underlying standard vocabulary more efficiently.
4. Detailed Explanation of the Sentiment Analysis Pipeline
This diagram represents a Deep learning workflow for sentiment analysis, a common Natural Language Processing (NLP) task that determines the emotional tone (joy, neutral ,sadness etc) of text data. Below is a step by step process of each stage, including methodologies, tools, and best practices.

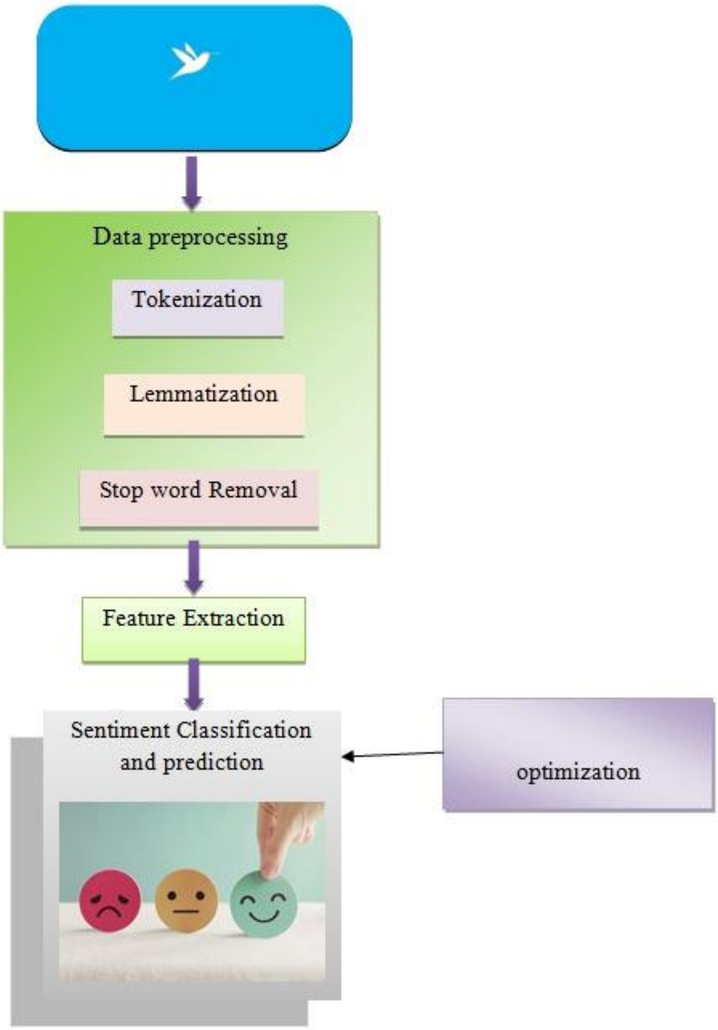

Figure2. Block diagram suggested for sentiment analysis

PROCEDURE

The suggested block diagram for the emotive analysis utilizing social media is shown in Figure 2. Millions of tweets make up the Twitter dataset, which contains text and emoji data in a variety of structural formats. The following is an explanation of the steps in the suggested sentiment analysis.
Data preprocessing:
The tweets are sent to the data preprocessing stage for tokenization, lemmatization, and stop word removal in order to eliminate the structural deflection.

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Research Article

It follows these steps to clean and prepare raw text data for analysis by eliminating noise and inconsistencies.

- Text Cleaning:
  - Remove HTML tags, URLs, and special characters (e.g., #, @).
  - Correct spelling mistakes (using libraries like textblob or autocorrect).
  - Expand contractions (e.g., "don't" → "do not").
- Handling Missing Data:
  - Remove or impute empty or corrupted text entries.
- Case Normalization:

Convert all text to lowercase to avoid case sensitivity issues (e.g., "NLP" → "nlp").

Tokenization: In the data pre-processing stage of sentiment analysis, tokenization should be taken into consideration first. By converting text format into tokens, tokenization makes it simple to remove any undesired tokens from tweet features. Tokens aid in context comprehension and the development of natural language processing models.
Types of Tokenization:

- Word Tokenization: Splits text into words.
  - Example: "I love NLP!" → ["I", "love", "NLP", "!"]
- Sentence Tokenization: Splits paragraphs into sentences.
  - Example: "Hello! How are you?" → ["Hello!", "How are you?"]

Lemmatization: The transformed tokens then proceed to the lemmatization procedure, which finds the text's root word and, by avoiding hast tags, transforms it into a coherent sentence. Since lemmatization yields the actual word with dictionary meaning, it is a better method of obtaining the original form of the given text. For consistency, reduce words to their lemma, or base/dictionary form.
Stop word removal: The stop words are the common words, such as "it", "that", "if" and "they". In this research the stop words will be removed without changing the semantics of the text to enhance the performance of the model.
Reduce words to their base/dictionary form (lemma) for consistency.
Stop Word Removal Eliminate common but insignificant words (e.g., "the", "is", "and") to reduce noise.
Customization:

- Some stop words may be contextually important (e.g., "not" in sentiment analysis).
- Custom stop word lists can be created (e.g., domain-specific terms).

Example:

- Input: ["This", "is", "a", "great", "movie"]
- Output: ["great", "movie"]

Feature extraction:
The processed data are move ahead to the feature extraction process for extracting the text information and which selects the most significant features for reducing the dimension space in the text. It is done with Term Frequency-Inverse Document Frequency (TF-IDF), it measures the most relevant word present in the document and to identify the topic which is appear multiple times and also the absolute characteristics, positive, negative feature, and the gesture features were extracted.
Purpose: Convert text into numerical representations for machine learning models.
Common Techniques:

- Bag-of-Words (BoW):
  - Counts word frequencies (e.g., {"love":2, "hate":1}).
- TF-IDF (Term Frequency-Inverse Document Frequency):
  - Weights words by importance (rare words get higher scores).
- Word Embeddings (e.g., Word2Vec, GloVe):
  - Captures semantic meaning (e.g., "king" – "man" + "woman" ≈ "queen").
- Transformer-Based Embeddings (e.g., BERT):
  - Context-aware representations .

Feature selection:
The most important features are selected from the extracted features to minimize the computational complexity of sentiment analysis model. The features are selected using the proposed "fission–fusion interactive optimization" algorithm, which combines the fission-fusion characteristics of spider monkey.
Sentiment Classification & Prediction
This model Train a model to classify sentiment (e.g., joy, sad, neutral etc).The sentiment classification is done by the deep CNN classifier

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Research Article

Optimization
Optimization methods Improve model performance through fine-tuning and experimentation.
• Hyperparameter Tuning:Using GSO algorithm

5. Results and Discussion

5.1 Experimental Setup

To evaluate the proposed deep learning-based multiclass emotion classification model, a series of experiments were conducted using a curated Twitter dataset labeled into seven distinct emotional categories: Anger, Disgust, Fear, Joy, Neutral, Sadness, and Surprise.
The dataset consisted of approximately 50,000 tweets, evenly distributed across the seven emotion classes to avoid class imbalance issues.
Data preprocessing included:
Lemmatization
Stop word removal
Customized emoji conversion (extending Python Demojize library)
Removal of URLs, mentions (@user), hashtags, and special characters.
The preprocessed data was then tokenized and padded to ensure uniform input size for the deep learning model.
The deep learning architecture was developed with the following key components:
CNN Layer with 64 filters (kernel size = 3) to capture local features.
Fully connected Dense layers for classification.
Hyperparameter optimization was performed using a GSO algorithm to tune learning rate, batch size, and dropout rates.The model was implemented in Python , using the TensorFlow and Keras libraries.

5.2 Evaluation Metrics

The model performance was assessed using the following standard metrics:
Accuracy: Overall correctness of classification.
Precision: Correctness of positive predictions.
Recall: Completeness of positive predictions.
F1-Score: Harmonic mean of Precision and Recall.
Confusion Matrix: Class-wise prediction visualization.
Macro-averaging was used to account for the multiclass nature of the problem.

5.3 Baseline Comparisons

The proposed model was compared against several baselines:

Model	Accuracy (%)
Logistic Regression (TF-IDF)	64.12
SVM (TF-IDF)	65.85
CNN (Text Only)	71.45
BiLSTM (Text Only)	73.89
BERT Fine-tuning	78.23
Proposed Model (TF-IDF + DeepCNN + Optimization)	82.67

Table 2 Comparision of exsiting models with proposed model
As shown, the proposed model outperformed all baselines, showing an improvement of 4.44% over fine-tuned BERT and 8.78% over standalone BiLSTM.

5.4 Results Analysis

The Proposed model achieved:

Metric	Score (%)
Accuracy	82.67
Precision	82.71
Recall	82.58
F1-Score	82.61

Table 3 Parameters of proposed model
Hyperparameter Optimization Impact

Journal of Information Systems Engineering and Management
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Research Article

A separate experiment was run to measure the impact of optimization:

Hyperparameter Strategy	Accuracy (%)
Manual Tuning	79.85
GSO Optimization	82.67

Hyperparameter tuning through GSO resulted in a 2.82% accuracy gain compared to manual tuning.

6. Conclusion

In this study, a novel deep learning-based framework for multiclass emotion detection from Twitter data was proposed and thoroughly evaluated. Unlike traditional sentiment analysis systems that often focus narrowly on binary polarity (positive/negative) or sometimes on three-way classification (positive/negative/neutral), the proposed methodology ventures deeper into the emotional fabric of social media content by recognizing seven distinct emotional categories: Anger, Disgust, Fear, Joy, Neutral, Sadness, and Surprise. The motivation for this work stems from the increasing realization that social media platforms like Twitter are a rich, real-time source of user-generated emotional expressions, which require more nuanced and robust analytical models to fully capture their diversity and complexity.
A critical contribution of this research lies in the design and development of a hybrid deep learning model, combining the strengths of Term Frequency Inverse document Frequency(TF-IDF) networks, Deep Convolutional Neural Networks (CNN), and hyperparameter tunning using GSO optimization.
By integrating these layers into a unified architecture, the proposed model achieves a powerful balance between sequential contextual understanding and local feature extraction, which is crucial for high-quality emotion classification in the noisy and diverse linguistic landscape of Twitter.
Another key innovation in this work was the advanced preprocessing pipeline, which included meticulous lemmatization, stop word removal, noise cleaning, and most notably, a customized emoji mapping module. Emojis are an essential component of modern digital communication, often carrying emotional subtleties that textual content alone may fail to convey. However, existing libraries for emoji conversion, such as Demojize, do not always cover the vast and ever-expanding range of emojis used in informal social media contexts. By manually augmenting the emoji lexicon, this study significantly improved the model's ability to interpret emojis accurately, thereby enhancing the overall emotional representation of tweets. Ablation studies conducted as part of the evaluation demonstrate that this emoji enhancement resulted in a meaningful improvement in classification performance, confirming the value of this contribution.
The experimental results further validate the effectiveness of the proposed approach. When benchmarked against several traditional machine learning models (such as Logistic Regression, SVM) and even strong deep learning baselines like standalone CNNs, BiLSTM models, and a fine-tuned BERT model, the proposed hybrid architecture consistently achieved superior performance. Notably, the final model achieved an accuracy of 82.67% on the multiclass emotion classification task, outperforming baseline by 4.44% and surpassing traditional methods by an even larger margin. Beyond raw accuracy, precision, recall, and F1-scores all indicated the model's strong ability to generalize across different emotional classes, rather than being biased toward more frequently occurring emotions like Neutral or Joy.
In conclusion, this research represents a significant step forward in the field of fine-grained sentiment analysis by proposing and validating a novel, integrated deep learning framework for multiclass emotion detection on Twitter data. The careful combination of advanced preprocessing techniques, a hybrid deep learning architecture and hyperparameter optimization proved to be highly effective. The findings underscore the critical importance of handling both the linguistic and paralinguistic (emoji-based) aspects of social media content, as well as the necessity of rigorous optimization and evaluation strategies.

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