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Harnessing GPT-2 Sequence Models for Sentiment Analysis on Twitter Data

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ABSTRACT
Instant messaging platforms like Twitter have become integral parts of modern communication, facilitating rapid exchanges of information and fostering interpersonal connections. However, extracting and understanding sentiments from these conversations pose significant challenges due to their unstructured and dynamic nature. Leveraging AI approaches, particularly natural language processing (NLP) and machine learning algorithms, enables the automated analysis of sentiments within these contexts. This paper includes various Artificial Intelligence (AI) techniques utilized for sentiment analysis, including supervised learning, unsupervised learning, and deep learning methods. Additionally, it discusses the implications of sentiment analysis in enhancing user experience and their views about any things, person or product as positive or negative opinion. This paper used Bernoulli Distribution, Decision Tree Classifier, Logistic Regression as machine learning (ML) algorithms and GPT2 Sequence Classifier (Deep learning) to analyze the attitudes in real-time Twitter data opinion mining. Finally, the performance of these approaches as evaluated using well known parameter of classifier and learning outcome.
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KEYWORDS: Machine learning, Artificial intelligence, Natural Language Processing, Sentiment Analysis, Deep learning

1. INTRODUCTION

In recent years, instant messaging applications have transformed the landscape of communication, becoming ubiquitous tools for personal and professional interactions. With the rise of platforms like WhatsApp, Facebook Messenger, Slack, and WeChat, individuals and organizations rely heavily on these digital channels for real-time conversations, information sharing, and collaboration [1]. Amidst this surge in messaging app usage, understanding the sentiments expressed within these exchanges has garnered significant attention. Sentiment analysis, a branch of natural language processing (NLP), offers a promising avenue for extracting insights from the vast amounts of textual data generated through instant messaging. Sentiment analysis, also known as opinion mining, involves the automated extraction and categorization of sentiments expressed in text, such as positive, negative, or neutral [2]. While sentiment analysis has been extensively studied in various domains like product reviews, social media, and news articles, its application to instant messaging presents unique challenges and opportunities. Unlike more formal textual sources, instant messaging conversations often exhibit informal language, slang, emojis, and context-dependent expressions, making sentiment analysis in this context particularly nuanced. Artificial intelligence (AI) approaches, including machine learning and deep learning techniques, have emerged as powerful tools for sentiment analysis in instant messaging applications. These approaches enable algorithms to learn patterns and semantic representations from large datasets of conversational text, thereby automating the sentiment analysis process. Supervised learning algorithms, such as support vector machines (SVM) and neural networks, can be trained on labeled datasets to classify messages into sentiment categories [3]. Unsupervised learning methods, such as clustering and topic modeling, offer alternatives for analyzing sentiment without the need for labeled data. Additionally, advancements in deep learning, particularly with recurrent neural networks (RNNs) and transformers, have further improved the accuracy and effectiveness of sentiment analysis models on instant messaging data [4]. The integration of sentiment analysis into instant messaging applications holds tremendous potential for enhancing user experiences, personalized interactions, and decision-making processes. By automatically detecting sentiments in real-time conversations, these applications can offer tailored recommendations, sentiment-aware chatbots, and sentiment-based content filtering. Moreover, sentiment analysis on instant messaging data can provide valuable insights for businesses, including customer feedback analysis, brand perception monitoring, and sentiment-driven marketing strategies. However, alongside these opportunities, several challenges and considerations must be addressed, including privacy concerns, ethical implications, and the inherent subjectivity of sentiment interpretation [5]. This paper aims to explore the current landscape of sentiment analysis on instant messaging applications, highlighting the methodologies, applications, challenges, and future directions in leveraging AI approaches for extracting sentiments from conversational data. Through a comprehensive analysis, we aim to shed light on the potential benefits and limitations of sentiment analysis in enhancing the functionality and user experience of instant messaging platforms. There are three layers make up the workflow for sentiment analysis, which is used to categorize different sentiment analysis techniques [6]. This section summarizes numerous case studies carried out at all sentiment analysis levels as featured in Figure 1.

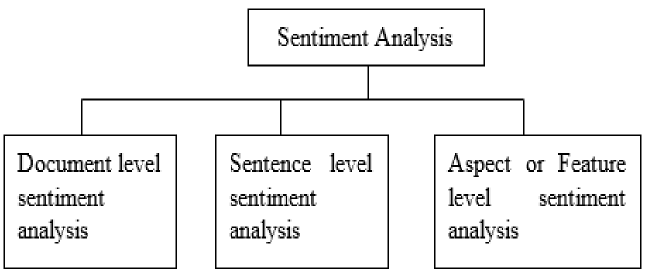

Figure 1 Sentiment Analysis Levels

2. LITERATURE REVIEW

In this paper author presented about the multilevel system for classify the sentiment analysis of twitter data using hybrid model of machine learning [6]. The hybrid approach of Spiking neural network and naïve Bayes suggested in this paper in order to indicates Naive Bayes (NB) classifiers provide better decisions by giving NB an additional input. The Performance metrics for hybrid model (SNN+NB) methods achieve the accuracy, precision, recall, and F1score are 90%, 81%, 82%, 70% respectively.

The author discusses the Bidirectional Encoder Representation from Transformer (BERT) method which is used to extract the text representations based on the context and its position of words used in sentences [7]. The sentiment analysis, which takes input in the form of text data is firstly converted into a numerical representation which is an embedded fine tuning method. These simulations predict that the BERT representation of accuracies of all hybrid architectures.

This paper delves into the inquiry of whether sentiment expressed in tweets discuss about pros in AI can forecast day-to-day fluctuations in stock prices of associated with companies. This investigation involves the analysis of tweets containing hashtags related to ChatGPT[8]. Using Natural Language processing techniques, we extract features, and predict the positive as well as negative sentiment scores, from the collected tweets. A classifier machine learning models as gradient boosting, decision trees and random forests which are employed to train on tweet sentiments analysis and associated features prediction such as Microsoft and OpenAI. These models undergo training and testing phases utilizing an empirical dataset gathered during the stipulated timeframe.

The author of this article, study about the natural language processing, data collected between 12 May and 3 April 2023 from twitter and analyze the public sentiment data on Finland's decision to join NATO. There are total number of 28,993 tweets were collected and analyses them using the VADER algorithm for sentiment analysis and the LDA algorithm for topic modelling [9]. Using these models the results show that overall sentiment analysis provide the Finland's NATO membership was mostly positive. The public opinion of Finland's NATO membership and highlights the better result of natural language processing techniques for the analysis of social media data.

This research article introduces the multiple criterion decision-making (MCDM) that based on "Negation data Handling of the Text format applied on the Optimization Technique" (NEGVOT) model, which effectively handles negation prediction in sentiment analysis [10]. By using the decision classifier method, the NEGVOT model provides a better solution for accurately labeled the text sentiment in both regions like as negation-free and negation-containing texts. The NEGVOT model achieves the accuracy of 83%, 85%, and 82% over three datasets respectively. These consistent results while exhibiting a strong generalization capacity, enabling sentiment classification of texts containing compliments.

In this article, the presenter provides the information of Twitter is a prodigious platform that containing a large amount of data and Analyzing these data is of first priority. One of them, the most widely utilized approaches for classifying with uniquely emotions that displayed in subjective data is sentiment analysis [11]. Sentiment analysis is provide using various algorithms of machine learning such as Support Vector Machine (SNM), Naive Bayes (NB), Long Short-Term Memory (LSTM), Decision Tree Classifier (DTC) and etc, but this paper aims at the generalized way of performing Twitter sentiment analysis using flask environment. After containing the data and analyzing the results get displayed on a webpage having the percentage of positive, negative, and neutral tweets for a phrase in a pie chart.

Assessing authors knowledge based, the literature writing using some traditional qualitative methods but it is time consuming process [12]. For improving the speed and consistency of text analysis, the author presents the mixed methods for development a machine learning model to predictive analyze text content. These approaches involve two stages: first an exploratory sequential design, and second an iterative complex design. The contribution to mixed methods research lies on this innovation use of the machine learning techniques as a rapid, consistent additional coder, and a resource that can predict better results

Baharuddin et al. (2022) investigates the application of sentiment analysis together with text search on Twitter to forecast Indonesian presidential candidates for 2024[19]. The authors applied a strong analytical framework which used Twitter data to study audience sentiment towards possible political candidates. More extensive data collection alongside improved discussions regarding model weaknesses specifically related to Twitter demographic biases would enhance the study. The study presents strong empirical evidence about using social media analytics to predict public preferences in politics while becoming an important research advancement in computational social science.

Hashim et al. (2025) conducted a comprehensive systematic review about using social media sentiment assessment for disaster management operations[20]. The paper effectively explains main analytical methods together with assessment tools and chief concerns consisting of data inconsistencies and ethical difficulties. The systematic review extensively evaluates the topic but additional case studies might strengthen the research findings for practical implementation. The suggested research plan for the future provides valuable insights about expanding analysis capabilities between different platforms together with scalability features. The research provides essential knowledge for both researchers and practitioners dedicated to improving social media-based disaster management systems.

3. MATERIALS AND METHODS

The sentiment140 dataset has been used for experimentation purpose in this paper and, It contains 1,600,000 tweets extracted using the twitter api . The tweets have been annotated (0=negative, 1=positive) and they can be used to detect sentiment. It contains the following 6 fields:

1. **target**: the polarity of the tweet (*0* = negative, *2* = neutral, *4* = positive)
2. **ids**: The id of the tweet (*2087*)
3. **date**: the date of the tweet (*Sat May 16 23:58:44 UTC 2009*)
4. **flag**: The query (*lyx*). If there is no query, then this value is NO_QUERY.
5. **user**: the user that tweeted (*robotickilldozr*)
6. **text**: the text of the tweet (*Lyx is cool*)

According to the creators of the dataset: Our approach was unique because our training data was automatically created, as opposed to having human's manual annotate tweets. In our approach, we assume that any tweet with positive emoticons, like :), were positive, and tweets with negative emotions, like :(, were negative. We used the Twitter Search API to collect these tweets by using keyword search". Performing sentiment analysis on instant messaging applications using artificial intelligence approaches involves several key steps. Here's a generalized outline of the process:

Data Collection: Obtain a dataset of instant messaging conversations. This could be obtained through APIs if analyzing real-time data or through pre-existing datasets. Ensure the dataset is representative and diverse to capture a wide range of sentiments and conversation styles. In this experiment dataset is used from Kaggle 1.6M sentiment dataset from twitter.

Data Preprocessing: Clean the data to remove noise, irrelevant information, and ensure consistency. This step involves tasks such as tokenization, removing punctuation, stop words removal, and normalization (e.g., converting text to lowercase). Additionally, handling special characters, emojis, and slang terms specific to messaging apps is crucial.

Feature Engineering: Extract relevant features from the preprocessed text data. Common features for sentiment analysis include word frequency, n-grams, part-of-speech tags, and sentiment lexicons. Consider incorporating additional features like user metadata, timestamps, and conversation context if available and relevant.

Model Selection: Choose appropriate AI-based models for sentiment analysis. Options include supervised learning models like Bernoulli's distribution, logistic regression, decision tree classifier and deep learning as Generative Pre-trained Transformer 2 (GPT2) models. Consider the trade-offs between model complexity, interpretability, and computational resources.

Training: Split the dataset into training, validation, and test sets. Train the selected model(s) using the training data and fine-tune hyperparameters using the validation set. Utilize techniques like cross-validation and grid search to optimize model performance.

Evaluation: Evaluate the trained model(s) using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, or area under the receiver operating characteristic curve (AUC-ROC). Consider the imbalance in sentiment classes when interpreting evaluation results.

Model Deployment: Deploy the trained model(s) to perform sentiment analysis on new or real-time instant messaging data. Ensure scalability, efficiency, and reliability of the deployed system. Integration with messaging platforms may require APIs or custom solutions depending on the application requirements.

Monitoring and Maintenance: Continuously monitor the performance of the deployed model(s) and update them as needed to adapt to changes in user behavior, language trends, or messaging platform updates. Regular maintenance ensures the effectiveness and relevance of sentiment analysis in the long term.

By following these steps, one can effectively implement sentiment analysis on instant messaging applications using artificial intelligence approaches, providing valuable insights into user sentiments and enhancing user experiences.

Steps involved in Sentiment Analysis from twitter data: Twitter is currently the most well-known social networking service for microblogging. As a means of information sharing, it provides its services internationally. Therefore, it became very interesting to extract thoughts from tweets on numerous issues, assess the influence of certain events, or categorize attitudes. The general procedure of twitter sentiment analysis is given below:

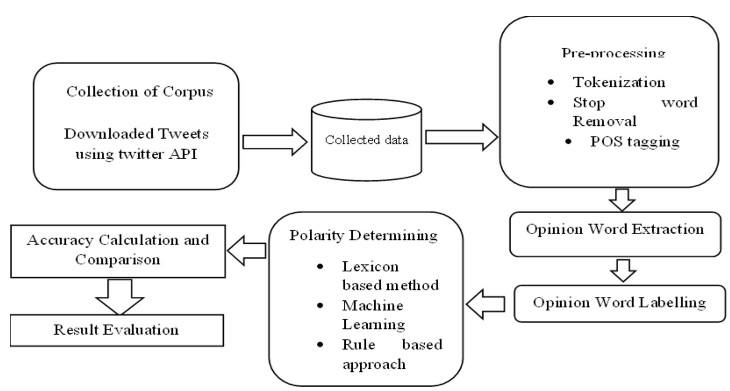

Figure 2: Steps involved in Sentiment Analysis from

4. PROPOSED APPROACH

Classification of sentiment analysis involves categorizing text data into predefined sentiment classes such as positive, negative. Bernoulli Distribution method, Logistic Regression, Decision Tree and GPT2 Sequence Classifier are prominent Artificial Intelligence algorithms used for this purpose.

Bernoulli Distribution Model: In this type of model, each feature (text) in twitter related to a binary random variable, where binary variable 1 represents the presence of the text in twitter and 0 represents the text is not presents [14]. The probability parameter **p** for each text can be estimated from the training data in twitter datasets. Where each tweet represented as a feature vector. So, the sentiment can be classified using the Bernoulli Naive Bayes classifier. Bernoulli classifier evaluate the probability of the tweet from twitter data that belonging to each sentiment class (positive, negative) based on the binary variable like as present or not present the text in the twitter using the Bernoulli distribution method.

Logistic Regression: Logistic Regression is a famous technique of statistical model which is used for binary classification instance [15]. It makes it better suited for sentiment analysis of twitter datasets where the main goal is achieved to classify the text data of binary variable like as positive or negative sentiment categories. When we applied the logistic regression for sentiment analysis on Twitter data, the it operates to mapping by learning from input features (such as text or n-grams) to the probability of predicting a tweet being positive or negative.

Decision Tree Classifier: Decision Tree algorithm constructs a tree-like structure where each internal node represents a decision based on feature values, leading to leaf nodes representing class labels [16]. Decision Trees are intuitive, easy to interpret, and can handle both numerical and categorical data, making them suitable for sentiment analysis tasks where interpretability is important.

GPT2 Sequence Classifier: The GPT-2 Sequence Classifier model used to sentiment analysis of the Twitter data. Which is typically involve fine-tuning parameters of features of the GPT2 model on a dataset of tweets labeled with binary sentiment variables are positive, negative [17]. The model architecture of GPT2 Adds the classification layer on upper side of the GPT-2 model to predict sentiment. It is improving the weights of classification layer and create the better fine-tune of the lower layers of the GPT-2 model.

Each of these algorithms has its strengths and weaknesses in sentiment analysis. GPT2 sequence classifier offers high accuracy and finding the careful parameter tuning. Bernoulli Distribution is robust but can be computationally expensive with large datasets [18]. Decision Trees are interpretable but prone to overfitting. By understanding the characteristics of these algorithms, practitioners can choose the most suitable approach based on the specific requirements of their sentiment analysis task.

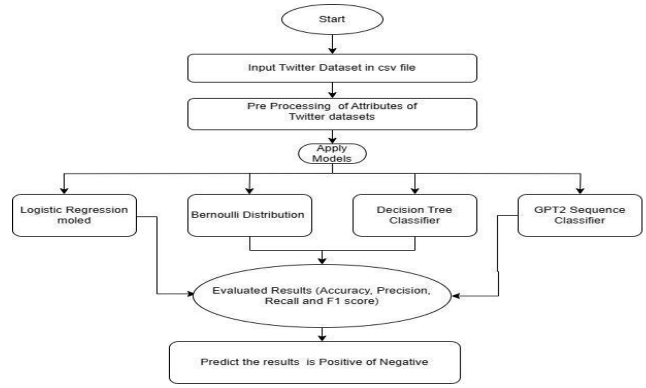

Figure 3: Proposed approach for sentiment analysis

In Figure 3 shows the Data preprocessing for Twitter sentiment analysis includes the various key steps to clean and prepare the data for analysis. Preprocessing includes the important point of text cleaning, which used to remove special characters like as punctuation, hashtags, mention and different URLs values to sentiment analysis. After cleaning the text, we can use import step to remove the noise and the Normalization of data which reduce the words and streaming the text. After the preprocessing data, the dataset split in the from training and testing for applying the various artificial intelligence approaches. Here 80% of data used for training purpose and rest of 20% data used for testing purpose. These training data applying on various artificial intelligence model like logistic regression, Bernoulli distribution, decision tree classifier and GPT2 sequence classifier. All approaches evaluate on the performance parameter metrics like accuracy, precision, recall, and F1-score on a separate test dataset.

Evaluation of Metrics: In this paper the different type of evaluation metrics is applied for evaluate the performance of the machine learning. We are evaluating the confusion matrices from the auto generated model of the experiments Whereas TP, FP, FN, TN are the number of true positives, false positives, false negatives and true negatives, respectively. Using the confusion matrices to determine the four parameter such as Precision, Recall, F1 Score and accuracy which is described in below.

Precision: It is measuring how many types of predicted samples to be positive are true positive samples. Precision concentrate on the positive part of the predicted sample

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

Recall: It is ratio of the number of positive samples that correctly predicted to the total number of true positive samples-

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

F1 Score: F1 score is the classification matrices. It is combination of Recall and Precision that referring of two metrics for harmonic average. F1 Score is calculated as-

$$F1\ Score = \frac{2*P*R}{P+R} \quad (3)$$

Accuracy: Accuracy is defined as the ratio in between the all-correct predicates and the all predicates.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

The confusion matric often after implementation of GTP2 sequence classifier model represented in figure 4.

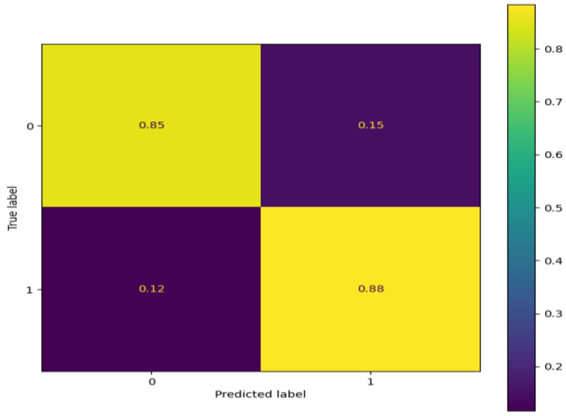

Figure 4: Confusion matric of GPT2 Sequence Classifier

5. EXPERIMENTAL RESULTS

The experiment performs on intel core i5 on windows 11 platform with 8 GB Ram and 500GB SSD drive. 1.6 million of twitters sentiment data has been used from Kaggle platform. Three machine learning model and one deep learning model have been used for classification of sentiment as positive or negative prediction. The performance of different classifier implemented in this paper has been recorded in table 1. The evaluation metrics of classifiers are also represented in figure 5.

Table 1: Bernoulli Distribution, Decision Tree Classifier, Logistic Regression and GPT2 Sequence Classifier (Deep learning)

Model	Precision	Recall	F1 Score	Accuracy
Bernoulli Distribution	50.01	50.03	50.01	50.03
Decision Tree Classifier	78.76	79.66	71.77	70.89
Logistic Regression	76.71	79.74	78.19	77.76
GPT2 Sequence Classifier (Deep learning)	**92.1**	**88.4**	**90.2**	**87.3**

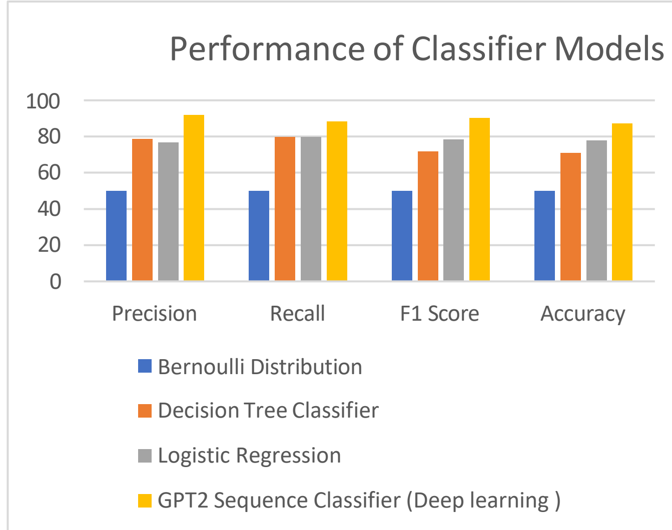

Figure 5: Performance of Classifiers used in this Experiment

6. ANALYSIS OF THE RESULTS

After applying above implementation over this dataset the results summarized in table 3. The table 3 show that after applying Bernoulli distribution the value of accuracy, precision, recall and f1 score is 50.03,50.01,50.03 and 50.01 respectively.

The value of precision, recall, f1 score and accuracy is 78.76, 79.66, 71.77 and 70.89 respectively in the case of decision tree classifier machine learning approach.

In the case of Logistics regression, the value of precision, recall, f1 score and accuracy includes 76.71, 79.74, 78.19 and 77.76 respectively.

Similarly, after applying GPT2 sequence classifier (deep learning) the associated value of precision, recall, f1 score and accuracy is 92.1, 88.4, 90.2 and 87.3 respectively.

Finally above results shows that the deep learning approach providing better results in term of all evaluation parameters of classifier.

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7. CONCLUSION AND FUTURE SCOPE

From above results and analysis, it is clear that after applying machine learning approaches on this dataset the value of accuracy, precision, recall and f1 score not achieve at the promising level. But after applying GPT2 Sequence classifier which belongs to deep learning techniques includes better results in the term of accuracy, precision, recall and f1 score. Finally proposed approach performing better in all the evaluation parameters of classification of opinion mining on this twitter data. In future soft computing approaches may be applied for sentiment analysis.

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