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Fine-Grained Sentiment Classification Using Generative Pretrained Transformer

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Abstract:** Social media platforms have seen a significant increase in the number of users and content in recent years. Owing to the increased usage of these platforms, incidents of teasing, provocation—both positive and negative—and harassment, and community attacks have increased tremendously. There is an urgent need to automatically identify such content or tweets that can hamper the well-being of an individual or society. Analyzing social media messages from Twitter and Facebook has become the focus of sentiment analysis in recent years, which formerly focused on online product evaluations. Sentiment analysis is used in a wide range of fields besides product reviews, including harassment, stock markets, elections, disasters, and software engineering. After the tweets have been preprocessed, the extracted features are categorized using classifiers like decision trees, logistic regression, multinomial nave Bayes, support vector machines, random forests, and Bernoulli nave Bayes, as well as deep learning techniques like recurrent neural network (RNN) models, long short-term memory (LSTM) models, bidirectional long short-term memory (BiLSTM) models, and convolutional neural network (CNN) model for sentiment analysis. In this paper, different techniques are compared to classify Twitter tweets into three categories: "positive," "negative," and "neutral." We proposed a novel data-balancing technique for text classification. A text classification technique is proposed for analyzing textual data using the Generative Pretrained Transformer model owing to its contextual understanding and more realistic data generation capability. Comparative analysis of different Machine learning and Deep learning models are performed with and without data balancing. The experiments show that the accuracy and F1-measure of the Twitter sentiment classification classifier are improved. The proposed ensemble has outperformed and achieved an accuracy of 90%, precision of 88%, and 81% F1 score.

***Keywords:** Sentiment Analysis, Generative Models, Fine-Grained Analysis.*

1. INTRODUCTION

Public opinion is now most comprehensively compiled on social media, covering ideas, products, locations, companies, and people. Individuals frequently share their views on regional and international issues, often commenting on each other's opinions, which generates extensive opinionated data. Accurate monitoring and analysis of this data provide crucial insights for marketing companies about preferences, views, trends, issues, and opportunities [1]. The rise in user-generated web content has led to significant attention on automatic sentiment analysis [2]. Deep learning algorithms are often employed in sentiment analysis, as in many other fields [2]. Computer science has merged with management and social sciences through marketing, finance, political science, communications, health science, and history, highlighting its importance to business and society [3]. Sentiment analysis involves identifying emotions and classifying them as binary or multi-class [4], and public opinion can be comprehensively described using argument extraction and opinion summarization [5]. Analysis can be performed at varying levels of granularity, from general document emotion to sentence-level perspectives. Some methods use unsupervised learning, while others employ supervised or semi-supervised learning to address text mining challenges [2]. The pre-trained BERT model has demonstrated effectiveness in initialization and fine-tuning for unsupervised self-training using code-switched data for sentiment analysis, although it has only been tested with positive and negative sentiment classifications, excluding the neutral class [5]. Lexical analysis, due to its simplicity, is highly effective for sentiment analysis and does not require labeled training data, though it is considered syntactic rather than semantic [4]. Alharbi et al. [5] developed a lexical analyzer and toolbox for natural language processing to evaluate opinions, while Sahayak et al. [6] used deep learning methods for sentiment analysis, demonstrating success with a composite model merging long short-term memory (LSTM) and convolutional neural networks (CNN) [7].

Advanced deep-learning structures identify discussion participants before modeling context data, with Appel et al. [8] introducing the bidirectional emotional recurrent unit for conversational sentiment analysis, achieving context compositionality and sentiment classification through a two-channel classifier and generalized neural tensor block. Chakraborty et al. [9] presented a method enhancing classification performance by utilizing extensive data through TML (topic-aware multi-task learning) for customer service conversations [11], though they did not address class imbalance in sentiment classification, which often shows fewer negative samples than positive or neutral ones [12]. Various strategies using knowledge bases such as lexicons, corpora, and dictionaries can improve results [12]. Sattar et al. [13] introduced the BERT model to categorize tweet emotions and sentiments using a contextual-based transformer model, which produced better outcomes than lexicon-based techniques by considering language semantics. Sentiment analysis examines how individuals express their feelings, judgments, attitudes, and emotions about entities in written language [14].

Current sentiment analysis methods overlook sentence internal features due to model training limitations, particularly with small datasets, making them inefficient for tasks like text classification. The third-generation generative pre-trained transformer model (GPT-3), a deep learning-based language model trained on over 499 billion tokens, has not yet been explored for various text classification tasks, such as sentiment analysis, Covid detection, and e-commerce review examination. This study recommends using the generative transformer model for these tasks and evaluates its performance using a variety of datasets [15].

2. RELATED WORK

Different methods of market sentiment analysis are employed to understand people's feelings. In addition to traditional opinions—positive, negative, or neutral—other types of sentiment analysis help in comprehending genuine intentions, feelings, and emotions. These approaches are described below. Sentiment classification is a straightforward and widely used method to gauge client feedback, categorizing it into positive, neutral, and negative. Another approach involves offering a rating option from 1 to 5, which many e-commerce companies use to understand customer feedback. Sentiment classification involves categorizing text into predetermined classes and is a supervised machine learning problem. Binary sentiment classification involves categorizing sentiments as positive or negative, but finer scale annotation is needed for sensitivity.

Emotion detection in sentiment analysis accurately determines the emotion in a text, identifying moods like anger, sadness, joy, frustration, fear, panic, and concern. This helps businesses understand why a client feels a certain way, though detecting emotions in words can be challenging due to varied meanings, like sarcasm. Aspect-based sentiment analysis focuses on specific features of a product or service, enabling businesses to automatically classify and analyze client data and gain insights for addressing issues. Intent classification involves automatically classifying text based on client intent, such as "Buy," "Downgrade," or "Unsubscribe," helping automate processes and understand client motivations, improving customer assistance and sales.

The rise of mobile information systems and smartphone availability has integrated social media into daily life, generating massive amounts of data. Sentiment analysis processes this data to extract significant information, classifying emotions in text as neutral, positive, or negative. This data helps marketers assess advertising campaigns, understand demographic responses, predict user behavior, and forecast election results Kabakus et al. [17]. Sentiment analysis has become a prominent research field in natural language processing since the early 21st century, aiming to build automatic tools that extract valuable information from texts written in natural languages, such as opinions and sentiments [17]. People use social networks to express opinions on products, events, or news, and sentiment analysis, or opinion mining, combines statistics, natural language processing, and machine learning to recognize attitudes, judgments, and emotions about a topic [19]. This field has been a recognized study area and developing market for at least ten years [14]. Training a model to understand emotions involves marking texts as happy, negative, or neutral and using sources like movie reviews, which convey clear opinions and numerical ratings, to train learning algorithms. Movie reviews were used to train

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an algorithm that recognizes sentiment in text in the pioneering work in sentiment analysis [20].

Proposed Work

Machine learning has been the main foundation of prior sentiment analysis studies. The proposed machine learning approach has several major advantages. Firstly, we will collect datasets related to twitter tweets for sentiment analysis; secondly, we will pre-process the tweets; and thirdly, we will analyze the sentiment of the tweets using a generative pre-trained model. This paper presents a novel approach in which the generative pre-trained transformer model is more efficient than other existing sentiment analysis models.

The proposed work methodology is based on various existing datasets. Each dataset is an independent group of item sets. The workflow is illustrated in Figure 1. As shown in Table 1, we will use a variety of data to conduct sentiment analysis. To evaluate the effectiveness of our proposed methodology, we gathered a large number of datasets and analyzed the performance of the model on these datasets. Each collection contains a different number of tweets, and the classifications to which they belong define various occurrences. It is crucial to determine the essential characteristics of the attributes utilized in this literature before proceeding to data visualization since each dataset has a different number of attributes.

Dataset name	Records	Classes	Description
Clothing review [21]	23,486	Dresses, Pants, blouses, knits & sweaters	Women's e-commerce reviews
Twitter airline sentiment [21]	14,640	Confidence level in the numeric value 0, 1, 2	Airline sentiment analysis
CovidSenti [22]	30,000	either favourable, bad, or neutral 0, 1, 2	Curfew, confine, and remain at home
Twitter sentiment analysis [21]	29,530	Hostile & Sympathetic	Sentiment analysis for speech detection
Stanford Sentiment Treebank (SST) [23]	11,855	Extremely negative, unfavourable, neutral	Movie reviews

Table 1. Datasets list with class descriptions

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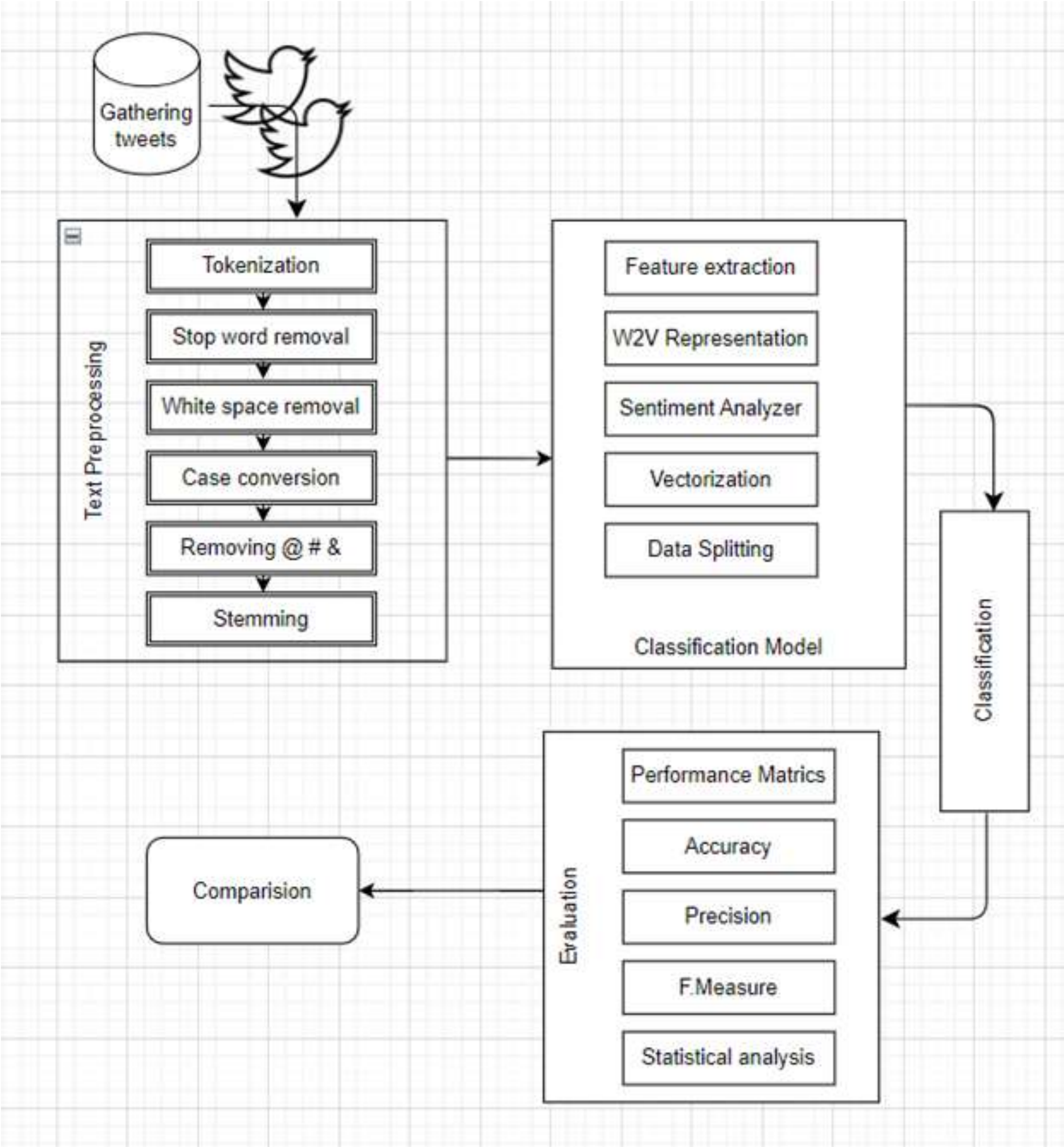
Fig. 1. Architecture diagram of proposed sentiment analysis of Twitter tweets



3. METHODOLOGIES

In the realm of sentiment analysis, researchers have explored various methodologies to extract valuable insights from textual data, particularly from social media platforms like Twitter. Previous studies have delved into aspects such as deep learning and machine learning, often leveraging different models to analyze sentiments expressed in tweets. However, despite

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advancements, these approaches have encountered limitations, prompting the need for innovative solutions.

In response to these limitations, a proposed framework for sentiment analysis emerges, anchored on machine learning principles. This framework offers distinct advantages, beginning with the collection of datasets related to twitter tweets for sentiment analysis. Subsequently, the preprocessing of tweets occurs to enhance data quality, followed by sentiment analysis utilizing a generative pre-trained model. Notably, this approach posits the superiority of the generative pre-trained transformer model over existing sentiment analysis models, signifying a step towards more efficient sentiment analysis methodologies.

Central to this framework is the utilization of multiple datasets, each representing an independent group of item sets. This multi-dataset analysis ensures comprehensive coverage and robustness in sentiment analysis outcomes. Moreover, tokenization techniques are employed to segment and normalize text, facilitating subsequent natural language processing (NLP) tasks. Stop words removal further enhances sentiment analysis accuracy by eliminating noise from the textual data.

Additionally, preprocessing steps involve the elimination of short words and the application of stemming and lemmatization algorithms to normalize words and reduce feature complexity which is shown in Figure 2. These techniques contribute to refining the sentiment analysis process, ensuring more accurate insights extraction from textual data. Symbol and numeric removal further streamline text analysis and model training, enhancing the efficiency of sentiment analysis methodologies.

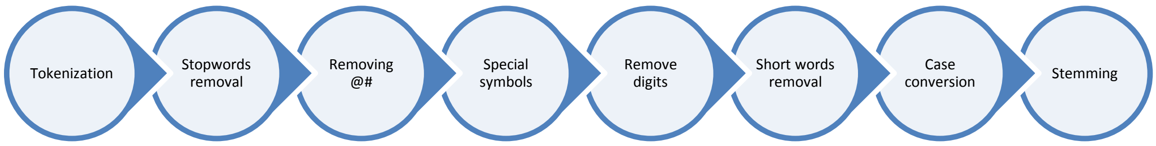

Fig. 2. Data pre-processing steps in our proposed methodology.

In essence, the proposed framework represents a holistic approach to sentiment analysis, integrating diverse methodologies to address the limitations of existing techniques. By leveraging machine learning principles and advanced preprocessing techniques, this framework offers a robust and efficient solution for analyzing sentiments expressed in Twitter tweets, thereby paving the way for enhanced understanding and interpretation of textual data in the digital age.

4. RESULTS AND DISCUSSION

In this section, we introduce our proposed models in detail. Our approach aims to contextualize input sentences and extract sentiment analysis information. Using the GPT-3 pre-trained model as a base extractor, we constructed several models employing various classifiers. These models generate vector representations of input data, accommodating both plain text and non-text elements such as emojis and emotional cues. GPT-3, a third-generation Generative Pre-trained

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Transformer, is a state-of-the-art neural network trained on diverse internet data. Initially proposed by OPENAI, GPT (Generative Pre-Training) functions as a traditional autoregressive language model. By utilizing challenge inputs, GPT enhances transfer accuracy while maintaining flexibility in adapting to diverse tasks, obviating the need for significant architectural changes per task. Evaluation tasks such as human language understanding, problem-solving, mutual information, and text analysis assess the efficacy of GPT across various language comprehension domains. Developed by OpenAI, GPT-3 surpasses its predecessors in scale, boasting 175 billion parameters compared to GPT-2's 1.5 billion. This substantial increase enables enhanced performance in Natural Language Processing tasks and text classification. Applications where GPT-3 excels include question-and-answer formats, lengthy prose, language translations, and text categorization. Access to the OpenAI beta API is required to evaluate GPT-3's capabilities effectively.

4.1 Text Classification

Sentiment analysis falls under the broader category of text categorization with similar modeling goals. It involves gathering input data and categorizing opinions into groups based on learned representations. Accurately inferring and assessing emotions from natural language input poses a challenging task, requiring substantial data and costly training. This challenge is particularly pronounced in applications like Twitter, where nuances in language use are complex. Leveraging knowledge gained from trained models, our approach comprehends global language patterns.

To implement our model, uploading labeled data samples to the GPT-3 documents server is necessary. Each sample is formatted as a JSON file, where each line represents a training example (e.g., a tweet) with one of three labels specified in the "label" field. Optionally, a "metadata" field can be included without affecting the output. Notably, the same API endpoint supports various categorization tasks depending on the labels assigned to examples.

Upon reducing and ranking tagged tweets based on semantic search results, the "search model" parameter, preferably "davinci," significantly enhances performance across different tasks. Our findings indicate that Davinci outperforms other models, particularly when fine-tuning is required. Exploring the API guide for the search API provides deeper insights into its functionality and benefits.

Using this API endpoint improves accuracy when ranking tagged tweets by semantic relevance. Output results include a list identifying which tweet instances from the input file were utilized, along with a "score" indicating similarity to the example. Scores typically range between 0 and 300, varying with different search queries.

Understanding the mean and standard deviation of scores across a randomly selected test set of labeled tweets is crucial for effectively analyzing sentiment on platforms like Twitter, given the dataset's size and diversity.

4.2 Evaluation of Machine Learning Models

The processed dataset included features essential for training models in a classification task. To facilitate text classification, we transformed our textual data into vector representations using word2vec. Our findings indicated that unigram features outperformed bi-grams when

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applied to a dataset of tweets, ensuring consistent results. Following thorough data cleaning and preprocessing, we employed a generative pre-trained model for analysis.
Machine learning involves using statistical methods to predict outcomes based on historical data. Given our focus on classification, clustering, reinforcement learning, and linear regression techniques were not applicable, restricting us to using classifiers. Since sentiment analysis involves binary classification, our approach involved experimenting with various algorithms to select those yielding optimal precision, recall, and F1 scores for positive and negative sentiment identification.
We evaluated the model's efficacy on our dataset by assessing metrics such as accuracy, precision, recall, and other relevant measures. This brief overview summarizes the evaluation metrics employed in our study.

5. CONCLUSIONS

This paper evaluates the efficacy of sentiment analysis on Twitter using feature extraction with a Generative Pre-trained Transformer model across multiple datasets. These datasets are categorized into distinct classes for analysis. The study employs deep learning and natural language processing techniques, aimed at enhancing daily user experiences and social media interactions.

Model name	Accuracy	Precision	F1 score	Recall
Naïve Bayes	57%	52%	50%	50.3%
Random Forest	55.7%	51%	46%	45.3%
SVM	80%	80.2%	83.8%	83.4%
XGBoost	59%	55.3%	51.3%	50.3%
CNN-LSTM	79%	67%	70%	76%
BERT	86%	90%	77%	68%
AdaBoost	82%	83.5%	82.5%	82.5%
Logistic Regression	80%	80%	80%	80.6%
KNN	58%	58%	58.3%	58.2%
GPT-3	89%	87%	80%	83%

Table 2. Accuracy of Classifier

Key contributions include the application of classifier models on diverse datasets utilizing multi-layer transformer encoders for feature extraction. Evaluation metrics such as F1 score and attention mechanisms assess the model's performance on textual data. While the Generative Pre-trained Transformer model effectively processes and classifies complex inputs, experiments reveal its superior performance compared to prior models trained on smaller datasets, which often struggle to achieve high accuracy.
Each machine learning approach exhibits varying degrees of success across different datasets, demonstrating how dataset structure and sample size influence model accuracy. Comparing

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accuracy rates across various test sizes within the Twitter dataset highlights the Generative Pre-trained Transformer model's superior performance, with Naive Bayes showing comparatively lower accuracy. Experimentation is done using different datasets to evaluate the model performance; experiments results are mentioned in Table 2.
Analyzing sentiment in tweets, particularly regarding vaccination hesitancy, holds potential for informing healthcare strategies and interventions. Leveraging social media sentiment analysis in pandemic prevention could facilitate more effective healthcare planning and implementation strategies.

Future Work
To boost the accuracy of feeling order and responsiveness to a variety of contexts and dialects, we can focus our efforts on the study of fusing Artificial intelligence with an assessment dictionary strategy. The existing classifiers could be tested in larger datasets to verify the high levels of accuracy achieved in sentiment detection. Finally, the impact of explainable machine learning can be also considered for future work as the produced explainable models will maintain a high level of learning performance (in terms of prediction accuracy).

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