Sentimental Analysis Of Twitter Data

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***Abstract*—Analyzing sentiment from Twitter data is crucial for grasping public perception in areas like politics, healthcare, and finance. Nonetheless the casual and disruptive character of Tweets that contain brevity, informal language, and sarcasm complicate accurate sentiment analysis. This document showcases a framework for sentiment analysis that assesses conventional machine educational frameworks, advanced deep learning methods, combined strategies, and a specialized transformer model based on Twitter data. Conventional models such as Logistic Regression, Multinomial Naive Bayes and Support Vector Machine were utilized, succeeded by a Long Short-Term Memory network deeplearning model. Two hybrids models TF-IDF combined with SVM and Word2Vec combined with LSTM enhanced performance attaining accuracies of 88.6 and 89.3 respectively. To boost performance even more, a BERTweet model that was pre trained on extensive Twitter data was refined for three class sentiment analysis and reached around 91 accuracy. Interpretable AI employing SHAP was established to offer interpretability at the token level. Findings demonstrate the efficacy of transformer-based sentiment examination.**

***Index Terms*—Sentiment Analysis, Twitter Data, BERTweet, Hybrid Models, Explainable Artificial Intelligence, SHAP, Natural Language Processing, Transformer Models**

I. Introduction

Social media sites have emerged as a key channel for conveying thoughts, feelings, and responses to reality happenings. Among these platforms Twitter stands out as a good source of real time textual information and is extensively utilized for analysis in various fields including such as politics, healthcare,economics, finance, and social issues. Despite its usefulness sentiment analysis on Twitter continues to be difficult because of the brevity, casual and loud characteristics of tweets, which frequently contain slang, emojis, abbreviations, and irony creating precision interpretation challenging.

Initial research on Twitter sentiment analysis predominantly depended on lexicon based approaches and conventional machine learning algorithms. Even though these methods are computationally efficient these approaches frequently do not convey contextual meaning and semantic connections inherent in social media text. Due to the presence of bigger Twitter datasets utilized deep learning models such as Long Short-Term Memory networks were introduced to model sequential patterns.Although models based on LSTM have enhanced effectiveness compared to conventional methods they remained limited in handling long range context and ambiguous expressions commonly found in tweets.

To improve these limitations hybrid approaches combining feature based representations with learning-based models have been explored.TF-IDF with Support Vector Machine (SVM) and Word2Vec with LSTM are evaluated to balance computational efficiency and representation learning. Although these hybrid models demonstrate improved performance compared to baseline methods, they are still insufficient for capturing complex contextual semantics.

Recent advances in transformer based architectures have further improved sentiment analysis through self-attention mechanisms. In particular a transformer model BERTweet pre trained on Twitter data exhibits strong capability in learning tweet specific linguistic patterns. However despite its high predictive accuracy the model lacks interpretability. To address this issue, a unified Twitter sentiment analysis framework is proposed that evaluates traditional, hybrid, and transformer-based models while integrating Explainable Artificial Intelligence (XAI) using SHAP to provide transparent, token-level explanations of model predictions.

To give a summary of the suggested methodology, Fig. 1 illustrates the workflow of the Twitter sentiment analysis framework used in this study. The figure summarizes the key stages, including data preprocessing, feature extraction, baseline and hybrid modeling, BERTweet fine-tuning, sentiment prediction, and explainability using SHAP, offering a clear view of the overall approach.

II. Literature Review

The analysis of sentiments expressed on Twitter has grown to be a significant subject in natural language processing due to this platform mirrors public sentiment instantly and on a broad scale. Unlike traditional sentiment analysis on long documents Twitter data is short, informal, and highly dynamic. Tweets often include emojis, hashtags, slang, sarcasm, and rapidly changing discussion topics, which makes sentiment interpretation difficult and calls for specialized modeling techniques.The sentiment analysis has been widely studied due to its impact on public opinion, finance, healthcare, and political discourse. Early research mainly relied on lexicon-based and traditional machine learning methods. Qi and Shabrina [1] showed that such approaches struggle to capture contextual meaning in short and noisy tweets, while Hassan et al. [2] demonstrated that emotion-based sentiment analysis can explain cryptocurrency market trends but remains limited to specific domains.

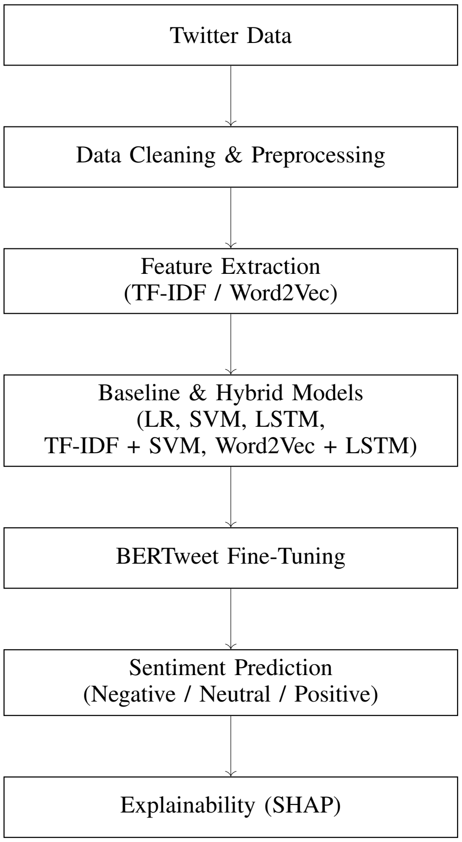

Fig. 1. Proposed Twitter sentiment analysis workflow.

With the rapid growth of Twitter data, deep learning models became increasingly popular. Neelakandan et al. [3] proposed a Deep Learning Modified Neural Network (DLMNN) supported by large-scale preprocessing to improve sentiment classification accuracy.

Recent studies have focused on transformer-based and hybrid architectures to enhance contextual understanding. Al-Badani et al. [5] combined ULMFiT with SVM to outperform traditional classifiers, while Bello et al. [9] demonstrated that BERT-based models significantly outperform Word2Vec-based methods. Hybrid models such as RoBERTa-LSTM and RoBERTa-GRU further improved performance by addressing long-range dependencies and class imbalance [14], [16].

Domain-specific applications have also been explored. Bengesi et al. [10] analyzed public sentiment during the Monkeypox outbreak, and Lee et al. [7] achieved high accuracy in detecting racist content using ensemble deep learning models. Boukabous and Azizi [17] further showed that combining lexicon-based labeling with BERT is effective for crime-related sentiment analysis.

Multilingual sentiment analysis remains an active research area. Garg and Sharma [11] emphasized robust preprocessing for multilingual tweets, while Barbieri et al. [18] introduced XLM-T, a Twitter-specific multilingual transformer. More recently, Miah et al. [15] demonstrated that ensemble-based cross-lingual sentiment analysis using translation is effective for low-resource languages.

Despite these advances, most existing approaches prioritize accuracy while offering limited interpretability. Challenges related to bias, domain generalization, and explainability remain open, motivating the development of explainable and domain-aware transformer-based sentiment analysis frameworks [20].

Table I provides a structured summary of representative studies on Twitter sentiment analysis, outlining the methodologies adopted, the application domains or datasets examined, and the principal limitations observed across traditional, deep learning, and transformer-based approaches.

TABLE I
SUMMARY OF TWITTER SENTIMENT ANALYSIS STUDIES

Ref.	**Method**	**Domain / Dataset**	**Key Limitation**
[1]	Lexicon + ML	General Twitter	Weak contextual understanding
[2]	Emotion Lexicon	Cryptocurrency Tweets	Domain-dependent insights
[3]	DLMNN + Hadoop	Large-scale Twitter	High computational cost
[4]	ML + VADER	Election Tweets	Demographic bias
[5]	ULMFiT + SVM	Airline / Debate Tweets	Poor interpretability
[7]	Ensemble GCR-NN	Racism-related Tweets	Task-specific model
[9]	BERT-based DL	Multi-domain Twitter	Black-box behavior
[10]	ML + TF-IDF	Monkeypox Tweets	Manual labeling reliance
[14]	RoBERTa-LSTM	Sentiment140, IMDb	Limited explainability
[16]	RoBERTa-GRU	Airline Tweets	Increased model complexity
[17]	Lexicon + BERT	Crime-related Tweets	Sensitive to lexicon quality
[18]	XLM-T Transformer	Multilingual Twitter	Heavy pretraining required
[15]	Transformer Ensemble	Cross-lingual Tweets	Translation errors
[20]	Survey / Review	Multi-domain	No empirical validation

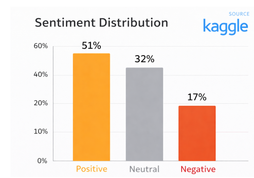

Fig. 2. Sentiment distribution of the Kaggle Twitter dataset.

III. DATASET AND DATA PROCESSING

A. Dataset Description

The dataset utilized in this research was obtained from Kaggle and comprises of Twitter posts labeled for sentiment analysis. Each tweet is labeled into one of three sentiment categories: positive, neutral, or negative. Twitter was chosen as the data source due to its real time nature. The dataset captures the characteristics of social media text including short sentence length, informal language, hashtags, user mentions, emojis, abbreviations, and domain-specific expressions. These properties introduce significant variability and noise, making the dataset both challenging and appropriate for evaluating traditional, hybrid, and transformer-based sentiment analysis models.

The overall distribution of sentiment classes in the dataset is illustrated in Fig. 2, which shows that positive tweets form the majority, followed by neutral and negative samples.

B. Data Cleaning and Preprocessing

Before the model training the unprocessed Twitter data went through multiple preprocessing steps to minimize noise and enhance overall data quality. These steps included the removal of URLs, user tags, hashtag symbols, numerical values, special characters, and extra whitespace. All text was changed to lowercase to maintain uniformity throughout the dataset. Tokenization was then applied to divide each tweet into individual tokens, followed by stopword removal to eliminate commonly occurring but semantically uninformative words. These preprocessing operations help reduce data sparsity and enhance the effectiveness of subsequent feature extraction and model learning.

The data preprocessing workflow is illustrated in Fig. 3. It summarizes the key steps involved in noise removal, tokenization, normalization, and emoji handling, resulting in clean and normalized tweets suitable for feature extraction and sentiment classification.

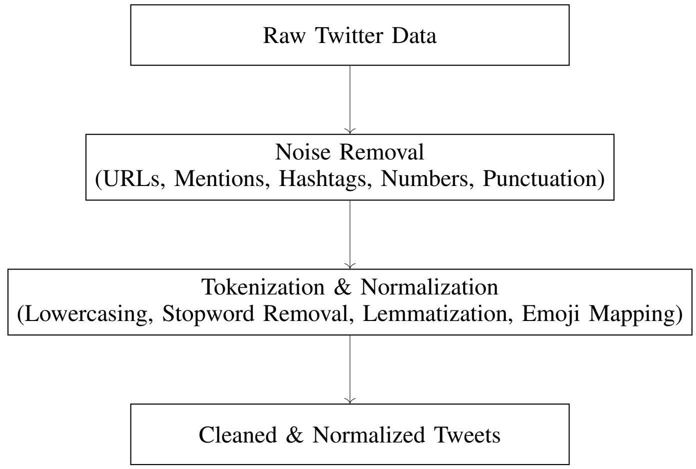

Fig. 3. Data preprocessing pipeline for Twitter sentiment analysis.

C. Feature Extraction

Two methods of feature extraction techniques were utilized for the baseline and hybrid models. Term Frequency Inverse Document Frequency (TF-IDF) was utilized to represent word importance based on frequency distribution throughout the corpus and Word2Vec embeddings were utilized to grasp semantic connections among terms in a continuous vector space. TF-IDF features were primarily utilized with traditional machine learning models whereas Word2Vec embeddings were combined with deep learning models to incorporate contextual information. Models based on transformers like BERTweet perform do not necessitate clear feature extraction, since they acquire contextual representations straight from unprocessed text.

D. Preparation of Data for Modeling

After preprocessing and feature extraction the dataset was split into training and testing subsets to assess model execution. The same data partitions were used consistently through baseline, hybrid, and transformer based models to guarantee an equitable and reliable comparison. This standardized data processing pipeline contributes to the robustness and reproducibility of the experimental results.

IV. Methodology

This part outlines the sentiment analysis methodology adopted in this study including traditional machine learning models, hybrid approaches, deep learning models, and a transformer-based model with explainability. The overall workflow is illustrated in Fig. 1.

A. Traditional Machine Learning Models

Baseline classifiers were based on traditional machine learning models because of their straightforwardness, computational efficiency, and ease of interpretation. To allow these models to analyze textual data, tweets were initially converted into numerical formats employing Term Frequency–Inverse Document Frequency (TF-IDF), which assigns weights to words based on their occurrence in a tweet and their prevalence throughout the corpus. The TF-IDF value is calculated as

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \log\left(\frac{N}{N_t}\right) \tag{1}$$

where t denotes a term, d represents a tweet (document), TF(t, d) is the frequency of term t in tweet d, N is the total number of tweets in the dataset, and N_t is the number of tweets containing the term t. The TF-IDF formulation in Eq. (1) follows the standard definition reported in [21] and emphasizes discriminative terms while reducing the influence of frequently occurring words, making it well suited for sparse social media text.

Three traditional machine learning classifiers—Linear Regression, Support Vector Machine , and Multinomial Naive Bayes were evaluated as baseline models for sentiment analysis utilizing TF-IDF feature representations. These techniques are commonly utilized in text classification tasks and serve as a dependable benchmark for assessing more sophisticated methods.

Linear Regression was utilized as a probabilistic classifier to learn the connection between TF-IDF features and sentiment labels. By attributing weights to separate features, the model calculates the probability of a tweet fitting into a particular sentiment category. Its straightforwardness and efficiency establish it as a solid foundation for high-dimensional text data.

Support Vector Machine (SVM) was employed to create an ideal decision boundary among sentiment categories within the feature space. SVM provides strong performance by maximizing the margin between classes, especially when handling sparse representations like TF-IDF vectors.

Multinomial Naive Bayes was utilized as a generative model that reflects word distributions specific to classes based on the assumption of feature independence. Even with its simplifying assumptions, this model stays computationally efficient and frequently produces competitive outcomes in sentiment analysis tasks.

Together, these conventional classifiers set baseline performance metrics, allowing for significant comparisons with hybrid, deep learning, and transformer models examined in subsequent phases of the research.

B. Hybrid Models

To enhance representation capability while maintaining computational efficiency, two hybrid models were explored.

1) Hybrid Model 1: TF-IDF + SVM: In the first hybrid approach, TF-IDF features were combined with an SVM classifier to improve discrimination between sentiment classes. This model leverages statistical feature weighting and margin-based classification, providing better performance than standalone traditional models.

2) Hybrid Model 2: Word2Vec + LSTM: The second hybrid approach merges Word2Vec embeddings with a Long Short-Term Memory (LSTM) network to grasp both semantic significance and sequential relationships in tweets. Word2Vec encodes words as dense vectors that maintain semantic associations, which are processed in sequence by the LSTM. Through the use of an internal memory, the LSTM recognizes contextual and sentiment trends within the tweet that are frequently overlooked by feature-based methods. This hybrid approach offers more nuanced sentiment representations than conventional classifiers while being computationally more efficient than models based on transformers.

C. Deep Learning Model

An independent LSTM-based deep learning model was additionally executed to directly represent tweet sequences utilizing words representations. LSTM networks are capable of capturing temporal dynamics dependencies, their capacity to manage long-range context data in tweets stays restricted, driving the application of models based on transformers.

D. Transformer-Based Model: BERTweet

To achieve deeper contextual understanding, BERTweet, a transformer-based model pre-trained on large-scale Twitter data, was fine-tuned for sentiment classification. BERTweet is built upon the transformer architecture, which utilizes self-attention mechanisms to model contextual relationships between words in a sequence [22], [25]. The self-attention operation employed by the transformer is defined as

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

where Q, K, and V denote the query, key, and value matrices, respectively, and d_k represents the dimensionality of the key vectors. Equation (2) follows the standard transformer self-attention formulation [22] and adopted by BERTweet for contextual representation learning [25]. This mechanism enables the model to focus on relevant contextual information across the entire tweet.

The final sentiment prediction is obtained using a softmax classifier Equation (3) , which converts the model output scores into normalized class probabilities for multi-class sentiment classification [23]. The softmax-based probability estimation is given by

TABLE II
PERFORMANCE COMPARISON OF SENTIMENT ANALYSIS MODELS

Model	**Accuracy**	**Precision**	**Recall**
Linear Regression (TF-IDF)	84.2	83.6	82.9
Naïve Bayes (TF-IDF)	82.5	81.9	81.2
SVM (TF-IDF)	86.1	85.4	84.8
TF-IDF + SVM (Hybrid)	88.6	87.9	87.2
Word2Vec + LSTM (Hybrid)	89.3	88.7	88.1
LSTM (Deep Learning)	87.4	86.8	86.1
BERTweet (Transformer)	91.57	90.4	90.1

$$P(y = c|x) = \frac{e^{z_c}}{\sum_{j=1}^{C} e^{z_j}} \tag{3}$$

where C denotes the number of sentiment classes and z_c represents the output score corresponding to class c.

E. Explainable Artificial Intelligence Using SHAP

To enhance model transparency, Explainable Artificial Intelligence (XAI) was incorporated using SHAP , which interprets predictions through additive feature attributions derived from cooperative game theory [24]. The SHAP explanation model is defined as

$$g(x) = \phi_0 + \sum_{i=1}^{n} \phi_i \tag{4}$$

where $g(x)$ denotes the model output, ϕ_0 represents the base value, and ϕ_i indicates the contribution of the i^{th} token. This formulation enables token-level interpretation of sentiment predictions and mitigates the black-box nature of transformer-based models [24].

Fig. 4 illustrates the BERTweet-based sentiment analysis workflow, highlighting the major stages from preprocessing to explainable sentiment prediction.

V. RESULTS, EVALUATION, AND ERROR ANALYSIS

This part covers discusses the experimental results obtained from conventional machine learning models, hybrid approaches, neural network models, along with a transformer-oriented sentiment analyzer. Model performance is assessed through standard classification metrics to allow for an equitable and uniform comparison throughout all methods.

A. Evaluation Metrics

The effectiveness of the sentiment classification models was assessed using three standard metrics: Accuracy, Precision, and Recall, which are frequently employed in supervised classification assignments [23]. Precision assesses the overall accuracy of forecasts, Precision measures the ratio of accurately forecasted positive cases, while Recall assesses the capability of the model to recognize all pertinent positive instances.These metrics are defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

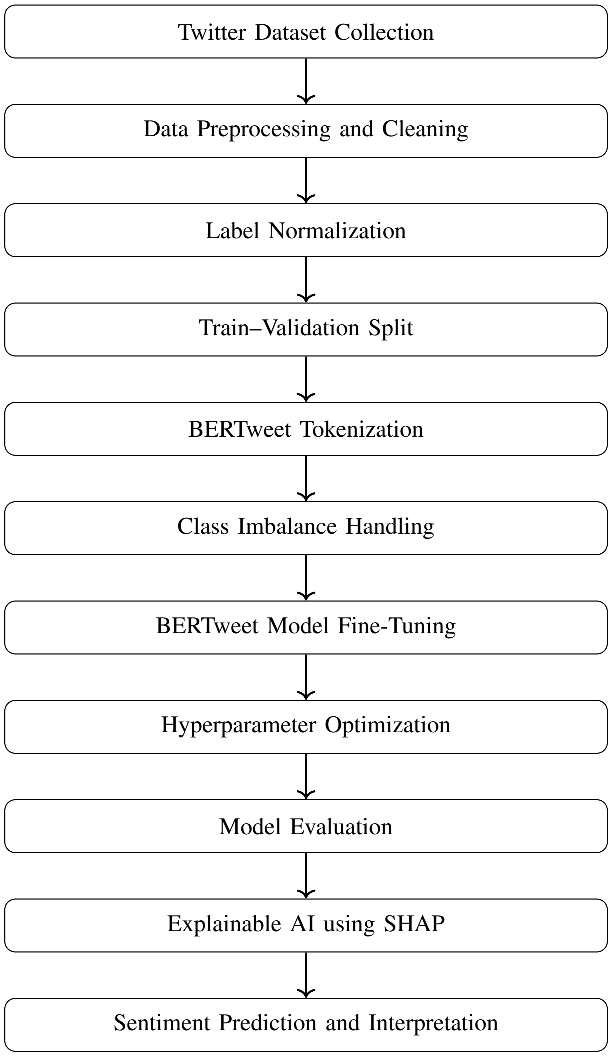

Fig. 4. BERTweet-based sentiment analysis workflow with explainability.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

B. Model Performance Comparison

TTable II outlines the performance of every assessed models regarding accuracy, precision, and recall. Among among these, the BERTweet model achieves the highest accuracy of 91.57

The results show that traditional machine learning models provide a strong baseline for sentiment classification. Hybrid models further enhance performance by combining feature-based representations with learning-based techniques. Among all assessed methods, the transformer-driven BERTweet. The model reaches the top scores in every metric, showcasing its capability to accurately grasp contextual and semantic nuances data in Twitter information.

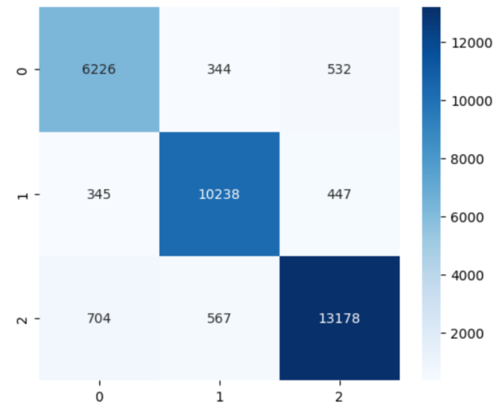

Fig. 5. Confusion matrix of the BERTweet model for three-class sentiment classification.

C. Error Analysis

Although the overall performance is strong, several sources of classification errors were identified. Traditional and hybrid models often misclassified tweets containing sarcasm, idiomatic expressions, or sentiment that depends heavily on context. Neutral tweets were particularly difficult to classify due to lexical overlap with both positive and negative classes. While the BERTweet model significantly reduced such errors, misclassifications still occurred in tweets with implicit sentiment or ambiguous phrasing. The use of SHAP-based explainability enabled the identification of influential tokens responsible for incorrect predictions, providing valuable insight into model behavior and highlighting potential directions for future improvement. Fig. 5 illustrates the confusion matrix of the BERTweet model, where rows correspond to actual sentiment labels and columns indicate predicted labels, with 0, 1, and 2 representing negative, neutral, and positive classes, respectively.

Discussion

The experimental findings show distinct performance differences among traditional, hybrid, and transformer-based sentiment analysis methods, highlighting the intricacies of Twitter text along with the advantages and drawbacks of each modeling technique. Conventional machine learning models like Linear Regression, Naïve Bayes, and SVM serve as useful baselines but are constrained by their dependence on manually created features, limiting their capacity to grasp contextual and implicit sentiment typically present in tweets.

Hybrid models demonstrate steady enhancements in performance by combining feature-based representations with learning-driven methods. TF-IDF + SVM and Word2Vec + LSTM both obtain greater accuracy and more balanced precision-recall metrics compared to conventional approaches, highlighting the advantages of integrating semantic data. Nonetheless, these improvements are modest, indicating that hybrid models continue to face challenges with long-range dependencies and subtle contextual hints.

The BERTweet model, which is based on transformers, attains the best overall performance on all assessment metrics, leveraging pretraining on extensive Twitter datasets. Even with its higher accuracy, an examination of errors shows persistent difficulties in identifying neutral sentiment, underscoring the intrinsic ambiguity present in social media vocabulary. Incorporating SHAP-based explainability strengthens the framework by offering clear, token-level insights into model predictions, fostering reliable and functional sentiment analysis solutions.

Conclusion and Future Work

This research explored Twitter sentiment analysis through a structured comparison of traditional machine learning models, hybrid approaches and a transformer based architecture. The results show a gradual improvement in performance as the models move from simple lexical representations toward context aware learning techniques. Classifiers such as Linear Regression, Naive Bayes and SVM provide dependable baseline outcomes. Nonetheless, their dependence on handcrafted features restrict their capacity to manage the informal, context-dependent characteristics of Twitter text.

Hybrid models present a reasonable compromise between efficiency and representation learning. The TF-IDF + SVM and Word2Vec + LSTM approaches deliver more consistent and improved results compared to traditional methods particularly in noisy data settings. Despite these gains the improvements remain moderate indicating that hybrid models still struggle in capturing long range dependencies and nuanced sentiment variations commonly found in tweets.

The BERTweet model, which is based on a transformer architecture, attains the top performance overall, achieving a maximum accuracy of 91.0. Its effectiveness can be attributed to pretraining on large scale Twitter data and its ability to model contextual relationships using self attention. However the complexity of transformer models introduces challenges in interpretability. This limitation is addressed through the use of SHAP based explainability which provides clear token level insights into prediction behavior.

Overall the proposed framework strikes a balance between predictive performance and interpretability making it well suited for real world sentiment analysis tasks. Future work can explore more effective strategies for handling neutral sentiment, mitigating class imbalance, and extending the framework to multilingual and cross-domain social media datasets.

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