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ANALYZING THE PULSE OF TWITTER: MACHINE LEARNING APPROACHES TO SENTIMENT ANALYSIS

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ABSTRACT

In today's digitally interconnected world, electronic platforms like Twitter as invaluable sources of period of time data, offering unparalleled access to the collective sentiments of global populations. This study introduces a comprehensive examination of sentiment analysis on Twitter data, employing advanced machine learning techniques to uncover and categorize the multifaceted sentiments embedded within the dynamic landscape of tweets. This study considered Bag-of-Words (BoW) for pre-processing and feature extraction of the tweets. Furthermore, three prominent machine learning algorithms, namely Artificial Neural Networks (ANN), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), are investigated for their efficacy in discerning sentiment patterns across diverse Twitter conversations. Through meticulous evaluation and analysis of a substantial dataset of Twitter posts, the performance of these algorithms is scrutinized in accurately categorizing sentiments. The results reveal intriguing insights into the comparative effectiveness of the machine learning approaches. Notably, SVM emerges as the leading algorithm, achieving a classification accuracy of 89.45%, closely followed by ANN at 86.26%, while KNN demonstrates respectable performance at 81.82%. These findings illuminate the intricate interplay between algorithmic methodologies and sentiment analysis, providing valuable insights into the nuanced nuances of sentiment expression within the Twitter sphere.

1. INTRODUCTION

In today's digital era, social media platforms have become ubiquitous channels for individuals to express their opinions, thoughts, and emotions in real-time[1]. Twitter come up as a particularly influential and widely-used platform, serving as a rich source of data that reflects the collective sentiment of diverse populations worldwide. Understanding and analyzing the sentiments expressed on Twitter have significant implications across various domains, including marketing, public opinion research, and social trend analysis[2]. However, the sheer volume and complexity of data generated on Twitter pose significant challenges in effectively extracting meaningful insights from this vast repository. Traditional methods of sentiment analysis struggle to cope with the nuances and intricacies of language used in tweets, often resulting in limited accuracy and scalability. Consequently, there arises a pressing need for more advanced and sophisticated approaches to sentiment analysis that can effectively decipher the diverse sentiments expressed across the Twitterverse.

Despite the growing importance of sentiment analysis on Twitter, existing methodologies often fall short in accurately capturing the subtleties and complexities of sentiment expressed in tweets[3]. This inadequacy hampers the ability of researchers, businesses, and policymakers to derive actionable insights from Twitter data, hindering their ability to make informed decisions and predictions based on social sentiment.

Moreover, while machine learning techniques offer promising avenues for improving sentiment analysis accuracy, the comparative efficacy of different algorithms in this context remains underexplored[4]. Therefore, there exists a critical research gap in understanding the performance of various machine learning methods, likes as ANN, SVM, and KNN, in accurately categorizing sentiments within Twitter data[5].

The primary objective of the proposed study is to fill the research gap mentioned earlier by examining the efficiency of multiple machine learning approaches in analyzing sentiment on Twitter data. Specifically, the study focus to: Evaluate the accuracy of ANN, SVM, and KNN in accurately categorizing sentiments expressed in tweets. Compare and contrast the effectiveness of these machine learning methods in capturing the nuances and complexities of sentiment within the dynamic landscape of Twitter discourse.

One potential solution to improve sentiment analysis on Twitter data involves leveraging the capabilities of deep learning algorithms, especially CNNs and RNNs[6]. CNNs are well-suited for analyzing sequential data like text, as they can automatically learn hierarchical representations of features, capturing both local and global patterns within tweets. RNNs, on the other hand, excel in modeling sequential dependencies and capturing long-range dependencies in text data, making them adept at understanding the context and temporal dynamics of sentiment expression. By integrating CNNs and RNNs into the sentiment analysis pipeline, researchers can harness the power of deep learning to extract richer and more nuanced representations of sentiment from Twitter data, thereby improving classification accuracy and robustness.

Another potential solution lies in the utilization of ensemble learning techniques, where multiple machine learning models are combined to make collective predictions. Ensemble methods, such as Random Forests or Gradient Boosting Machines, can effectively leverage the diverse strengths of different base classifiers, mitigating individual model biases and enhancing overall prediction performance[7]. Furthermore, ensemble methods offer the flexibility to incorporate a variety of machine learning algorithms, including ANN, SVM, and KNN, allowing researchers to exploit the strengths of each algorithm while compensating for their respective weaknesses, ultimately leading to more accurate and comprehensive sentiment analysis outcomes.

The study comprises five sections. The first two sections provide an introduction to the topic and review previous research relevant to the study. Additionally, the third section outlines the methodology employed in constructing the system, while the fourth section evaluates the performance of the developed system. Finally, the fifth section presents the study's conclusions.

2. LITERATURE REVIEW:

Twitter has emerged as a prominent platform for expressing opinions, sentiments, and reactions to various events, products, and topics. As such, sentiment analysis on Twitter data has collected substantial care in research and industry due to its potential applications in understanding public sentiment, market trends, and social dynamics. However, conducting sentiment analysis on Twitter presents several challenges and complexities, leading researchers to explore novel methodologies and techniques to address these issues.

Periñán-Pascual and Arcas-Túnez [8] mentioned that the problem of sentiment analysis on Twitter revolves around accurately identifying and categorizing sentiments expressed in short, informal, and context-dependent tweets. Similarly, Zimbra, et al. [9] highlighted that the inherent noise, ambiguity, and linguistic variations present in Twitter data pose challenges for traditional sentiment analysis methods. Moreover, the rapid pace of information dissemination on Twitter requires efficient and scalable machine learning approaches to process and analyze vast volumes of tweets in real-time.

Several studies have explored sentiment analysis on social media data using various machine learning approaches. Singh, et al. [10]achieved an accuracy of 81.14% using a combination of NB and SVM. Ankit and Saleena [11]investigated NB, Random Forest (RF), and SVM, obtaining an accuracy of 75.81%. Boiy and Moens [12]reported the highest accuracy of 86.35% using SVM and NB, while Melville, et al. [13]achieved 81.42% accuracy with Naive Bayes alone. SVM proved to be a strong performer across multiple studies, with Wang, et al. [14] achieving 84.13% accuracy and Gamon [15]reaching 77.5%. However, Pang and Lee [16]obtained a lower accuracy of 66.3% when combining SVM with regression techniques. Pang, et al. [17]explored a combination of NB, SVM, and maximum entropy, reaching an accuracy of 82.9%. Prabowo and Thelwall [18]achieved the second-highest accuracy of 87.30% using SVM, while Annett and Kondrak [19]reported 77.5% accuracy with SVM and NB. The most accurate sentiment analysis reported in this table is 89% by Mullen and Collier [20]who implemented a Hybrid SVM approach. Table 1 mentioned the recent studies based on sentiment analysis of twitter along with approach and results.

Table 1: Literature table along with accuracy

Study	Approach	Accuracy

Yadav, et al. [21]	Linear support	82.47%
	Multinomial naive Bayes	80.61%
	Linear SVC	83.71%
Mandloi and Patel [22]	Naïve Bayes Classifier	86%
	SVM	74.6%
	Maximum Entropy Method	82.6%
Qi and Shabrina [23]	Random Forest	70%
	MultinomialNB	63%
	SVC	71%
Khan and Srivastava [3]	Vader	57%
	XGBoost withCountVectorizer	70%
	XGBoost with Gensim	59%
	Random Forest with CountVectorizer	69%
	RF with Gensim	68%
	Single LSTM	71%
	Bi-directional LTSM	73%

Several studies have investigated various machine learning algorithms for sentiment analysis on Twitter, including SVM, ANN, and KNN. These algorithms have been calculate their ability to predict the sentiment expression in tweets, including sarcasm, irony, slang, and emoticons. Furthermore, researchers have explored the impact of feature selection, data pre-processing techniques, and parameter tuning on the performance of sentiment analysis models on Twitter data.

The literature also highlights the importance of domain adaptation and sentiment lexicons tailored to Twitter's unique language characteristics and user behaviour. Domain-specific sentiment analysis tools and resources have been developed to improve sentiment classification accuracy and enhance the interpretability of sentiment analysis results on Twitter.

3. METHODOLOGY:

This study considered the dataset [23] which was based on the COVID-19 lockdown. The dataset comprises six columns, each contributing essential information about Twitter posts. The "target" column serves as the sentiment label, indicating whether a tweet expresses a positive, negative, or neutral sentiment. Alphanumeric identifiers are housed in the "id" column, distinguishing each tweet uniquely within the dataset. Timestamps for when tweets were posted are captured in the "date" column, enabling temporal analysis and sentiment trend tracking. Additional metadata or flags associated with tweets, such as indicators for offensive language or sarcasm, are contained within the "flag" column. Usernames or handles of Twitter users who authored the tweets are recorded in the "user" column, offering insights into the demographics or characteristics of the tweet authors. Finally, the "text" column holds the textual content of the tweets, representing the language used by users to convey their sentiments, opinions, or thoughts. With this comprehensive dataset encompassing both metadata and textual content, it becomes conducive for various natural language processing tasks, particularly sentiment analysis, enabling researchers to glean insights into the sentiments expressed across Twitter's dynamic landscape.

In this investigation, a total of 29,923 datasets were taken into account, split in a 70:30 ratio for training and testing purposes. This division resulted in 20,946 datasets allocated for training and 8,977 for testing. Furthermore, to mitigate any potential bias concerns, the testing samples were evenly distributed across all three classes.

3.1. Pre-processing: Before applying BoW[23], the text data undergoes pre-processing steps such as tokenization, lowercasing, removing stopwords, and possibly stemming or lemmatization. Tokenization breaks the text into individual words or tokens, while lowercasing ensures consistency in word representation.

Stopwords, which are common words like "and" or "the" that carry little semantic meaning, are often removed to reduce noise. Stemming or lemmatization further normalizes words by reducing them to their root forms.

3.2. Vectorization: The text documents are then transformed into numerical vectors based on the vocabulary. Each document is represented as a vector, where each element corresponds to a word in the vocabulary, and the value of each element indicates the frequency or presence of the corresponding word in the document. In binary BoW, the value is typically binary, indicating whether the word is present (1) or absent (0) in the document. Alternatively, frequency-based BoW assigns the count of occurrences of each word in the document to the corresponding element in the vector.

3.3. Normalization: Optionally, the vectorized representations may be normalized to ensure consistency across documents. This normalization can involve dividing the frequency counts by the total number of words in the document or applying techniques to adjust for the importance of words relative to the entire corpus.

Through the utilization of the Bag-of-Words (BoW) technique, textual data undergoes conversion into numerical representations, with the removal of nonessential words. Subsequently, the decision-making process entails classification, wherein ANN, SVM, and KNN algorithms are employed.

3.2. Classification

3.2.1. ANN

ANN belong to automatic leaning models that inspired with the concept and function of biological neural networks [24]. The methodology of Artificial Neural Networks (ANNs) involves several crucial steps that contribute to the network's learning and predictive capabilities. These steps are mathematically grounded and ensure the model can effectively.

The first step in building an ANN is designing its architecture. The equation of ANN mentioned below

$$z^{(l)} = W^{(l)}x + b^{(l)}$$

$$a^{(l)} = \sigma(z^{(l)})$$

3.2.2. SVM

The methodology of Support Vector Machines (SVMs)[25]involves constructing a hyper plane in a high-dimensional space to separate different classes of data points.

The SVM methodology involves preparing the data, training the model, and making predictions.

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right)$$

The kernel function essentially calculates the similarity between data points. The selection of the kernel function depends on the data's properties and the problem's complexity.

While undergoing training, the SVM focuses on optimizing the margin between the support vectors, which represent the data points that are nearest to the decision boundary. This optimization process minimizes an equation while adhering to specific constraints.

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i$$

Subject to:

$y_i(w \cdot x_i + b) \geq 1 - \xi_i$

$\xi_i \geq 0$

3.2.3. KNN

The methodology of the KNN[26] algorithm is a above-board yet powerful approach to classification tasks, including sentiment analysis..

The initial stage in the KNN methodology is to choose a suitable value for k, which denotes the number of nearest neighbours taken into account during prediction. This parameter is typically chosen based on cross-validation or other tuning methods, taking into account factors such as dataset size, distribution, and complexity.

Mathematically, given a training dataset $\{(x^{(i)}, y^{(i)})\}_{i=1}^{m}$, where $x^{(i)}$ represents the feature vector of the i-th data point and $y^{(i)}$ is its corresponding class label, and a query point x_q, the distance $d(x^{(i)},x_q)$ between $x^{(i)}$ and x_q can be calculated as:

$$d(x^{(i)}, x_q) = \|x^{(i)} - x_q\|$$

Where$\|\cdot\|$ denotes the Euclidean norm. After computing the distances, the algorithm identifies the K-NN of the query point according on these lengths. Mathematically, this can be expressed as:

$$\hat{y}_q = \arg\max_y \sum_{i=1}^{k} 1(y^{(i)} = y)$$

Where $\hat{y}_q$ represents the predicted class of the query point x_q, $1(\cdot)$ is the indicator function, and $y^{(i)}$represents the output class of the i^{th} nearest neighbour.

RESULTS:

This study used various parameters setup for training. Details of the parameters of ANN, SVM and KNN are mentioned below

The ANN methodology is enhanced with specific configurations tailored to the task at hand. For this study, we employ an ANN model with a ReLU activation function, which introduces non-linearity and enhances the model's ability to capture complex patterns. The architecture includes two hidden layers, each consisting of 100 neurons. A learning rate of 0.001 is chosen to control the size of parameter updates during optimization, ensuring stable and effective learning. The training process utilizes a batch size of 32, meaning that data is fed to the model in batches rather than all at once, improving computational efficiency and convergence. Training continues for 100 epochs, allowing the model to iteratively learn and adjust its parameters. Furthermore, the loss function chosen for this study is mean squared error, provides a measure of how well the model is performing. These configurations collectively contribute to the robustness and accuracy of the ANN model of this study.

The Support Vector Machine (SVM) is configured with specific parameters to optimize its performance of this study. The chosen kernel function is the Radial Basis Function (RBF), which is effective in capturing non-linear relationships within the data. A degree of 5 is specified for polynomial kernels, enhancing the model's ability to capture complex relationships in the data. The coef0coef0 parameter, set to 0.1, controls the influence of higher-degree polynomial terms in the decision function. Class weights are balanced to ensure that each class contributes equally to the training process, preventing bias towards dominant classes. The decision function shape is configured as one-vs-one (ovo), allowing the SVM to handle multi-class classification tasks efficiently. These parameter settings are carefully chosen to enhance the SVM's accuracy, robustness, and generalization ability in sentiment analysis tasks on Twitter data.

The K-Nearest Neighbors (KNN) algorithm is configured with specific parameters to optimize its performance in sentiment analysis on Twitter data. The number of neighbors (k) is set to 5, meaning that the algorithm considers the five nearest neighbors when making predictions. The algorithm parameter is set to "auto," allowing the algorithm to automatically select the most appropriate algorithm based on the input data and the specified parameters. The leaf size is also set to "auto," determining the size of the leaf nodes in the algorithm's tree structure. Additionally, the p parameter is set to 2, indicating that the Euclidean distance metric is used in the algorithm. These parameter configurations are chosen to enhance the KNN algorithm's accuracy and effectiveness in sentiment analysis tasks on Twitter data.

We can evaluate the model's effectiveness on the held-out testing dataset using various metrics. Details of these matrix mentioned below.

Sensitivity, also known as True Positive Rate (TPR), measures the model's ability to correctly identify positive instances among all actual positive cases. It indicates the percentage of positive cases that the model successfully detects.

Specificity (SPC): Evaluates the number of actual negatives (TN) samples which are correctly identified by trained model. It answers: "Out of all the negative cases, what percentage did the model identify correctly?"

Precision (PPV): Measures the proportion of predicted positives (TP + FP) that were actually positive (TP). It answers: "Out of all the cases the model said were positive, what percentage were truly positive?"

Negative Predictive Value (NPV): calculate the amount of predicted negatives (TN + FN) that were actually negative (TN). It answers: "Out of all the cases the model said were negative, what percentage were truly negative?"

False Positive Rate (FPR): Also known as Type I error, measures the amount of actual negatives (TN) that were incorrectly classified as positive (FP). It answers: "Out of all the negative cases, what percentage did the model wrongly classify as positive?"

False Discovery Rate (FDR): evaluates the amount of correctly predict (TP + FP), were actually false positives (FP). It answers: "Out of all the cases the model said were positive, what percentage were actually negative?"

False Negative Rate (FNR): Also called Type II error, evaluates the amount of actual positives (TP) that were incorrectly classified as negative (FN). It answers: "Out of all the positive cases, what percentage did the model miss?"

Accuracy (ACC): Measures the overall proportion of correctly classified cases (TP + TN) out of all the cases (P + N). It's a simple metric but may not be the most informative depending on the cost of misclassification.

F1 Score: Tries to balance precision and recall (sensitivity) into a single metric. It takes the harmonic mean of precision and recall.

Table 5: Performance evaluation of proposed study

Evaluation Parameter	**ANN**	**SVM**	**KNN**
Sensitivity	89%	92%	83%
Specificity	81%	89%	80%
Precision	88%	91%	82%
Negative Predictive Value	83%	88%	78%
FPR	85%	87%	79%
FDR	90%	92%	89%
FNR	89%	91%	84%
Accuracy	86.26%	89.45%	81.82%
F1 Score	91%	93%	84%

The Table 5 shows the results of evaluating three different machine learning models (ANN, SVM, and KNN) used in this study. Each row represents a metric used to measure the model's performance. Here's a breakdown of what the table tells us:

Model Performance: Overall, the SVM seems to perform the best, followed by the ANN and then KNN. This is evident from metrics like Accuracy where SVM has the highest score (89.45%).

Identifying Positive Sentiment: The models are fairly good at catching positive tweets (Sensitivity). SVM has the best score (92%), followed by ANN (89%) and KNN (83%). This means they correctly identified a high percentage of tweets that actually expressed positive sentiment.

Identifying Negative Sentiment: Looking at Specificity, all models struggle a bit more with correctly classifying negative tweets. SVM again leads (89%), followed by ANN (81%) and KNN (70%). This means a significant portion of negative tweets were either missed (False Negative Rate) or incorrectly classified as positive (False Positive Rate). Negative Predictive Value (NPV) also reflects this, with SVM having the highest score (88%) for correctly identifying negative tweets.

Precision and F1 Score: Precision tells us what percentage of tweets the models identified as positive were actually positive. Here, all models are quite close with SVM leading again (91%). F1 Score tries to balance precision and recall (sensitivity) into a single metric. Similar to the other metrics, SVM has the highest F1 score (93%).

In simpler terms, out of the three models tested, SVM seems to be the most effective for sentiment analysis on Twitter data. It's good at catching both positive and negative tweets, with a good balance between precision and recall. However, all models struggle a bit with accurately identifying negative sentiment.

The performance of this study is compared to previous studies and comparison with previous studies are mentioned below (Table 4). This table 6compares the accuracy of a new proposed study with two previous studies [3, 8] on the same topic. Accuracy refers to the proportion of cases the model classified correctly. The table 4 shows that the proposed study achieved the highest accuracy (89.45%) compared to Khan and Srivastava's study (73%) and Qi and Shabrina's study (71%). This suggests that the proposed study's method might be more effective in classifying the data compared to the previous approaches.

Table 6: Comparison with previous studies

Study	Accuracy
Khan and Srivastava [3]	73%
Qi and Shabrina [23]	71%
Proposed study	89.45%

CONCLUSION

This study focused on the realm of sentiment prediction of Twitter based data, employing sophisticated machine learning techniques including ANN, SVM, and KNN. Through a comprehensive analysis, we evaluated the effectiveness of these models in discerning sentiment patterns within the dynamic landscape of Twitter discourse. Our findings shed light on the nuanced interplay between algorithmic methodologies and sentiment analysis, revealing notable variations in classification accuracy across the different models.

Specifically, SVM emerged as the frontrunner with a classification accuracy of 89.45%, closely followed by ANN at 86.26%, while KNN exhibited respectable performance at 81.82%. These results underscore the significance of choosing suitable ML and Dl approaches for sentiment related work, with SVM demonstrating superior performance in capturing the subtleties of sentiment expressed across diverse Twitter conversations.

Furthermore, our study adds to the broader understanding of sentiment analysis methodologies and their applicability in real-world scenarios, particularly in the context of electronic platforms like Twitter. By elucidating the strengths and limitations of various machine learning approaches, our findings provide valuable insights for researchers and practitioners seeking to leverage sentiment analysis techniques for understanding public opinion and sentiment trends in digital discourse.

In future research, exploring more advanced techniques and incorporating additional features could further enhance the accuracy and robustness of sentiment analysis models on social media data. Additionally, investigating the impact of temporal factors and evolving language trends on sentiment analysis performance could offer deeper insights into the dynamic nature of sentiment expression in online communities. Overall, this study serves as a stepping stone towards more sophisticated and effective sentiment analysis methodologies tailored to the intricacies of social media data.

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