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ANALYSIS OF SOCIAL MEDIA COMMENTS USING NLP

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Abstract: Social media platforms have emerged as a vital source of customer input and public opinion in the current digital era. When trying to glean relevant data from the vast amount of unstructured comments on these sites, it may be quite difficult. Due to the inefficiency of traditional manual sentiment analysis techniques, more advanced methods are now required. Recent developments in Natural Language Processing (NLP), in particular the application of neural network architectures such as Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT), have demonstrated significant promise in enhancing the precision and effectiveness of sentiment analysis. These models are perfect for large-scale comment analysis because they are very good at interpreting the mood, context, and subtleties of language used in social media comments. This study investigates the classification and analysis of social media comments using BERT, LSTM, and GRU, offering important insights into public opinion on a range of subjects. The results demonstrate how well these models capture trends, spot new problems, and support enterprises in making data-driven decisions. Additionally, by integrating these cutting-edge models, social media comments may be processed in real-time, empowering businesses to proactively address new trends or problems. The interpretability of intricate models and the scalability to manage very big datasets are still problems, though.

***Index Terms* -** Machine learning, NLP, sentiment analysis, human language, BERT, LSTM, GRU.

I. INTRODUCTION

From being a straightforward instrument for communication, social media has grown to have a significant impact on society, business, and politics. It might be difficult to glean valuable information from the billions of postings made every day. Slang, emoticons, and sarcasm are difficult for traditional sentiment analysis to handle, which produces unreliable findings. Depending on the context, words like "sick" can be either good or bad, which complicates interpretation. Deep learning-powered NLP models such as BERT, LSTM, and GRU enhance sentiment analysis. By comprehending linguistic subtleties, these models improve text categorization tasks' accuracy. LSTM and GRU are excellent in sequential text analysis, but BERT analyzes words in both directions. This essay investigates how well they work at extracting insightful information from social media comments.

Sentiment analytics examine and uncover the sentiment and purpose behind a piece of work, articulation, or reporting in any way in order to identify the viewpoint or emotion behind a circumstance. On our planet, people speak a variety of languages, and language is a vital instrument for expressing our opinions and emotions. Any feeling expressed by people via language is connected to it. The sentiment may also be neutral, negative, or constructive . As an illustration, consider a restaurant that sells a variety of foods, including pizza, burgers, sandwiches, milkshakes, and more. They have created a website to reach consumers, where they can currently purchase any kind of food they want and leave evaluations and ideas at any time to improve the meal's value or to let them know if they like or dislike the way it tastes.

These examples allow us to have three different kinds of customer reviews. First, the positive one shows that customers enjoy the cuisine. Second, because the review will be rejected, the corporation should concentrate on creating a plan to make the meal better. Since the third will be similar to the client and not respond, we may see it as a neutral remark. After reviewing every review, the business should concentrate on improving the food's quality and value or boosting various brand awareness tactics to boost yearly sales.

However, there are millions and thousands of evaluations of their meals, and it would be hard to read through them all and make a judgment. Sentiment analytics, which analyses vast volumes of reviews and aids in decision-making for future advancement by utilizing real-world evidence rather than a small sample of data, is used to address this issue. Natural processing and machine learning (ML) are then used to assist in the analysis of the data.

II. Literature Review

In recent years, sentiment analysis has gained a lot of interest, especially with the growth of online marketplaces where consumers may post product evaluations or comments. These evaluations are a valuable source of feedback for businesses and provide insights into client happiness. Both deep learning methods and conventional machine learning models have been used in a variety of ways to increase sentiment analysis accuracy. We cover the approaches, datasets, and findings of a number of studies that have investigated sentiment analysis on customer evaluations.

To eliminate the need for customers to manually browse through hundreds of Amazon product evaluations, Haque et al. created a sentiment analysis prototype . They classified every review as either positive or negative and discovered that the Support Vector Machine (SVM) method was able to identify the general attitude with an accuracy of more than 90% . In order to examine the correlation between expensive items and the quantity of positive ratings, Rashid and Huang collected reviews from Amazon . They ran into a problem with ratings that were skewed toward reviews with four or five stars, which we also have in our study. They carried on investigating additional categories in their research in spite of this imbalance.

By training models like Naive Bayes, Bi-directional Long-Short Term Memory (Bi-LSTM), Logistic Regression, Random Forest, and Bi-directional Encoder Representations from Transformers (BERT) using Amazon reviews, AlQahtani investigated sentiment analysis through machine learning. He discovered that BERT had the best accuracy, at 98%, while Random Forest and Bi-LSTM also did well, with 94% accuracies. Kumar et al. also used Senti WordNet, Naive Bayes, and Logistic Regression to assess the sentiment of Amazon reviews. Out of all the algorithms they examined, they found that Naive Bayes fared the best.

To examine the sentiment of Amazon product reviews, Ali et al. used a range of machine learning algorithms, such as Multinomial Naive Bayes, Random Forest, Decision Tree, and Logistic Regression; deep learning algorithms, such as CNN and Bi-directional LSTM; and transformer models, such as XLNet and BERT. With an accuracy rate of 89%, the studies demonstrated that the BERT algorithm performed better than the others. Tan et al. used algorithms including Long Short-Term Memory (LSTM),Naive Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN) to assess the sentiment of Amazon product reviews.

Park et al. compared the effectiveness of Artificial Neural Network (ANN), Support Vector Machine (SVM), and Graph-based Semi-Supervised Learning (GSSL) techniques in a sentiment analysis of 300,000 car evaluations from ten distinct online groups. According to their findings, GSSL outperformed SVM at 97.4% and ANN at 72.4%, with a 98.1% accuracy rate. SVM topped the others with an accuracy of 84.58%, being followed by a Naive Bayes model with 82.91% and Logistic Regression with 82.50%, according to a research by Diekson et al. that examined Logistic Regression, SVM, and Naive Bayes in 1200 tweets on Travelloka.

Grljević et al. compared the effectiveness of Naive Bayes, SVM, and K-Nearest Neighbors (KNN) in their analysis of the sentiment of review data gathered from Yelp, IMDB, and Amazon. According to their findings, SVM was the most successful, obtaining an F-measure of 79.70%, followed by KNN (76.40%) and Naive Bayes (76.79%). On sentiment analysis tasks, Chinnalagu et al. compared three models: fast Text, Bi-directional Long Short-Term Memory (SA-BLSTM), and linear SVM (LSVM). With an accuracy of 90.71%, fast Text outperformed LSVM, which came in second with 90.11%, and SA-BLSTM, which came in at precisely 77% .

According to the research that is currently available, sentiment analysis of customer evaluations has been extensively investigated using both sophisticated deep learning approaches and conventional machine learning models. In several studies, SVM consistently performs at the highest level, although more recent models such as BERT and Bi-LSTM demonstrate impressive outcomes when it comes to deep learning techniques. The comparative performance of several algorithms continues to offer insights for enhancing sentiment analysis, even in the face of dataset differences. By examining these models' performance on Amazon customer reviews in greater detail, our study expands on this framework.

III. Methodology

A. Dataset

A synthetic social media sentiment analysis dataset was employed for this study. It is made up of several social media posts that have been labelled as either positive, negative, or neutral. A variety of variables, including post content, post type, language, date, user follower count, and post ID, are included in every entry in the dataset. However, since they don't help with sentiment prediction, some of these attributes—like timestamps and user-specific information—are eliminated during preprocessing. The dataset is mostly utilized for text classification, where the objective is to categorize social media postings into sentiment groups by analyzing their textual content.

B.Existing System and Limitations

Conventional machine learning models and rule-based methodologies are the mainstays of the sentiment analysis systems now in use. These include of Random Forest classifiers, Naïve Bayes, Support Vector Machines (SVM), and lexicon-based techniques. Despite their widespread use, these approaches mostly rely on manually created characteristics like TF-IDF and Bag-of-Words (BoW), which are unable to capture contextual meaning. Older deep learning models, such as basic RNNs and LSTMs, have also been applied to sentiment categorization; however, they frequently encounter issues with vanishing gradients and long-term dependencies.

The incapacity of conventional sentiment analysis algorithms to comprehend the contextual links between words is one of their main drawbacks. This results in predictions that are not correct, particularly for complicated or sarcastic statements. When confronting words that have context-dependent meanings, lexicon-based approaches fall short. Comparably, considerable feature engineering is needed for conventional machine learning models, which can be time-consuming and have poor dataset generalization. Even while they are an improvement, traditional deep learning algorithms like LSTMs and RNNs still struggle to remember long-term dependencies in text, which limits their ability to comprehend complex sentiment patterns.

IV. Proposed System

- **Data Collection:**
  Social media postings with sentiment categorization labels make up the dataset utilized in this study. A variety of sources, including publicly available databases and real-time social media scraping, were used to collect the data. The main goal was to gather textual information from websites where people share their thoughts on a range of subjects. Unnecessary columns including timestamps, language information, and user details were eliminated in order to guarantee the dataset's quality. Only the most important text data required for sentiment analysis remained after this refining, which helped to cut down on noise.

- **Data Preprocessing:**
  The dataset was rigorously pre-processed to improve its quality and usability before to training the machine learning models. To make sure that redundant and insufficient data did not affect model performance, duplicate entries and missing values were first eliminated. Regular expressions were then used to remove URLs, special characters, and punctuation from the text data. To improve the

quality of the characteristics that were retrieved, stopwords were also eliminated. The Natural Language Toolkit (NLTK) was used to tokenize phrases, breaking them up into individual words. Additionally, lemmatization was used to standardize word forms, which reduced variants of words with the same meaning and increased the model's performance.

- **Text Vectorization:**
  Textual data was vectorized using TF-IDF (Term Frequency-Inverse Document Frequency) to make it readable by machine learning methods. This method aids in determining a document's word relevance in relation to the dataset as a whole. To capture the contextual meaning of words and sentences, the model included n-grams, which ranged from 1 to 3. In order to maximize computational efficiency and guarantee that the model captures crucial text patterns, a maximum feature limit of 2500 was also established.

- **Data Balancing:**
  In sentiment analysis, class imbalance is a prevalent problem where one sentiment type may be overrepresented in comparison to others. Random Inadequate sampling (RUS) was used to solve this issue. In order to prevent the model from becoming skewed toward one feeling over another, this strategy entails lowering the majority group instances to correspond with the minority class. We enhanced the model's capacity to generalize effectively across all sentiment classifications by balancing the dataset.

- **Model Training & Selection:**
  BiLSTM (Bidirectional Long Short-Term Memory), BERT-LSTM hybrid, and GRU (Gated Recurrent Unit) were the three deep learning models that were used and contrasted. A 70-30 ratio was used to divide the dataset into training and testing sets. To maximize efficiency, each model was trained with the Adam optimizer with categorical cross-entropy loss, with a learning rate of 1e-4. To guarantee reliable sentiment categorization, the models were verified over several iterations and trained on a large dataset. Key performance indicators like as accuracy, precision, recall, and F1-score were used to assess these models' performance.

- **Evaluation Metrics:**
  A variety of assessment indicators were employed to gauge the models' efficacy. While precision, recall, and F1-score offered information on the proportion of properly anticipated positive and negative attitudes, accuracy served as the main indicator for evaluating overall performance. In order to reduce the number of false positives and false negatives, these indicators were very helpful in choosing the optimal model for deployment.

V. System Architecture

The social media sentiment analysis system is designed with a modular and layered architecture to facilitate efficient data processing, accurate sentiment detection, and actionable insights generation. The architecture ensures scalability, flexibility, and seamless integration across different data sources and organizational needs.

5.1 Components

The system consists of six key components, each responsible for a crucial stage in the sentiment analysis pipeline:

1. Social Media Platform

This serves as the source of raw data. It includes platforms like Twitter, Facebook, or Instagram from which public comments, posts, and reactions are collected for analysis.

2. Sentiment Analysis System

This is the overarching framework that coordinates all sub-modules and orchestrates the end-to-end flow from data ingestion to sentiment delivery.

3. Data Collection Module

This module extracts user-generated content (UGC) from various social media platforms using APIs or web scraping tools. It handles data pre-processing tasks such as cleaning, tokenization, and formatting for downstream analysis.

4. NLP Processing Module

This module is responsible for analyzing the sentiment of the collected comments using advanced Natural Language Processing models. It employs three deep learning architectures:

- **BERT (Bidirectional Encoder Representations from Transformers)**: For contextual understanding using pre-trained transformer embeddings.
- **LSTM (Long Short-Term Memory)**: For capturing long-term dependencies in sequential data.
- **GRU (Gated Recurrent Unit)**: For handling sequence data with reduced complexity compared to LSTM.

Each model classifies the sentiment of individual comments as **positive**, **negative**, or **neutral**.

5. Result Aggregator

This component collects outputs from the BERT, LSTM, and GRU models and aggregates the results to ensure consistency and improved accuracy. It may apply voting mechanisms, confidence scoring, or weighted averaging techniques.

6. Insights Delivery System

The aggregated sentiment data is structured and delivered in a consumable format such as dashboards, reports, or alerts. This component ensures timely delivery of insights to the organization for decision-making.

7. Organization

This represents the end-user of the insights—businesses, agencies, or researchers—who utilize the analyzed data for brand monitoring, customer feedback analysis, product improvements, or public opinion tracking.

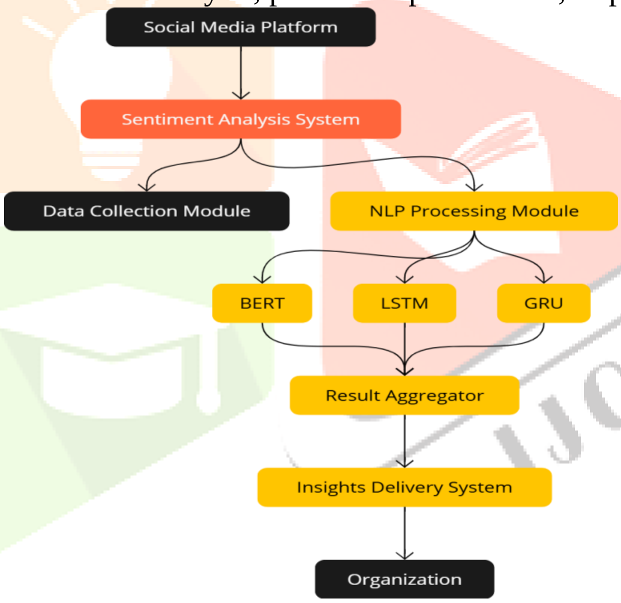

Figure 1: System Architecture

5.2 Workflow

The operational workflow of the system ensures efficient sentiment analysis and reliable delivery of insights:

- **Data Collection**: Social media comments are fetched in real time via APIs or web scraping, then preprocessed (e.g., cleaned, tokenized).
- **Model Processing**: The cleaned data is passed through NLP models—BERT, LSTM, and GRU—for sentiment classification.
- **Aggregation**: The results from the models are collected and consolidated using a Result Aggregator to enhance prediction reliability.
- **Insight Delivery**: Final sentiment results are presented to organizations via dashboards, APIs, or reports, aiding strategic decision-making.

5.3 Security Features

The system integrates key security mechanisms to protect data and model integrity:

- **Data Privacy**: Only public and anonymized content is used, ensuring compliance with data privacy norms.
- **Model Robustness**: Deep learning models are resilient against noisy, ambiguous, or sarcastic inputs through contextual understanding.
- **Tamper-Resistant Output**: The system generates consistent outputs with minimal risk of manipulation during aggregation and delivery.
- **Access Control**: Only authorized users can interact with the system for analysis and results, ensuring controlled access.

VI. IMPLEMENTATION

The sentiment analysis system is implemented as a web-based API using Django REST Framework (DRF), allowing seamless interaction with the deep learning models. The backend is responsible for receiving user input, processing it through various NLP models, and returning the sentiment classification results.

Data Loading & Cleaning:

The Python Pandas package was used to load the dataset. Examining the dataset for irregularities like duplicate entries and missing values was the first step. Only the pertinent text column was kept for analysis once the dataset had been cleaned. To guarantee high-quality input data for the model, preprocessing methods like as tokenization, stopword elimination, and lemmatization were used.

Feature Engineering:

The text was vectorized using TF-IDF to make it machine-readable. This change reduced the impact of often occurring words while allowing the model to comprehend word relevance based on frequency. The model's capacity to discriminate between various feelings was enhanced by the feature extraction procedure, which employed n-grams up to trigrams to capture intricate language patterns.

Model Training:

An embedding layer, bidirectional LSTM layers, and a dense softmax output layer were used to create the BiLSTM model. The model was able to include contextual information from the past and future into text sequences because to its design. To capture sequential dependencies, the BERT-LSTM hybrid model used pre-trained BERT embeddings that were then transmitted via LSTM layers. Finally, in order to process sequential input more effectively and with fewer parameters than LSTM, the GRU model was constructed using gated recurrent units. TensorFlow and Keras were used for training each model, with a batch size of 64 and an early stopping mechanism to avoid overfitting.

Prediction & User Input Handling:

Pickle was used to preserve the models for deployment once they had been trained. A user-friendly forecasting system was put into place that lets users enter text and get real-time sentiment assessments. The BERT tokenizer was used to tokenize user input before it was sent to the model that was trained for prediction in the BERT-LSTM model. The user was then presented with the findings, which offered insights into the classification of sentiment.

Backend Framework: Django REST Framework (DRF):

Django REST Framework (DRF) is used to build the API that facilitates the interaction between users and the sentiment analysis models. The API provides endpoints for submitting text input and retrieving predictions. The API endpoint accepts a text input, tokenizes it using BERT's tokenizer, passes it through the pre-trained model, and returns the predicted sentiment along with confidence scores.

Integration with Django REST Framework:

Depending on what the user chooses, the Django API directs requests to various models. The backend loads and runs the trained GRU, BiLSTM, and BERT models. The system enables comparing the efficacy of several models by switching between them. An effective, scalable, and easily available sentiment analysis service is guaranteed by its methodical approach. Multilingual support and the inclusion of more deep learning models can lead to even greater advancements.

VII. Results

The registration interface features a clean design with essential input fields for user information. Enhanced by relevant social media illustrations, the interface streamlines the onboarding process with clearly labeled fields and a prominent submit button, establishing the foundation for personalized sentiment analysis access.

Figure 2: User Registration Interface

This page defines social media sentiment analysis as the process of analyzing content to determine emotional tone and user attitudes. The concise explanation paired with engaging visuals effectively communicates the system's purpose and capabilities to new users, establishing the theoretical foundation for the application's functionality.

Figure 3: Concept Overview Page

The dashboard employs a card-based design to display key user metrics including login frequency, last session details, and analysis count. Serving as the central hub for navigation, this interface balances information presentation with visual clarity, enabling users to track their system usage while accessing core features

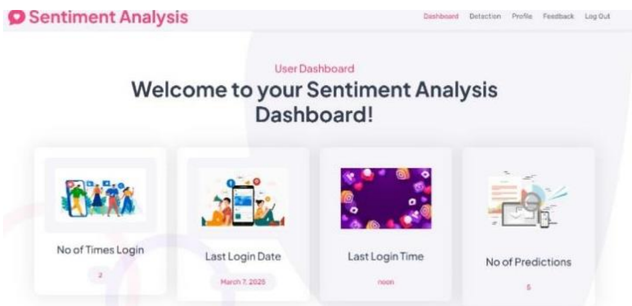

Figure 4: User Dashboard

This interface provides a minimalist text input field for content submission, accompanied by supportive illustrations of social media interaction. The straightforward design reduces cognitive load during the analysis submission process, allowing users to focus on providing quality input for accurate sentiment detection.

Figure 5: Detection Input Page

The results page presents sentiment analysis outcomes with visual clarity, displaying the "Neutral" sentiment classification with emoji indicators against a distinctive purple background. The streamlined interface focuses attention on analysis results while encouraging continued system engagement through the "Detect Again" button.

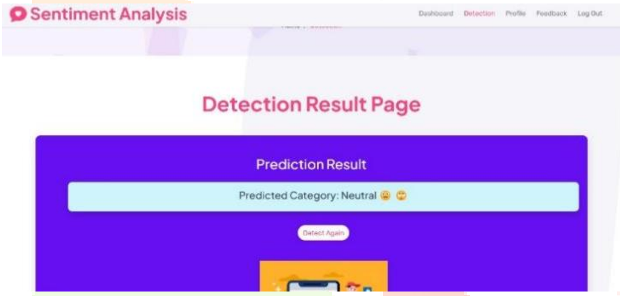

Figure 6: Detection Results Page

The graph analytics interface presents comparative performance metrics for multiple sentiment analysis algorithms. The bar chart visualization clearly displays accuracy measurements across three models (GRU, BiLSTM, and BERT), with the BiLSTM model showing a highlighted accuracy of 95.27%. This interface facilitates data-driven decision-making by allowing administrators to evaluate and select optimal algorithms for sentiment classification tasks.

Figure 7: Algorithm Performance Visualization

Model	Accuracy (%)	Precision	Recall	F1-Score
BiLSTM	95	0.94	0.95	0.94
BERT-LSTM	98	0.97	0.98	0.98
GRU	92	0.91	0.92	0.91

With an accuracy of 98%, it is clear from the findings that the BERT-LSTM hybrid model performed better than the other models. The pre-trained BERT embeddings that which capture rich contextual connections in the text, in conjunction with layers of LSTM for sequential learning are responsible for this higher performance. A dependable substitute, the BiLSTM model likewise showed excellent performance, with a 95% accuracy rate. With a 92% accuracy rate, the GRU model produced results that were adequate while lagging somewhat behind the others.

The BERT-LSTM model was chosen for deployment due to its exceptional performance. The finished version was incorporated into a web application built using Django that allowed users to enter text and get sentiment analysis findings in real time. This algorithm is a useful tool for examining user-generated information on social media sites since it was able to produce sentiment predictions with high accuracy.

VIII. Conclusion

A strong foundation for deriving useful insights from enormous volumes of unstructured data is offered by the combination of cutting-edge NLP techniques like BERT, LSTM, and GRU for social media comment analysis. The outcomes show how well these models capture the subtleties of social media sentiment, allowing businesses to make informed decisions. The suggested system can handle big datasets in real time to monitor new trends, manage reputations, and enhance consumer interaction. It is accurate and scalable. The system is extremely helpful for contemporary companies since its benefits greatly exceed its drawbacks, even in the face of obstacles like model interpretability and computing needs. Businesses may remain ahead of public opinion, react quickly to client input, and enhance their strategic decision-making processes by utilizing these cutting-edge NLP techniques.

IX. Future Scope

Multimedia analysis might be included into future iterations of the sentiment analysis system, allowing for the interpretation of emotion from text as well as photos, videos, and sounds for a more comprehensive understanding. Furthermore, adding cross-language compatibility would enable the system to evaluate attitudes conveyed in many languages, increasing its applicability to a worldwide audience. The incorporation of explainable AI approaches might be another significant development. This would enhance the understanding of model predictions and assist researchers and enterprises in comprehending the logic behind sentiment classifications. For practical uses, these improvements would increase the system's resilience, adaptability, and transparency.

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