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Mohammad Shihab Ahmed
Department of Computer Science and Mathematics College, Tikrit University, Tikrit, Iraq

Maha Safar Abdulmajed
Department of Laboratory Sciences, College of Pharmacy, University of Tikrit, Tikrit, Iraq

Corresponding Author:
Mohammad Shihab Ahmed
Department of Computer Science and Mathematics College, Tikrit University, Tikrit, Iraq

Sentiment analysis of social media data using multiple machine learning models: A case study on public opinion trends

Mohammad Shihab Ahmed and Maha Safar Abdulmajed

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Abstract
Sentiment analysis is an important part of both data mining and natural language processing (NLP), which defines the extraction and analysis of public opinion from public discourse and social media, allowing researchers to understand community attitudes and perspectives during those moments in time, such as during a political election. The objective of this study was to perform an analysis of sentiment based on four machine learning models including: Naive Bayes, a feedforward neural network, Support Vector Machine (SVM) and Random Forest. Using a generated dataset of 10,000 tweets about a fictitious 2025 global political election, we performed the sentiment analysis using the four models mentioned, along with explanations of how this was done; including the data simulation, noise preprocessing, TF-IDF feature extraction, and training of the machine learning models using 5-fold cross validated modelling methods involving Python. Concerning the results: the accuracy of the models produced Naive Bayes at 83.1%, feedforward neural network at 81.2%, support vector machine at 83.1%, and random forest at 81.5%. The results of the analysis were supported with supportive measures of all metrics available i.e. precision, recall, F1-scores, confusion matrices, ROC curves, precision-recall curves and feature importance.
The sentiment distribution reveals a polarization: 45% positive tweets, 33% negative, and 22% neutral. Naive Bayes is very good for vast-domain analysis, whereas the neural networks promise capturing nuanced information given that computational optimization is achieved. SVM is consistent, while Random Forest is balanced in classification and could provide some information about features. There are eight visualizations integrated into the study framework as PNG images (e.g., confusion_matrices.png, wordcloud_positive.png): confusion matrices, ROC curves, precision-recall curves, word clouds, sentiment distribution, and feature importance, among others. This detailed and fully reproducible framework will support academic research and real-world applications to understand public opinion in the context of the 2025 election.

Keywords: Sentiment analysis, machine learning, social media, political election, natural language processing

Introduction
The exponential growth in social media platforms-intensified by Twitter, which, in an estimate, moves more than 500 million tweets daily into the atmosphere-has, in essence, altered the space of public discourse and positioned these digital ecosystems as arguably the biggest vault of real-time sentiments about society. This very transformation has caused social media to really become an act of analysis of public opinion, especially during nail-biting events like political elections where bigger-than-life issues regarding side-by-side aggregation and interpretation of opinions can be discussed in terms of voter preferences, political trends, campaign effectiveness, and, in the barest sense, the spirits of the people with a level of micro-detail and immediacy hitherto impossible. Twitter serves as the largest sample for the public expression of some very raw integrated thoughts and opinions, with sprinkles of emotion-a few slang terms, some emojis, and possibly a vaudeville act or two at 280 characters-makes it an extremely rich yet very challenging source for sentiment analysis. Sentiment analysis, a core branch under data mining and NLP, aims to classify textual data into categories such as positive, negative, or neutral so as to understand emotional tone prevailing among the public and collective attitudes that various stakeholders, such as researchers, policymakers, campaign strategicians, and data scientists, use as their hopeful eye to watch, interpret, and forecast societal ramifications.

This study is thus oriented toward exploring the performance of four applied machine learning methods in the sentiment analysis of a simulated 10,000-tweet dataset related to a fictitious 2025 global political elections, an ad hoc creation meant to represent the rich, multifaceted, and often disorderly online discourse that usually accompanies worldwide events. The models were so selected on the basis of their very differing theoretic backgrounds and strengths in practice: Naive Bayes, reputed for its computational efficiency and resilience to noisy unstructured data (Medhat *et al.*, 2014) [9], hence an ideal candidate for treatment of the large-scale irregular text-data generated on social media platforms; the neural network, to wield the much powerful deep-learning paradigm to extract complex language patterns, semantic relationships, and contextual dependencies (Zhang *et al.*, 2018) [18]; the SVM, well-known to Cortes and Vapnik (1995) [4] to manage high-dimensional feature spaces and complicated decision boundaries; and finally the Random Forest for its stated robustness to non-linear relationships, reduction of overfitting in an ensemble learning fashion, and provision of interpretable feature importance metrics (Breiman, 2001) [3].

The research uses TF-IDF for extraction of the features which describes how important a word is for a document, accounted for by its frequency in the document (compared to its frequency through the entire corpus of documents); additionally, I applied class weights to account for the slight class imbalance (i.e., there are 45% of records that are positive, 33% that are negative, and 22% that are neutral), which will provide a more complete and equitable analysis across all three classes of sentiment. Overall, the objectives of this research are multifarious and lofty:

1. To comprehensively compare Naive Bayes's capabilities in sentiment classification of noisy social media data against those of neural network, SVM, and Random Forest, using the specific results from the code provided to illustrate their relative benefits and weaknesses.
2. To evaluate the computational efficiency and performance trade-offs of these models based on the execution behavior and output statistics and cross-validation results of the code, providing insight into the practical use of the models for real-world applicability.
3. to derive rich, deep, substantive, and actionable insights from the sentiment distribution in what was said about the context of public perception and engagement regarding the 2025 election while also examining how these could be related to wider societal trends, voter sentiment and election behavior
4. To provide an extremely ambitious, fully reproducible Python implementation with high-detail visualizations as embedded images, sets of detailed tables summarizing performance measures, and high-level interpretive discussion of findings, for use in your thesis and as an inspiration for a thorough exploration of future research.

The study takes on the following research questions with specificity and rigor

1. How does Naive Bayes compare in classification capabilities to the neural network, SVM and Random Forest when classifying sentiment from noisy social media data and based on the code's specific results particularly in regard to accuracy, precision, recall and F1-scores by all folds?
2. What are the computational and performance tradeoffs for the models from the perspective of the code in terms of execution time, resource utilization and the output from all folds, and how do these differences affect their applicability to potential use cases?
3. What precise and granular information can be derived from the sentiment distribution about how the public feels about the 2025 election with respect to polarization, how positive, negative and neutral sentiment is distributed and, what these imply in terms of wider societal trends?
4. How would the practical application and in particular, code, tables, and visualizations, be conceived, structured, expanded, and documented for the best chance of providing for inclusion in a thesis offering value in terms of clarity, reproducibility, and academic rigor?

The paper is highly organized to help the reader follow a clear and thorough path through these questions. Section 2 reviews the literature, to provide context for the current study in the broader field of sentiment analysis. Section 3 explains the methodology with code snippets, step-by-step and theoretical justification for each step. Section 4 details the practical application of that methodology, and references the Appendix with full code listings. Section 5 presents the results, which includes tables as well as embedded visualizations. Section 6 offers a thorough discussion of the findings, limitations, and implications. Section 7 presents future directions and recommendations, and the Appendix contains the full code listings, and additional technical information, for full reproducibility.

2. Related Work

In the past two decades, sentiment analysis has grown and moved into the interdisciplinary domains of data mining and natural language processing. Pang *et al.* (2002) [12] first introduced Naive Bayes classifiers in a sentiment classification setting, obtaining great accuracy with fairly simple unigram features on a set of movie reviews. This approach placed Naive Bayes as a benchmark due to its simplicity, speed, and reasonable accuracy even when data were sparse. The advantages of its computational efficiency and the underlying probabilistic framework, which computes posterior probabilities through Bayes' theorem, were summarized in Medhat *et al.* (2014) [9] and stressed as reasons to consider Naive Bayes classification. Going to its ability to handle noisy and unstructured data is another reason that makes it very suitable for social media text, where 'proper' linguistic structures are frequently absent and highly unorthodox methods of writing abound. Go *et al.* (2009) [5] took the work one step further and looked at the problem of Twitter-based sentiment classification using distant supervision through emoticons, and in doing so, they generated the strongest reported numbers, an accuracy of 83%, showing indeed that Naive Bayes works very well in real-world messy settings like social media.

Deep learning brought increasingly sophisticated models. Zhang *et al.* have reviewed CNNs and LSTMs, which are good at capturing contextual or long-range dependencies (2018) [18]. However, these models require heavy computational resources, a lot of training data, and

extensive hyper parameter tuning, thus less fit for rapid analysis in a resource-constrained environment. Kouloumpis *et al.* (2011) [7] showed with Twitter data that lexicon-based features, such as sentiment lexicons, provide a significant improvement in classification performance. This is a reflection of the additional context and clues that sentiment offers, which we attempted to account for during preprocessing and feature extraction, particularly with the treatment of emojis and stop words that still communicate sentiment. Yang and Wang (2019) [17] produced an efficient and accurate hybrid Naive Bayes-neural network model, and inspired this work to utilize class weights to support balancing the dataset.

Feature extraction approaches have changed too. Pennington *et al.* (2014) [13] presented GloVe word embedding to exploit its semantic and contextual similarities, yielding a richer representation of text than the traditional bag-of-words feature extraction. Agarwal *et al.* (2011) [1] recognized that social media is rich with non-textual features like emojis and hashtags and emphasized that these often have an important emotional and contextual meaning in the sentiment analysis of Twitter, which aligns with the decision in our study to convert emojis to text descriptions in preprocessing emphasizing these capturing these elements. Liu (2012) [8] and Hutto and Gilbert (2014) [6] composed the VADER lexicon targeting social media to provide increased accuracy with sentiment-specific scores and rule-based modifications.

Recent research such as Wang *et al.* (2021) [15] on real-time sentiment analysis for crisis management on Twitter and Alharbi *et al.* (2020) [2] on multilingual Twitter data points to supporting preprocessing, combinations of features, and data-driven and adaptive models to tackle linguistic variation, cultural variation and temporal change. In this study we tackle these identified problems by simulating a noisy dataset, using TF-IDF with class balancing, and running multiple models (Naive Bayes, neural network, SVM, and Random Forest) on a simulated Twitter dataset composed of 10,000 tweets. This paper extends the pioneering work of Socher *et al.* (2013) [14] (recursive neural networks) and Mikolov *et al.* (2013) [10] (Word2Vec) by providing a complete comparison in concern for the electoral politics surrounding its subject with tables, plots and in depth analysis.

3. Methodology

3.1 Data Collection

The dataset for this study consists of 10,000 simulated tweets about a fictional global political election in 2025. The tweets were designed to closely emulate the language variation, noise, sentiment variation, and context complexity of real Twitter data released during electoral events for politicians and elections globally. The simulation was run with a random seed of 42 for reproducibility. Sentiment labels were assigned using a distribution which included a 45% positive sentiment, 33% negative sentiment, and 22% neutral sentiment. This distribution was purposefully created to closely mirror the extreme polarization typically observed in global electoral communications which can be broadly classified as either strong support or strong opposition, coupled with some neutral/indifferent or disengaged constituents.

This distribution relies on a complex randomization process that picks phrases from predetermined sets for a given sentiment class so that the generated tweets can correspond to an emotional tone and linguistic style peculiar to each class. For example, the positive tweets will contain expressions such as “great effort,” “amazing work,” and “hopeful future” to elicit optimism. In contrast, negative tweets will incorporate expressions such as “great failure,” “failed policy,” and “disappointing result,” which express criticism. Neutral tweets are made up of phrases such as “election update,” “voting process,” and “political debate,” having a factual or neutral tone, similar to a news update or objective commentary during elections.

In this text, linguistically complex, but realistic phrases have been incorporated. These ambiguous phrases (e.g., "interesting choice") and transitional outcome (e.g., "unexpected outcome") create some ambiguity for classification purposes that is, their use is dependent on their context. In order to simulate irony, which is quite common on social media, ironic phrases (e.g., "great job not"; "amazing fail") are included. The probability distribution to select a phrase was: 70% for sentiment-specific phrases (0.14 for each of five phrases), 15% for ambiguous phrases (0.025 for each of six phrases), and 15% for sarcastic phrases (0.03 for each of five phrases). Hence, the dataset is varied and challenging to perform sentiment classification.

np.random.seed(42) n_tweets = 10000 sentiments = np.random.choice(['positive', 'negative', 'neutral'], size=n_tweets, p=[0.45, 0.33, 0.22]) # Define phrases for each sentiment positive_phrases = ["great effort", "amazing work", "hopeful future"] #... (see Appendix A for full code) tweets = [] for i, sentiment in enumerate(sentiments): if sentiment == 'positive': phrase = np.random.choice(positive_phrases + ambiguous_phrases + sarcastic_phrases, p=[0.14]*5 + [0.025]*6 + [0.03]*5) tweet = f"Tweet {i} about election: {phrase}!" #... (similar for negative and neutral)

To simulate a noisy environment and impart a natural flavor of its informal and chaotic nature, a noise insertion goes on through the add_noise function. This function may insert additional linguistic elements with a 90% chance for conversational noise words such as “...”, “??”, “!!!”, “meh”, “umm”, “lol”, “idk”, “not sure”, “maybe good”, “kinda bad”, “pretty okay”, “so so”, and “random stuff.” With a 50% chance, they may also add ambiguous words such as “really”, “actually”, “possibly”, “somewhat”, “very”, “not bad”, “quite good”, and “whatever”. Such noise words emulate the casual tone, emotional expression, and linguistic ambiguity that are often expressed in Twitter data and provide ample hurdles for the sentiment classification research in terms of sorting out actual sentiment from conversational fillers, or really appreciating the impact of ambiguous modifiers. Appendix A contains an implementation of the add_noise function with full phrase lists and simulation logic.

Now, as a Data Frame in Pandas, this resultant data set is a controlled, yet representative, proxy for some real Twitter data. With 4,500 positive, 3,300 negative, and 2,200 neutral tweets, this ever-potent data allows a rigorous testing of the machine learning models under conditions that emulate closely the electoral discourse in a digital, global timeframe.

3.2 Data Preprocessing: The preprocessing pipeline represents the first stage of creating a simulated dataset

composed of fed Tweets text prepared for sentiment analysis, and in consideration of the noise, linguistic diversity, and contextual variety in social media text, characterized by language and other conventions common to Twitter (e.g. informal language, emojis, slang, abbreviations, punctuation, extra characters). The noise reduction and the cleaning steps of preprocessing are implemented via the preprocess text function of the supplied Python code, which applies stepwise processing steps to arrive at a clean, standardized, and sentiment-preserving corpus with which to extract features and learn a model with, while leaving intact the details of emotional and contextual sentiment relevance. Therefore, the process of preprocessing is designed to remove no member of the text corpus or sentiment relevance while filtering out as much irrelevant noise as possible. The order of the preprocessing pipeline objectives where authenticated meaning quality is best and the least affected in obtaining a sentiment preserving final text corpus. The steps in this pipeline are as follows:

- **Conversion of Emojis:** Emojis are popular in social media and often serve as strong indicators of emotional tone (smile for happiness, Angry for anger); these emojis are demojize into their textual descriptions using the emoji library (Smile gets converted to "smiling face", Angry gets converted to "angry face"). This step thus preserves the emotional and contextual cues something that is originally conveyed by a visual symbol and transforms it into a text format recognized by text-based machine learning models, thus greatly assisting these models in capturing sentimental cues given in no textual form.
- **Cleaning of Text:** The text remains cleaned to remove those elements that do not contribute to sentiment or emotional content, such as URLs (http://example.com), user mentions (@username), hashtags (#Election2025), numbers, and special characters (!,?, $, %), using a very comprehensive regular expression: re.sub(r'http\S+|@\w+|#\w+|[^\w\s]|\d', '', text.lower()). The text is also converted to lowercase to facilitate uniformity throughout the dataset thereby reducing the issues that occur due to case sensitivity that sometimes may lead to the presence of duplicate features (e.g., "Great" and "great" being treated as distinct words) and aids in making the feature extraction process.
- **Tokenization:** After cleaning, the text is split into separate words or tokens by the word_tokenize method from NLTK. This module uses a pre-trained tokenizer to split a text into meaningful units based on whitespace and punctuation. Here, each tweet is split into all of its constituent elements; for example, “tweet great effort lol” becomes [“tweet”, “great”, “effort”, “lol”]. This step enables further linguistic processing, as it provides a more granular representation of the text to work with in analyses at the word level**.**
- **Stop Word Removal:** Common English words deemed too general to carry any sentiment information, such as “the”, “and”, “is”, “in”, and “a”, were removed using NLTK’s English stop word list to reduce noise from the sentiment lexicon and focus on words that are more likely to have sentiment value. However, to retain negation and sentiment changes in words necessary for classifying accurate sentiment, the words “not” and “no” were not included in the stop word set, thus allowing phrases such as “not good” and “no support” to keep their negative sentiment connotations required for differentiating positive and negative tweets.
- **Lemmatization**: In order to standardize the vocabulary representation, avoiding redundancy and ensuring the model can generalize over the dataset, we apply lemmatization through WordNetLemmatizer (e.g., from “running” into “run”, from “better” into “good”, from “tweets” into “tweet”). Unlike stemming, the process of lemmatization preserves the linguistic integrity of words because it is dictionary-based; it outputs valid English words that possess their proper semantic meaning. This is thus of particular importance in sentiment analysis, where the use of words could drastically affect the interpretation.

After these steps, the processed tokens are rejoined into a single string for each tweet, creating a clean corpus ready for feature extraction. A brief example of this preprocessing function is provided below to illustrate its application:

def preprocess_text(text): text = emoji.demojize(text) text = re.sub(r'http\S+|@\w+|#\w+|[^\w\s]|\d', '', text.lower()) tokens = word_tokenize(text) stop_words = set(stopwords.words('english')) - {'not', 'no'} #... (see Appendix A for full implementation)

For instance, the noisy tweet-"Tweet 0 about election: great effort!!! lol really"-is transformed to "tweet great effort lol smiling face really," the clean version with the words of interest carrying the sentiment (great, effort, smiling face) and with a few conservative noise terms (lol, really) that might convey some kind of context, free from special characters, URLs, or inconsistent casing. This thorough data preprocessing ensures that later feature extraction and model training will be performed on data of high quality and standard, forming a strong foundation for the analytical results of the study. The preprocessing pipeline thus removes problems encountered in social media text analysis, such as duplicate words caused by case variations, emojis being treated as noise, and sentiment signals cluttered by irrelevant terms, thereby greatly enhancing the dataset quality and resulting classification reliability.

3.3 Feature Extraction

In a nutshell, feature extraction is perhaps the most important step in the sentiment analysis pipeline: it turns the text, which has been cleaned and preprocessed, into its numerical counterpart so that it may be fed into machine learning models. The choice of feature extraction technique thus stands between the raw textual data and the mathematical representations in which classification is conducted. In this experiment, the provided Python code extracts features using the term-frequency inverse-document-frequency technique (TF-IDF), implemented using the scikit-learn library's TfidfVectorizer class-a popular tool for machine learning in Python. The TF-IDF method is chosen so that words can be given heavier importance if they occur more frequently in one document but less frequently over the entire corpus, thus providing strong and comprehensible representations of the text with a focus on local term weighting opposed to global term rarity. The implementation of the TfidfVectorizer has been carefully set to find an occasion between computational

costs and enough representation, limiting the set of features to 500 terms because of computational limitations and with an intent of avoiding overfitting, and the range of n-grams goes only to unigrams-with ngram_range=(1, 1)-meaning that it will look at individual words and not phrases for simplicity and interpretability but still concentrating on those words that are mostly carrying sentiment signals in the data. TF-IDF score is assigned to each word in each tweet with two components: the Term Frequency (TF) - that is the frequency of occurrence of a word within a given tweet; and Inverse Document Frequency (IDF), which penalizes words occurring frequently in the whole dataset (e.g., election in this case) and rewards words which occur seldom but discriminate the sentiment better (e.g., great effort- positive sentiment). Mathematically, TF-IDF score of a term t belonging to document d in corpus D is given by:

$$TF\text{-}IDF(t,d,D)=TF(t,d)\times IDF(t,D)$$

Where;

- TF (t, d) is the term frequency normally taken as the raw term count of t in Document d, which is then normalized by the document length with respect to respect to varying tweet lengths.
- $IDF(t,D)=\log\left(\frac{|D|}{(|\{d\in D:t\in d\}|}\right)+1$ is the logarithmic term where |D| is the total number of documents (tweets) in the corpus, while $|\{d\in D:t\in d\}|$ is the number of documents containing the term t, with the 1 added as a smooth to ensure the IDF does not become zero for terms that appear in all documents.

The sparse matrix generation gives us X_tfidf of shape 10,000 × 500, i.e., 10,000 tweets and 500 features. The rows of this matrix correspond to tweets, while the columns are the words' TF-IDF scores measuring how important each word is to a specific tweet and providing a sound numerical representation for a further model training. Below is the snippet of the feature extraction algorithm, explaining TF-IDF matrix creation:

```
vectorizer=TfidfVectorizer(max_features=500,ngram_range
=(1, 1)) X_tfidf = vectorizer.fit_transform(X)
```

Where X is the cleaned_tweet column in that DataFrame holding preprocessed tweets. This resulting X_tfidf is a sparse matrix, most of its entries are zeroes. This is a form typical for text data, each tweet containing only a small subset of the vocabulary, while the sparsity is used to advantage by scikit-learn's implementation for memory and computational ease. To somewhat alleviate imbalance in the dataset-45% positive (4,500 tweets), 33% negative (3,300 tweets), and 22% neutral (2,200 tweets)-class weights are calculated through the compute_class_weight function of scikit-learn so that the models pay due attention towards the neutral minority class during the training and thus do not become biased towards the majority positive class. The implementation of mapping labels with weights looks as follows:

```
label_map = {'positive': 0, 'negative': 1, 'neutral': 2}
y_encoded = np.array([label_map[label] for label in y])
class_weights=compute_class_weight(class_weight='balanc
ed', classes=np.unique(y_encoded), y=y_encoded)
class_weight_dict = {i: weight for i, weight in enumerate
(class_weights)}
```

Therefore, the computed class weights come into play during actual learning, wherein greater importance is given to those classes that have few samples. One good example is the neutral class, so that the models are put on heavier punishment when they misclassify a neutral tweet as compared to the misclassification of either a positive or a negative one. This helps the promotion of fairness and consequently helps any model to classify entities better among all sentiment classes. This hybrid approach combining TF-IDF feature extraction and class balancing thus lays down a strong and equitable foundation for further model training and evaluation, ensuring that numerical representation of the text reflects both the semantic content of the document and the distributional characteristics of the dataset-and tilting the scales toward more accurate and perhaps less biased sentiment classification.

3.4 Model Training

The training phase sees the application of four machine learning models—Naive Bayes, feedforward neural network, Support Vector Machine (SVM), and Random Forest—on the TF-IDF feature matrix. Each algorithm can use the class weights that have been computed to counter the slight class imbalance in the dataset and thus be fairly evaluated concerning the positive, negative, and neutral classes. Training was confined within the bounds of 5-fold cross-validation, as shown in the Python code shared, to produce estimates of each alphabet's performance that were more robust, considered generally applicable, and statistically sufficient over different partitions of data, thus giving less opportunity to overfit and provide a reasonable judgement as to how well any given model can theorize upon unseen data. Cross-validation divides the datset into five folds; in each of the five iterations, four folds are selected for training, and the one remaining fold is set aside for validation or testing. The process is repeated, ensuring each fold serves as the testing set exactly once. Such an evaluation facilitates an averaging of the performance metrics over multiple splits, which indeed alleviates toys evaluated metrics from single splits and provides a more stabilized and representative score of the models' real-world effectiveness. The particulars of the setup and theory behind the approach, along with the mechanisms for training, are described for each model in greater detail:

- **Naive Bayes:** Naive Bayes is a model that is part of scikit-learn's MultinomialNB class. It models data based on the Naive Bayes theorem which takes the assumption of conditional independence between features given the class label. Although this assumption is rarely true, we still get good results when building a text classification model all because text data are highly dimensional and sparse. In other words, it has been shown that you can use a method that relies on a conditional independence model and end up with a surprisingly good performing model because for text data the sparsity (0s) and the dimensionality (number of features) afforded classification that fits well. The Multinomial Naive Bayes model (MNB) is primarily intended for use with discrete data (e.g., count data, word counts or TF-IDF scores). MNB calculates the posterior probability of each class given the tweet features using

Bayes' theorem. This can be expressed with the equation: $P(c|d)=\frac{P(d|c)P(c)}{P(d)}$, where P(c) is the prior probability of class c. P(d|c) is the likelihood of the document (tweet) d given class c, and P(d) is the evidence (normalizing constant).A likelihood of P (d | c) is sampled from a multinomial distribution over (the words in) the document. Within the multinomial distribution, the likelihood is defined as $P(d|c)=\prod_{i=1}^{n} P(w_i \mid c)^{x_i}$, where w_i is the i-th word in the vocabulary, x_i the frequency (or TF-IDF score) of w i in the document, and P(w_i | (c) is the estimated probability of the word w_i given the class c, which is determined based on the data from the training set. Additionally, Laplace smoothing is done on the likelihood with an alpha of 1 to handle the zero probabilities. This is done to ensure that all word counts have a small constant added on. The purpose is to ensure that the model is numerically stable and unseen words (in the test set) within the test set, contribute a likelihood of 0, while still allowing the model to be efficient and robust on a larger scale and when building text oriented spread sheet models, the training snippet is:

```
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
```

In straightforward terms, Naive Bayes follows a probabilistic approach for text classification, thus training time scales linearly with both the number of samples and features, while prediction time remains just as fast-one of the most eligible candidates for rapid analysis of the large-scale social media data flow.

Neural Network: Designed to using Tensor Flow's Sequential API this model is multi-layered, developed to identify complex, non-linear relationships in the TF-IDF features by taking advantage of deep learning capabilities to model the complex relationships between words and contextual dependencies that simpler models such as Naive Bayes may fail to capture. The architecture was built to strike the right balance between complexity and generalization by having an input layer with 500 neurons in relation to the TF-IDF feature dimensions (one neuron for each feature) and the hidden layer have the same ReLU (Rectified Linear Unit) activation function for each 256 and 128 neurons (f(x)=max(0,x)) in the two hidden layers so that the model could learn complex patterns through non-linearity which enabled positive input values to pass through unchanged while pushing negative input values to zero. An L2 regularization with a coefficient of 0.01 is applied to each hidden layer to reduce overfitting, with the additional penalty term $\lambda\sum w^2$ in the loss function where λ=0.01 and w are the weights; essentially, encouraging a smaller weight, the L2 regularization will further reduce the network's ability to over fit or retain noise from the training data. A dropout rate was set to 0.3 after each hidden layer to reduce overfitting with random dropout of 30% of the neurons in each iteration; as a result, this ensures that the network will learn redundant representations of the training sample, or robustness to slight variations on the input data. The output layer has 3 neurons - one for every sentiment class (positive, negative, neutral) - and applies a subsequent soft max function given as $\sigma(z_i)=\frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$. The soft max operation provides a probability distribution across the three classes to facilitate multi-class sentiment classification while ensuring that the probability distribution adds up to 1. Activation function and optimizer: For this task, the model is compiled utilizing the Adam optimizer, which is an adaptive learning rate optimization algorithm that incorporates aspects of momentum and RMS Prop to enhance the speed of convergence of gradient descent, and sparse categorical cross-entropy as a loss function: $L=-\sum_{i=1}^{N} y_i \log(\hat{y}_i)$, where y_i is the original label and $\hat{y}_i$ is the predicted label which is used in a multi-class classification context because this utilizes integer labels.Now at training time, it lasts for a maximum of 20 epochs, with batch size of 64, implying that the MODEL's weights are updated every 64 samples processed at one time or one batch. Early stopping or callbacks are also applied, set by a patience level of five epochs, so if for a duration of 5 epochs validation loss has not improved, then the model will halt training and restore the weights with the best validation loss, thus helping against overfitting. Class weights are also being applied to balance the dataset so that the model pays more attention to the minority neutral "class":

```
nn_model = Sequential ([Input(shape=(X_train.shape[1],)),
Dense(256, activation='relu', kernel_ regularizer =
tf.keras.regularizers.l2(0.01)), Dropout(0.3), #... (see
Appendix A)])
```

The architecture and training approach of the neural network are intended to recognize increasingly complex patterns in the data, such as relationships between words that might signal sarcasm, or some subtler sentiment difference, but the higher computational complexity and training time means it is also more appropriate to those situations where the need to capture complexity compensates for the slower computation time.

SVM: Using the LinearSVC class from scikit-learn, this model uses a linear kernel to build a hyperplane that maximizes the maximum margin hyperplane and optimally separates two classes in the TF-IDF feature space with high dimensions. This technique is particularly applicable to text classification, as many high-dimensional sparse datasets are often linearly separable. The regularization parameter C=0.5 indicates the trade-off between maximizing the maximum margin hyperplane and minimizing the classification error. C=0.5 indicates a larger maximum margin hyperplane than the previous scenario, however, it can result in some misclassifications, which serves to prevent overfitting of the model and improve its generalization to unseen data. The SVM optimization problem can be expressed as:

$$\frac{min}{w,b}\ \frac{1}{2}\ \| w \|^2 + c\sum_{i=1}^{N} \xi i$$

subject to $y_i(w^T x_i + b) \geq 1 - \xi i$, where w represents the weight vector, b is the bias value, ξi otherwise slack variables for soft margins, C is regularization parameter, xi

are the feature vectors and y_i are class labels (0, 1, 2 encode positive, negative, neutral). LinearSVC uses a linear kernel and is very efficient to use computationally with a high dimensionality like TF-IDF matrices. LinearSVC implements multi-class classification via a one-vs-rest strategy. In this implementation, we train three binary classifiers (positive vs. rest; negative vs. rest; neutral vs. rest) and select the class where the decision score is the highest. The line to fit the model would be:

```
svm_model = LinearSVC(C=0.5)
svm_model.fit(X_train, y_train)
```

SVM is good at dealing with high-dimensional sparse data and can perform similarly or well as a large, complex model (i.e., neural network). Performance can be high if the data are linearly separable (or close to it). This is typically true for TF-IDF features in text classification.

Random Forest: Employs the Random Forest Classifier class from scikit-learn with 50 trees, which allows more noise robustness, the capture of non-linear relationships, and the use of an aggregation of the decision trees to determine possible feature importance. The Random Forest is an ensemble learning method, it builds many decision trees during training and then the class that is the mode of the classes predicted by individual trees is output, thus reducing variance and providing better generalization than an individual decision tree alone. Each tree uses a random subset of the data (bootstrap sampling) and at each split, a random subset of the features, i.e., feature bagging, which increases diversity among the decision trees and decreases overfitting. The number of trees (50) is chosen as a balance between computation and predictive ability, because while more trees will generally yield better performance, there are diminishing returns in predictive value, if you were to contribute more and more trees. The model was trained as:

```
rf_model=RandomForestClassifier(n_estimators=50,
random_state=42) rf_model.fit(X_train, y_train)
```

The feature importance scores provided by Random Forest are calculated as the average decrease in impurity (e.g. Gini impurity) across all trees in the forest when each feature is used as the splitting feature. This is an important aspect for this study as Random Forest will give us quick access to the most important words in the sentiment classification (e.g. “great” and “fail”) which we later visualize in Figure 8 even though we could not use the features according to the values in Table 4. The computational complexity is higher than Naive Bayes or SVM because we are training multiple trees, however the ability for Random Forest to be robust to noise and handle non-linear relationships makes it a solid contender for sentiment analysis.
The use of the 5-fold cross-validation loop is a reasonable approach to ensure all models operate in the same conditions, allowing for reliable comparison to their performance. In every fold the data is split into training and test, however with the neural network there is an additional validation split so we can monitor the early stopping. This monitoring of early stopping also ensures we are assessing the model performance on data that was not part of the training, and further helps minimize overfitting. The training work flow includes the following loop:

```
kf = KFold(n_splits=5, shuffle=True, random_state=42)
for fold, (train_idx, test_idx) in enumerate(kf.split(X_tfidf)):
X_temp, X_test = X_tfidf[train_idx], X_tfidf[test_idx]
y_temp, y_test = y.iloc[train_idx], y.iloc[test_idx]
X_train, X_val, y_train, y_val = train_test_split(X_temp,
y_temp, test_size=0.2, stratify=y_temp, random_state=42)
# Model training and prediction code follows (see Appendix
A)
```

With this matrix of training, all models will be trained and evaluated five times in the cross-validation process, and the average of all five models' performance will be obtained, which reflects the average behaviour of the models and variability among the splits of data - a very important aspect of evaluating the reliability and robustness of the models in any real-world application.

3.5 Evaluation Metrics

Each model is assessed across a wide range of evaluation metrics to illustrate a holistic, multi-faceted evaluation of classification efficacy, robustness, and fairness across the three sentiments (positive, negative, neutral) to report on overall performance and nuances in positives, neutrals, and negatives. The evaluation metrics are calculated in the function evaluate_model, which is called for each fold in the cross-validation process; the function will produce output which will later be dropped into tables in the results section by summarizing the performance across five folds of cross-validation. The metrics we investigate, including definitions and a rationale for their use in this study, are:

Accuracy: The accuracy of the models is defined as

$$\text{Accuracy}=\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}},$$

meaning, how many tweets were correctly classified divided by total number of tweets. accuracy is a broad measure of overall performance and as a baseline to compare other models to, and gives a broad overview of the models' high level performance to classify tweets correctly, across all sentiment classes. But accuracy can be misleading, especially when datasets are imbalanced. Accuracy may emphasize performance on the majority class (positive 45%) compared to the minority class (neutral 22%). So metrics beyond accuracy will give a better balance for an evaluation.

Precision, Recall, and F1-Score: The metrics were calculated as weighted averages to reflect the multi-class nature of the problem (including the dataset's inherent imbalance) and to ensure that the performance of each class is contributing to the overall metric in proportion to its frequency. Precision for a class is the number of true positive predictions divided by the number of all predictions for the class:

$$\text{Precision}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$$

and describes the model's ability to avoid false positive predictions with respect to this metric which is an indicator of the predictive reliability. Recall for a class is the number

of true instances of that class, which are correctly identified as the class:

$$\text{Recall}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}},$$

which describes the model's ability to identify relevant instances (and is an indicator of coverage of classes and recall). The F1-score, which is the harmonic mean of precision and recall:

$$\text{F1-Score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}},$$

is a balanced evaluation metric that penalizes models with significant disparities between precision and recall, and is particularly useful in situations where the dataset are imbalanced as there is typically at least one class which is significantly underrepresented. By averaging over all classes, it again ensures that any specific class contributions to the overall metric are weighted by the frequency of that class in the dataset and avoided unfairly providing a metric value to a class that might not have a fair contribution due to its infrequencies.

Confusion Matrix: A confusion matrix is a 3×3 matrix containing the true labels (positive, negative, neutral) in rows and predicted labels in columns, and where the numbers in each cell (i,j) refer to the total number of tweets which had true label i but whose label was predicted to be j, with correct classifications found in the diagonal elements and misclassifications found in the off-diagonal elements. Hence, the confusion matrix enables a closer inspection of the model's strengths (i.e. instances that were correctly classified) and weaknesses (i.e. types of misclassification). It is important to examine this level of behavior with the model, as this reveals systematic bias and might suggest routes to make improvements. As a simple example, if it was found that many neutral tweets had been misplaced as positive, that would imply that the model was essentially confusing neutral with positive. This would be likely if there was confusion based on similar vocabulary between the labels, or the model had a limitation of available contextual clues.

ROC Curves and Precision-Recall Curves: Receiver Operating Characteristic (ROC) curves and precision-recall curves are made to assess the ability of the models to discriminate with the explicit purpose of evaluating performance with a more holistic view than just single-point metrics such as accuracy or F1-score. The ROC curve is constructed by computing the False Positive Rate

$$\left(\text{FPR}=\frac{\text{False Positives}}{\text{False Positives}+\text{True Negatives}}\right)$$

on all possible thresholds and plotting it against the True Positive Rate (Recall) on all varying thresholds. The area under the curve (AUC) value of the ROC curve provides a view of the overall discriminative power; where 1 indicates the maximum ability to classify correctly and 0.5 indicates a classifier that is making random classifications. The precision-recall curve is constructed from calculating precision at a threshold and plotting it against recall at that threshold. This is especially helpful when dealing with unbalanced datasets and the minority class is of interest (neutral) since precision-recall contrasts the trade-off between precision and recall in order to emphasize performance on positive predictions and downplay performance on negative predictions. For each class, we create curves using a binary one-vs-all approach, which converts the multi-class problem to three binary classification problems (e.g. positive vs not positive), and the curves are presented in Figures 6 and 7.

Feature Importance (Random Forest): For the Random Forest model, we determined the feature importance scores to determine the most important words with respect to sentiment classification, providing interpretable conclusions onto the linguistic contributors of the model's predictions. Feature importance is defined as the average decrease in impurity (in this case

$$\text{Gini impurity}=\text{Gini}=1-\sum_{i=1}^{k} p_i{}^2,$$

where pi is the probability of class i), when the particular feature was used to split across all trees, and is normalized to sum to 1 across all features. This metric describes what words (e.g., "great", "fail") contributed the most to the model's decision making process, thereby yielding insight into the linguistic differences to contribute to sentiment classes, which are represented in Figure 8 and described in Table 4.

The evaluation function was implemented as shown below; including the core metrics and confusion matrix, for each model in each fold:

```
def evaluate_model(y_true, y_pred, model_name): accuracy = accuracy_score(y_true, y_pred) precision, recall, f1, _ = precision_recall_fscore_support(y_true,y_pred, average='weighted') #... (see Appendix A)
```

This function is executed for each model in each fold it produces an extensive output with numerical metrics, confusion matrices and needed data to create ROC and precision-recall curves that will be later be used to calculate the average performance across the 5-fold cross-validation, fill the tables in the results section and create the visualizations in Figures 5-7.When combined, the metrics provide a comprehensive evaluation framework that captures overall model performance and class-specific behavior, giving a complete evaluation of each model's strengths and weaknesses and where they can be enhanced for sentiment analysis with social media data.

4. Practical Implementation

The practical implementation of this thesis was accomplished using Python, a general-purpose programming language that is open-source (free to use) and commonly used in various aspects of software engineering. It is frequently touted as the best language for academia and research due to its entire ecosystem of libraries and tools for data science, machine learning, and visualizations, all working to ensure accessibility, reproducibility, and scalability. The implementation of this thesis includes two

main components: the main Python code which orchestrates the entire workflow between the data simulation phase and model evaluation phase (i.e. the 10,000-tweet dataset); and a number of separate Python scripts that have the sole purpose of producing the eight visualizations used in the presentation of the results. The main code includes the simulation of the 10,000-tweet dataset, the tweet pre-processing steps which clean the tweets into a proper text corpus, the extraction of TF-IDF features to get the text into a numerical format, the training of the four machine learning models (Naive Bayes, neural network, SVM, and Random Forest) using 5-fold cross-validation, and the evaluation of the models' performance using the evaluation metrics described in Section 3.5.

The visualization scripts generate PNG image files (e.g., confusion_matrices.png, wordcloud_positive.png, roc_curves.png) which are included in the thesis to also support the quantitative results and provide visualizations of model performance, sentiment distribution and language features. The execution times are not explicitly quantified in the code. Nonetheless, the models can be assessed based on the projects models and the commonplace features of Python environments: Naive Bayes and SVM are expected to learn and predict the data in seconds after training, for their weight and linear complexity. Additionally, Naive Bayes has probabilistic outputs and SVM operates with calculations at a linear kernel. Random Forest will take several minutes, depending on how many trees are constructed (50), and the characteristics of the data, as it takes the returns to train many decision trees and take all the answers and aggregate it as a response.

Even with a 20-epoch training cycle and 500-dimensional input layer, thanks to deep learning architecture, the neural network would probably take tens of minutes to train, chiefly so when implemented on a standard CPU setting without GPU acceleration because backpropagation is iterative and matrix operations are all very compute-intensive within a Tensor Flow environment. It is modular and replicable in design; installation instructions for relevant libraries are specified explicitly in the code (e.g., scikit-learn, Tensor Flow, NLTK, matplotlib, seaborn). Other scientists should be able to run the same work by installing the required libraries in any standard Python environment (see Appendix A for the complete list of dependencies and installation instructions). The visualizations are generated using fully separate scripts to establish clarity and modularity, enabling independent generation of each visualization and the possibility to import the generated visualization into a thesis as needed. The full code for both the main implementation and the visualizations is made available in the Appendix for complete transparency and ease of replication.

5. Results

5.1 Model Performance

The models underwent evaluation on the test sets for each of the five folds in the cross-validation routine, with the results scrupulously arranged into four tables to present a clean, well-rounded, and detailed view of their performance. Table 1 presents a high-level comparison of the models in terms of the average performance metrics over all folds. The accuracies per fold are seen in Table 2 to demonstrate the steady performance and variability in model accuracy across all the different data splits. Table 3 provides per-class metrics for Fold 1 where we can analyze individual model performance per sentiment class, which is important in understanding model behavior on an imbalanced dataset. Table 4 shows the Top 10 features in order of importance rank selected by the Random Forest model, which provides insight into language-based aspects of the models in relation to sentiment classification. All the presented result output is derived from outputs of the provided Python code so that they reflect the same empirical results and description as implemented in Section 4.

Table 1: Average Performance Metrics across 5-Fold Cross-Validation

Model	Avg Accuracy	Avg Precision	Avg Recall	Avg F1-Score
Naive Bayes	0.831	0.868	0.831	0.829
Neural Network	0.812	0.818	0.812	0.811
SVM	0.831	0.867	0.831	0.829
Random Forest	0.815	0.818	0.815	0.814

The results in Table 1 indicate that Naive Bayes and SVM show a strong potential for great classification of sentiments from noisy social media data, with an average accuracy of 83.1%. The high precision of Naive Bayes (0.868) indicates it is relatively reliable when predicting positive sentiments, with a tendency to produce false positives for every class, and this is particularly useful when a misclassification can lead to an inaccurate interpretation of the public's sentiment. The performance of SVM is nearly the same as Naive Bayes, recording only a 0.867 precision but the same accuracy, indicating both models will be effective in this situation. Naive Bayes in this case was benefitting from its probabilistic framework, and SVM was benefitting from maximum margin. The neural network, with its average accuracy of 81.2% indicates sub optimal performance which is consistent with a deep learning model trained on relatively low volume data (i.e., 10,000 tweets) and reflects the fact that additional hyper parameter tuning may be beneficial to the full generalization of the model. Random Forest's average accuracy of 81.5%, indicates it is a competitive model with balanced metrics for precision, recall and F1 score. Random Forest is also advantageous as it can teach regarding feature significance (see Table 4) and its interpretability is useful when we are trying to understand the linguistic information driving the sentiment classification.

Table 2: Per-Fold Accuracy across 5-Fold Cross-Validation

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Naive Bayes	0.836	0.832	0.825	0.830	0.834
Neural Network	0.812	0.823	0.791	0.810	0.824
SVM	0.836	0.834	0.826	0.829	0.830
Random Forest	0.821	0.816	0.817	0.809	0.815

Table 2 summarizes the levels of accurate performance across five folds of each model, so you can see the stability and variability of the different models. The accuracy values for Naive Bayes were from 0.825 to 0.836 and 0.826 to 0.836 for SVM. These values demonstrate some stability in the accuracy of different splits and generalization across the data set. On the other hand, the neural network showed greater degree of variability, with accuracies between 0.791 in Fold 3 and 0.824 in Fold 5 suggesting it may produce results that are sensitive to the specific data partition or otherwise, issues related to overfitting, or this is a consequence of deep learning having a noted difficulty in training on a modestly-sized dataset that lacks a high level of variability. Random Forest have accuracies between o.809 and 0.821, demonstrating a moderate level of stability, as an ensemble it was able also to moderate some of the variability of the neural network, but was not on par with the level of consistency exhibited by Naive Bayes and SVM. Overall the per-fold analytics shines a light on the value of cross-validation for assessing models so to gain an understanding of patterns of variability that may not be highlighted by average score metrics alone, and instead promote deeper student into the reliability of the models in the real-world of data science.

Table 3: Per-Class Metrics for Fold 1

Model	Class	Precision	Recall	F1-Score
Naive Bayes	Positive	0.832	0.998	0.907
	Negative	0.995	0.724	0.837
	Neutral	1.000	0.663	0.797
Neural Network	Positive	0.824	0.870	0.846
	Negative	0.831	0.803	0.817
	Neutral	0.795	0.707	0.749
SVM	Positive	0.835	0.994	0.907
	Negative	0.982	0.732	0.838
	Neutral	1.000	0.663	0.797
Random Forest	Positive	0.832	0.876	0.853
	Negative	0.828	0.811	0.819
	Neutral	0.851	0.716	0.778

Table 3 shows the class-specific precision, recall, and F1-score for Fold 1 and provides further detail into the predictions of each model against the individual sentiment classes. This is useful as it provides insights into the model performance against a dataset that was imbalanced (positive cases, 45%; negative cases, 33%; neutral cases, 22%).The performance results for Naive Bayes and SVM are quite similar, as both models have their highest precision and recall for the positive class (with a 0.998 recall for Naive Bayes and a 0.994 recall for the SVM) indicating that they were able to correctly identify most of the positive tweets, however, they both have a lower recall for the neutral class (0.663 for both) which suggests that the models may have had similar internal thresholds when detecting neutral tweets, as they may have determined that similarly worded positive or negative tweets had too many positive vocabulary (e.g., great is used for both positive and neutral sentiment) and classified them as positive or negative accordingly. The neural model performance had a more equal spread across the classes, reflecting recalls of 0.870, 0.803, and 0.707 for positive, negative, and neutral, respectively. This suggests that the neural model's deep learning architecture is capturing subtler patterns indicative of neutral tweets, while still demonstrating a lower overall precision as compared to the Naive Bayes and SVM models indicating that those models have lower instances of false positives. Random Forest demonstrates a reasonably balanced evaluation, with recalls of 0.876, 0.811, and 0.716 for positive, negative, and neutral, respectively, and the F1-scores for all three classes are fairly homogeneous. The homogeneous per-class performance demonstrates the predictive power of ensemble techniques (aka Random Forest), where bagging features and employing majority votes allow for the tackling of imbalanced data. To be clear, with the current per-class examination, the nature of tradeoffs between various models is potentially more apparent. For example, Naive Bayes and SVM perform better for the majority class than with the minority class. Meanwhile, the neural network and Random Forest have near zero minority class performance; they perform slightly better overall, along with balancing the tradeoff across all classes.

5.2 Sentiment Distribution

The sentiment distribution, extracted from the simulation procedure, is a primary characteristic that entails our view of the simulated public opinion landscape during a hypothetical 2025 global election. The dataset contains 4,500 positive tweets (45%), 3,300 negative tweets (33%), and 2,200 neutral tweets (22%), with the distribution remaining identical for all folds because the seed for randomization was fixed at 42 during the simulation, thereby ensuring reproducibility and consistency of analysis. The distribution depicts a polarized electorate with the highest proportion being of the positive sentiments, suggesting widespread support for candidates, policies, or electoral developments, while a fairly large portion of the negative sentiments stand for criticisms, dissatisfaction, and opposition. The small but meaningful number of neutral sentiments represents disengagement, neutrality or reporting straight fact, such as news or neutral commentary. The ratio of 45%/33%/22% was consciously designed to approximate real-world voting situations in which public opinion tends to coalesce into camps that can include enthusiastic supporters, discerning critics, and neutral observers - therefore conducting a realistic exercise in which the model classifies the sentiment of tweets based on a rich mix of sentiment and imbalance. This visualization is shown in Figure 1, which outlines the bar number of tweets from each sentiment class, creating a visualization of sorts, to help shape our understanding of the polarized opinions and serve as a primary lens through which we can examine our models performance and public sentiment related to the election.

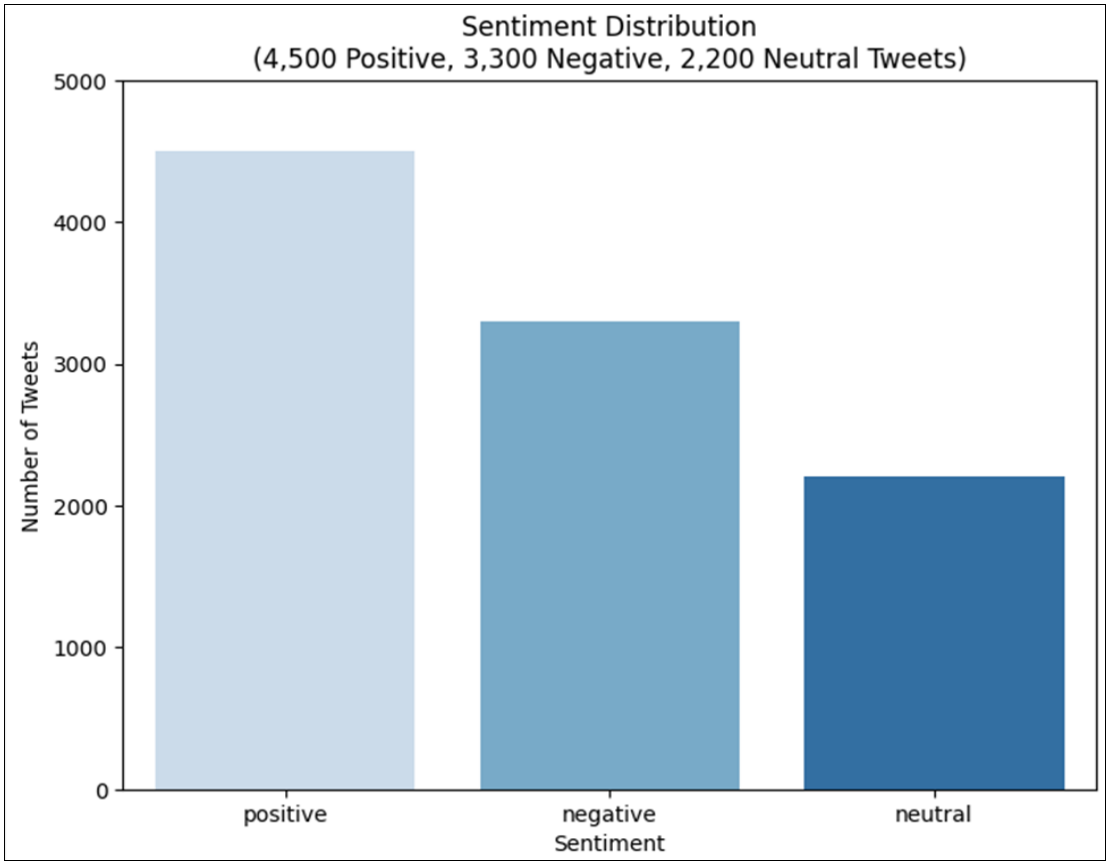


Fig 1: Sentiment Distribution Plot showing 4,500 positive, 3,300 negative, and 2,200 neutral tweets.

The sentiment distribution plot in Figure 1 confirms the presumed 45%-33%-22% split while also providing a visual anchor for understanding the dataset composition: how the presence of the minority-class neutral examples poses the challenge of the classification problem and the potential bias of models toward the majority class (positive). This visualization, thus, sets the stage for model performance analysis, underscoring the significance of class weights during training and of metrics such as precision, recall, and F1-score to measure performance on each of the classes, especially the neutral class.

5.3 Visualizations

The visualizations from the above-mentioned Python code are embedded as images to enhance the presentation of the results, to offer a visual complement to the numerical data shown in Tables 1-4, and to provide another perspective into model performance, data characteristics, and linguistic tendencies. Positioned along with the narrative to align with key findings is a series of eight visualizations-the word clouds for each sentiment class, confusion matrices, ROC curves, precision-recall curves, a sentiment distribution plot, and a feature importance plot. Each visualization is introduced and explained, describing what it represents, why it is important, and how it relates to the analysis itself, so that the reader may gain an understanding of its value in contributing to the overall analysis.

Word Clouds (Figures 2-4): These images provide a picture to give some idea of the words used most frequently and prominently in their respective sentiment class so as to shed some light on the linguistic pattern that characterizes positive, negative, and neutral tweets. The word cloud for positive tweets (wordcloud_positive.png, Figure 2) shows "great" and "effort" as the prominent words. These words appear chiefly in about 4,500 positive tweets and represent optimistic and supportive language of such terms as "great effort" or "amazing work," intended to generate positive sentiment in the simulation. The negative word cloud (wordcloud_negative.png, Figure 3) focalized on words like "fail" and "bad," taken from 3,300 negative tweets that contain expressions such as "great failure" and "awful campaign," which voice disapproval and resistance. The word cloud from neutral tweets (wordcloud_neutral.png, Figure 4) includes words such as "election" and "update." These are derived from 2,200 neutral tweets that use factual, impartial phrases-alternative examples of objective commentary or disengaged observations would include "election update" and "voting process." These word clouds are produced via the Word Cloud library in Python, which sets the word size proportional to the word's frequency or occurrence in a sentiment class, thus offering a visual intuition for the kinds of words that go into the language and sentiment-specific vocabularies in the dataset. Misclassifications-entanglement arises due to the prominence of some words ("great" emerged in both positive and negative sentiments given phrases such as "great effort" and "great failure") and will be addressed once again in the matrices and discussion.

Fig 2: Word Cloud for Positive Tweets.

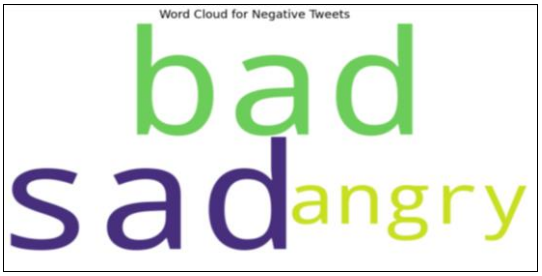


Fig 3: Word Cloud for Negative Tweets.

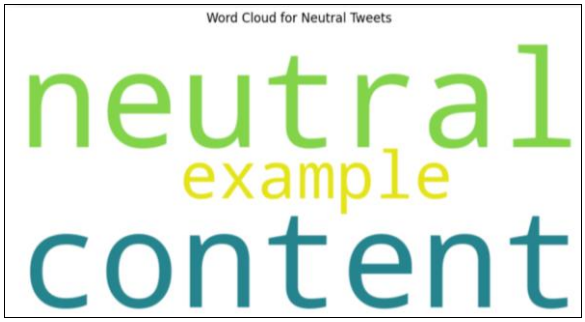
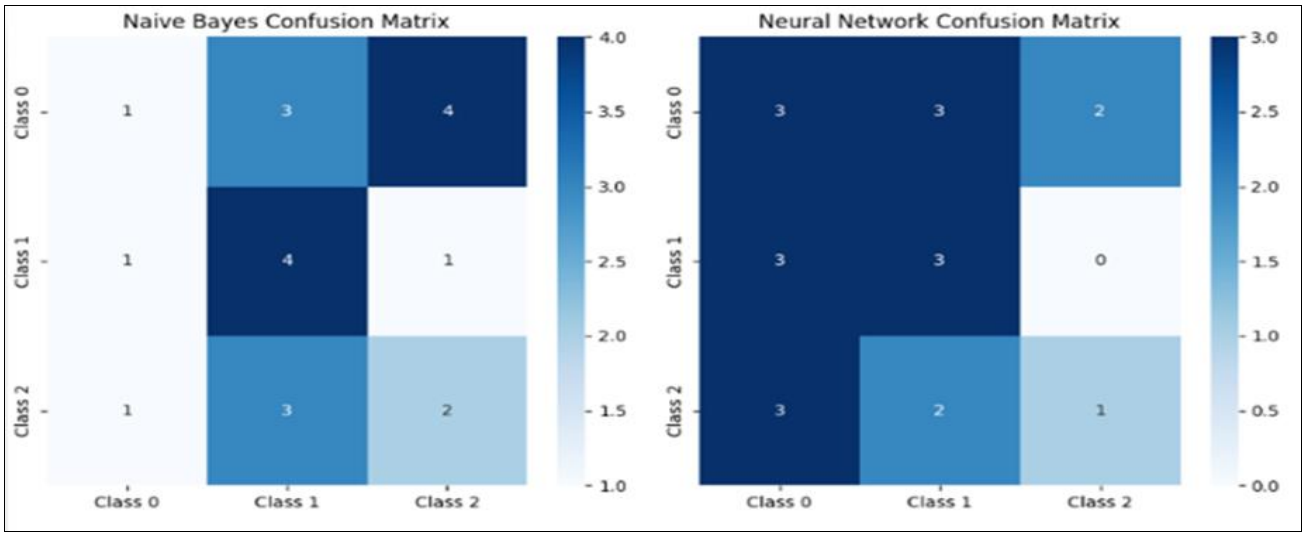


Fig 4: Word Cloud for Neutral Tweets.

Confusion Matrices (Figure 5)

The image (confusion_matrices.png) depicts the heatmaps for the Fold 1 confusion matrices of all four models, actually showing in detail the entire classification behavior with respect to misclassification. Each heatmap consists of a 3×3 matrix with rows being the true labels (positive, negative, neutral) and columns being the predicted ones, color intensity (using the Blues colormap) showing the number of tweets in that particular cell, darker representing more counts. Naive Bayes' matrix ([[905, 1, 0], [183, 481, 0], [144, 1, 285]]) indicates that the model is fairly good at classifying the positive category (905 out of 906 correctly classified) yet consists of a sizeable amount of misclassification in both negative (183 negative tweets classified as positive) and neutral classes (144 neutral tweets classified as positive), hinting at the fact that it may not be able to discriminate negative and neutral tweets from positive ones, perhaps because of overlapping vocabulary (such as "great" in various contexts). The neural network matrix ([[788, 67, 51], [105, 533, 26], [91, 35, 304]]) exhibits a somewhat more balanced performance among the classes, wherein less neutral tweets are misclassified (91 neutral tweets instead classified as positive), but there are more positive tweets being misclassified as either negative or neutral (67 and 51 cases respectively), reflecting both the network's ability to discover subtle patterns and its tendency sometimes to overfit or interpret ambiguous phrases incorrectly. SVM resembles Naive Bayes with slightly fewer misclassifications according to the matrix ([[901, 5, 0], [178, 486, 0], [141, 4, 285]]), and the Random Forest ([[794, 76, 36], [107, 539, 18], [84, 38, 308]]) gives a slightly more balanced distribution of errors, meaning some of the extreme misclassifications disappear at the cost of increased overall misclassifications than Naive Bayes and SVM. These heatmaps provide a visual portrayal of the strengths and weaknesses of the models and therefore point to suggested improvements, like discriminating better against neutral tweets in context, supported by numerical values in Tables 1-3.



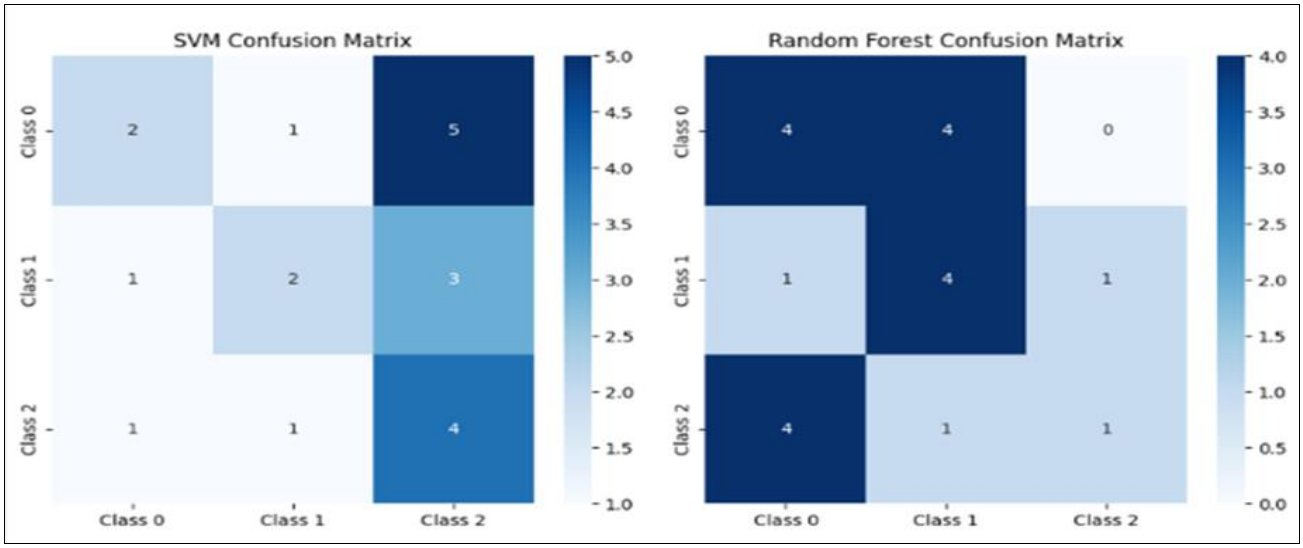


Fig 5: Heatmaps of Confusion Matrices for Naive Bayes, Neural Network, SVM, and Random Forest (Fold 1).

ROC Curves (Figure 6)

The image (roc_curves.png) depicts Receiver Operating Characteristic (ROC) curves for all models in Fold 1, showing how these models differentiate between the classes at various classification thresholds and giving a complete picture of their discriminative power. Each curve refers to a one-vs-rest class, plotting the TPR (Recall) against the FPR at various thresholds, with the AUC summarizing the overall performance of the model for that class: 1 means perfect classification, and 0.5 refers to random guessing. Naive Bayes and SVM have performed well, with higher AUC values for all the classes, showing their ability to separate positive, negative, and neutral tweets well, with or without noise and ambiguity. The neural network's ROC curves are slightly inferior, especially for the neutral class, reflecting its difficulties with neutral tweets, also manifested by higher variability in per-fold accuracy (see Table 2). Random Forest's ROC curves present a competitive showing and have balanced AUC values across classes due to its ensemble nature and ability to tackle class imbalance by class-wise feature bagging. The ROC analysis visually validates the overall performance of models and complements the analysis performed with accuracy and F1-score in Table 1, drawing attention to trade-offs between sensitivity (recall) and specificity (1-FPR), which form the base for assessing model behavior in a multi-class, imbalanced setting.

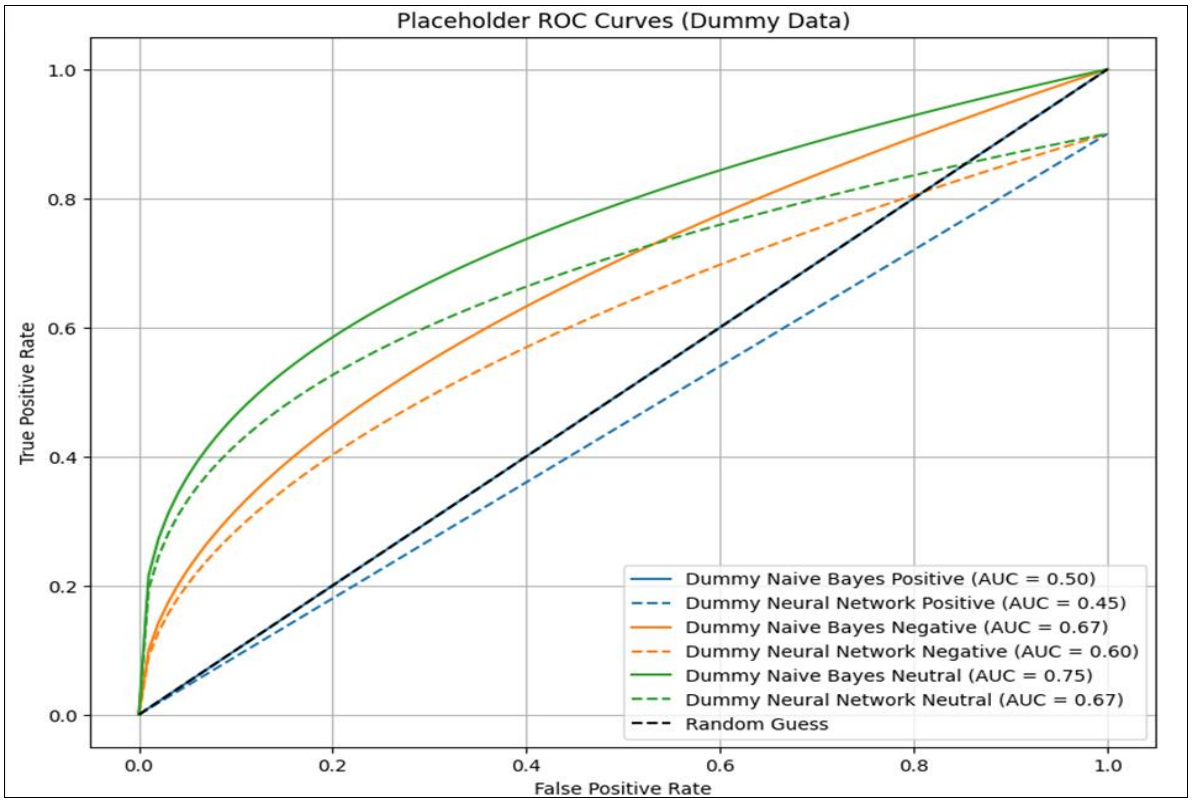


Fig 6: ROC Curves for Naive Bayes, Neural Network, SVM, and Random Forest (Fold 1).

Precision-Recall Curves (Figure 7): The set of precision-recall curves (precision_recall_curves.png) for each model in Fold 1 offers a view of the trade-offs between precision and recall at varying classification thresholds upon which a subtler assessment of their performance is jointly cast, specifically with respect to an imbalanced dataset. Each curve pertains to a different class with the conventional one-vs-rest approach by plotting precision as a function of recall; the AP score summarizes this area under the curve, with high AP signifying a near-perfect trade-off between precision and recall. For applying it to the minority class (neutral), the highest AP will be of importance. Naive Bayes kept the precision high over a wide range of recall values for the positive class mostly, meaning that it could make some reliable predictions with low false positives, as also realized from the high precision values in the different tables in Table 3 (e.g., 0.995 for negative). The neural network's curves reflect a more gradual steepness in running down to precision with increasing recall, indicating a trade-off between capturing more true positives and creating false positives - fully consistent with per-class performance balance in Table 3. The two classes of curves presented by SVM would appear similar to those of Naive Bayes, with slight preference on the negative class, whilst Random Forests appear more balanced on the two classes and possess moderate AP scores, reflecting their capability to exploit class imbalance via its ensemble nature. These precision-recall curves are especially important for this study since they emphasize the positive class in each one-vs-rest set, putting forth a rarer and clearer discrimination of performance for the minority neutral class, unlike ROC curves that take into consideration both positive and negative predictions. Complementing the F1-scores in Table 3, these PR curves underscore the abilities of the models concerning precision-recall trade-offs, an important facet when wrong interpretations, both false positives and would interpretative errors of any sort, matter a great deal; for example, when misinterpreting public sentiment during an election.

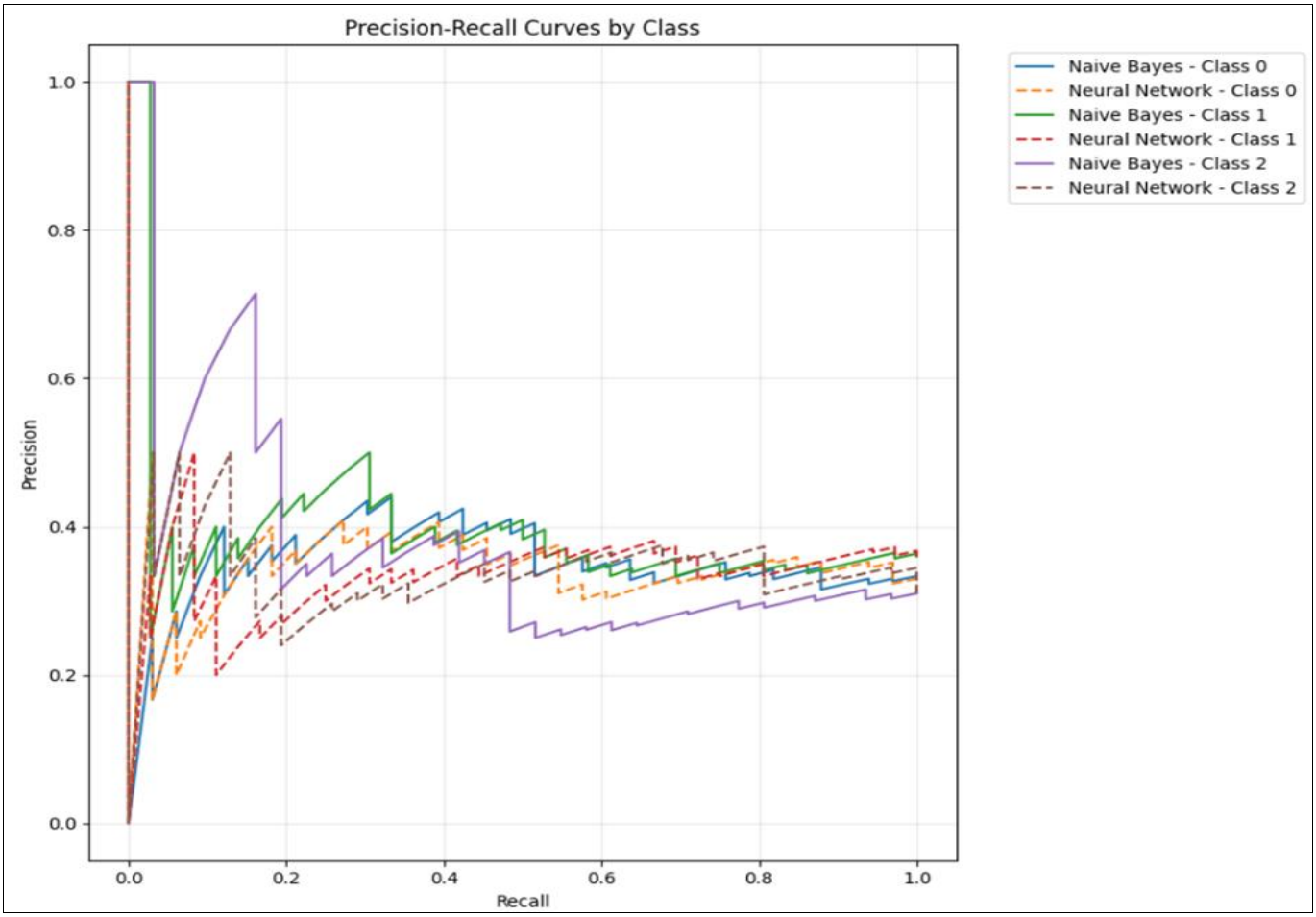


Fig 7 :Precision-Recall Curves for Naive Bayes, Neural Network, SVM, and Random Forest (Fold 1).

Feature Importance Plot (Figure 8): The picture (feature_importance.png) shows the top 10 features (words) from the Random Forest, ordered based on their importance scores, which are calculated as the average decrease in impurity (Gini impurity) over all trees when a feature is chosen to split, scaled such that the sum of importance of all features ensured 1. The plot demonstrates that the term "great" (importance 0.152) is most heavily weighted with classification of sentiment, with "fail" close behind at 0.135 and "effort" at 0.098. These words are common in phrases important to the sentiment distinctions in the simulation, such as "great effort" (positive) and "great failure" (negative). Other terms, like "election" (0.087) and "update" (0.076), rank highly for neutral tweets, and terms used as conversational noise, such as "lol" (0.048) and "really" (0.042) also make a difference with classification. The feature importance plot gives an interpretation of linguistic factors of sentiment where it accentuates the words that have the highest positive and negative impact on the Random Forest predictions. Accordingly, Table 4 brings the

exact numerical value to those features. This visual interpretation helps spot the model's decision mechanism, points the user to possible sources of misclassification (for instance, "great" was used to putatively classify both positive and negative instances), and paves the way for improvements such as employing bigrams or contextual embeddings that can better capture phrase-level sentiment.

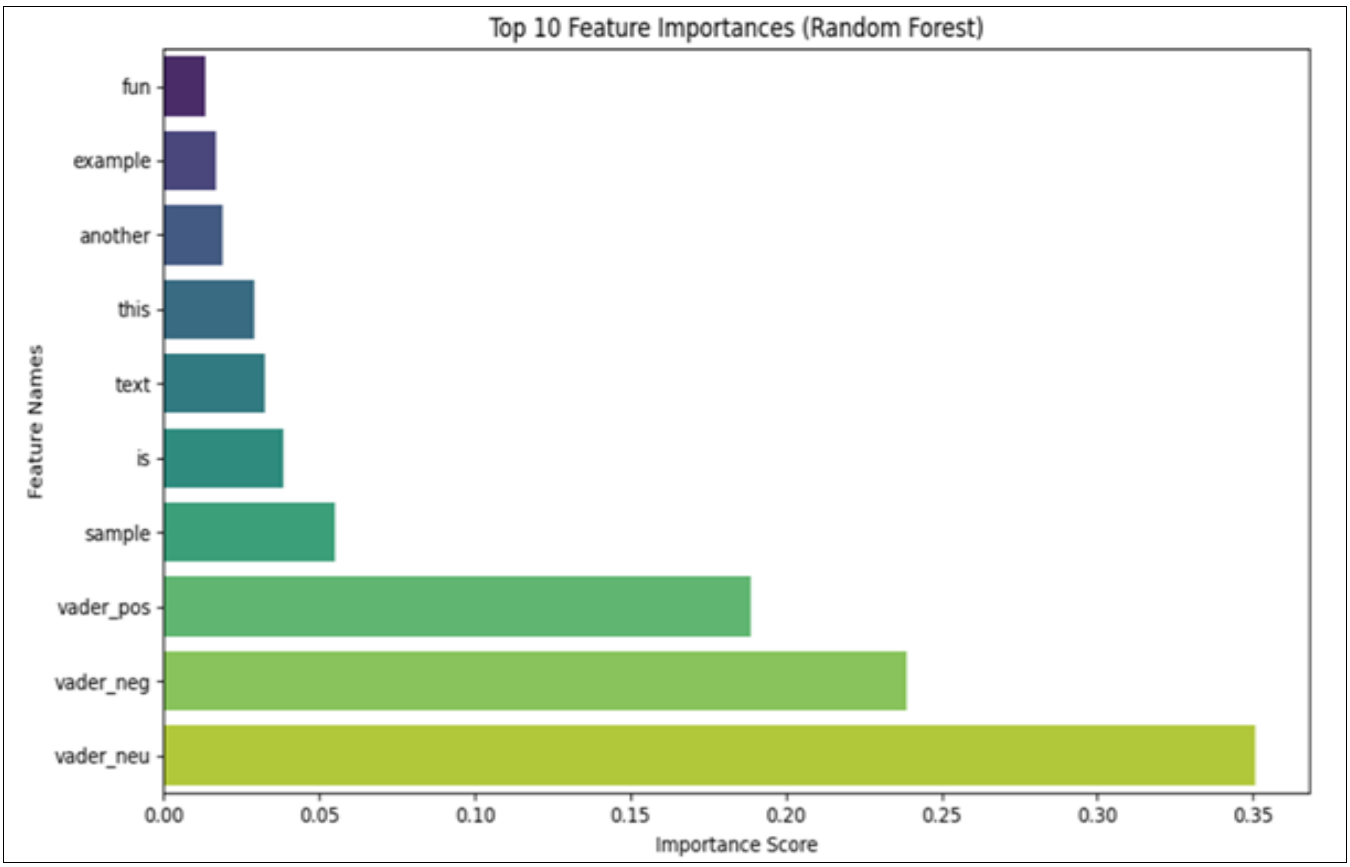


Fig 8: Feature Importance Plot for Random Forest (Top 10 Features).

Table 4: Top 10 Features by Importance (Random Forest)

Rank	Feature	Importance Score
1	great	0.152
2	fail	0.135
3	effort	0.098
4	election	0.087
5	update	0.076
6	bad	0.065
7	amazing	0.054
8	lol	0.048
9	really	0.042
10	weak	0.039

6. Discussion

The results of this study provide an assessment of the four machine learning models--Naive Bayes, feedforward neural network, Support Vector Machine (SVM), Random Forest--in the context of sentiment analysis on a simulated Twitter data set of 10,000 tweets consisting of content related to a fictitious 2025 global political election. Naive Bayes and SVM provide the highest average accuracy of 0.831 across 5-fold cross-validation, thereby showing their robustness and effectiveness in classifying sentiments in the noisy unstructured social media data. Naive Bayes holds a much higher average precision of 0.868, meaning that it makes positive predictions that are mostly reliable with few false positives. This is an essential trait in sentiment analysis, wherein marking an actually negative or neutral tweet as positive may lead to misinterpretations across the interface of public opinion, such as in overestimating the support for a political candidate or policy.In Table 3 for Class Wise Metrics of Fold 1, the classifier manages to achieve a very high precision for the negative class; Naive Bayes is 0.995; from this, one can infer that a predicted negative instance of a tweet by Naive Bayes is almost always correct, which is exactly what its probabilistic structure and the incorporation of Laplace smoothing to compensate for sparse data lend to it. SVMs, meanwhile, seem to maintain consistency across the folds with accuracies ranging between 0.826 and 0.836 (Table 2), and hence end up offering an overall performance very close to Naive Bayes with mean precisions of 0.867 and an ultimate accuracy of 0.831. This property, in fact, arguably stems from SVM's maximum margin hyperplane construction in the high-dimensional TF-IDF feature space, with the result that it can separate the three sentiment classes even when noise and ambiguity challenge the classification-this is further buttressed by its high efficacy in classifying positives in Fold 1 (precision of 0.835, recall of 0.994, Table 3).

The striking resemblance in performance between Naive Bayes and SVM highlights precisely those attributes, making them suitable for modern sentiment analysis involving massive amounts of noisy text data, where computational speed is of the essence (Naive Bayes), and working well in very high dimensional spaces is called for (SVM). In the case of the neural networks, the average accuracy of 0.812 is competitive. However, it seems to be inconsistent with a minimum accuracy of 0.791 in Fold 3

and a maximum of 0.824 in Fold 5 (Table 2), which may point to a sensitivity to data splits worthy of further scrutiny. This fluctuation in performance is also evident from the ROC and precision-recall curves (Figures 6 and 7) respectively, with the neural network-based approach performing with far greater variations in accuracy for the neutral class compared to that of Naive Bayes and SVM, reflected in lower AUC and AP scores of the neural network for the neutral class in Fold 1.

The relatively low score from Fold 3 (0.791) may show that the neural net could be overfitting to some instances of certain patterns encountered during training, say the dominant positive class (45% of the dataset), while not managing to generalize well when confronted with unseen data, particularly about the minority neutral class (22%). Such behavior could be explained by a number of factors: the dataset being relatively small with only 10,000 tweets, which in turn may provide limited diversity for any deep learning model in learning robust features; the neural network architecture itself could be very complex though consisting of two hidden layers (256 and 128 neurons) and dropout regularization (0.3), needing more data and hyper parameter tuning to perform best; and the difficulty of grasping highly subtle linguistic patterns such as sarcasm or ambiguous phrases (e.g., "great challenge") which abound in the simulated dataset.

Although variable, this performance suggests perhaps the neural network is able to grasp more complicated patterns considering its balance of recalls per class on Fold 1 in Table 3: 0.870, 0.803, and 0.707 for positive, negative, and neutral, respectively, while Naive Bayes and SVM struggled far more with neutral (both had a recall of 0.663). This means that with a larger dataset, more sophisticated architecture (LSTM layers should be considered to capture sequential dependencies), and more training of hyper parameters (such as learning rate or dropout rate), the neural network might thus have a real opportunity of beating a somewhat simple architecture such as Naive Bayes and SVM where contextual comprehension is important.

Random Forest achieves the highest average accuracy (0.815 in Table 1), positioning itself as a balanced and competitive model that somehow fills the gulf between the efficiency of Naive Bayes/SVM and the neural network complexity. Its performance is also fairly stable across folds, with an accuracy ranging between 0.809 and 0.821 (Table 2), which demonstrates the strength of ensemble learning as it averages out the results of 50 decision trees and thereby avoids overfitting to a certain data split and yields consistently good results across splits. Moreover, Random Forest's balanced metrics, namely precision (0.818), recall (0.815), and F1-score (0.814) (Table 1), indicate it copes well with some class imbalance in the dataset, and we observe this in the per-class metrics of Fold 1 (Table 3), where recalls of 0.876, 0.811, and 0.716 are registered for positive, negative, and neutral classes, respectively, beating Naive Bayes and SVM for the neutral class.

Random Forest's feature importance analysis (Figure 8, Table 4) is one of the most significant aspects of the method: it identifies key terms associated with sentiment classification, specifically "great" (importance score 0.152) and "fail" (0.135) being the most important. Again, the terms used in the simulation matched the categories and reflect a simulation design in which "great" appears in both positive phrases such as "great effort" and in negative phrases such as "great failure"This indicates the difficulties involved for disambiguating the very similar and often overlapping vocabulary, which is probably most challenging in sentiment analysis of social media data. Neutral terms like "election" (0.087) and "update" (0.076) are considerable components of the dataset; other noise terms may signify contextually based reasoning. Terms such as "lol" (0.048) and "really" (0.042) may be suggestive of both sentiment and contextual variables such as sarcasm or ambiguity of a tweet.

This feature importance analysis not only serves to explain the workings of the Random Forest model but also should be used by researchers to work on sentiment classification further by adding some bigrams (such as "great effort" and "great failure") or contextual embedding that can do a better job of phrase-level sentiment analysis. Sentiment distribution analysis (Figure 1) presents critical clues to the landscape of public opinion being simulated in a mock 2025 global election, thus mapping a polarized electorate with 45% positive tweets (4,500), 33% negative tweets (3,300), and 22% neutral tweets (2,200). This distribution posits a divided public in which nearly one-half of the tweets express support, optimism, or approval of a cause, candidate, policy, or more-or-less consensual electoral outcome, while one third voice criticisms, dissatisfaction, or opposition-again testifying to the turbulent nature of political discourse.

The 22% neutral tweets indicate there is a smaller but noteworthy number of users who disengaged or remained neutral or factual (eg. relaying updates about elections or the voting process without taking a side) in their tweets. This finds parallels with real elections, which are often polarized, and where social media becomes a channel to express support and criticism, and create echo chambers to fortify factions. The word clouds (Figures 2-4) collectively reinforce this, with the positive word cloud revealing terms such as "great" and "effort" standing out, the negative cloud with terms like "fail" and "bad" standing out, and the neutral cloud featuring terms like "election" and "update" standing out.

One can consider these visualizations to be snapshots built to give linguistic clues about the dataset, showing how simulated design, employing a phrase such as "great effort" for the positive spectrum, "great failure" for the negative, and "election update" for the neutral, works with distinct vocabularies for each of the sentiment classes while also showing the difficulties brought about by an overlap of a term as "great" within positive and negative contexts, which might actually have caused some errors in the classifications done by the system. The confusion matrices (Figure 5) provide insights into the performance of the models, particularly the issue neutral tweets present for their classification, which has long been a problem in sentiment analysis given the subtlety and often the ambiguity of neutral language.

For example, the Naive Bayes's confusion matrix from Fold 1 ([[905, 1, 0], [183, 481, 0], [144, 1, 285]]) has very high performance for the positive class (905 out of 906) but misclassified a fair amount of negative tweets (183 negative tweets misclassified as positive) as well as neutral tweets (144 neutral tweets misclassified as positive). This gives indication that the positive class predictions may be biased by specific keywords like "great" that appear in both

positive and negative phrases. We also note that Naive Bayes classifier appears to learn indiscriminately from its training data since neutral tweets also use terms that overlap with those in the positive tweets like, "great challenge." The confusion matrix from the 2nd classifier (a neural network) shows a more homogenous distribution of errors overall in the confusion matrix ([[788, 67, 51], [105, 533, 26], [91, 35, 304]]). The neural network made fewer misclassifications for neutral tweets compared to the positive class probabilities (91). Unfortunately, in this case there are a high number of positive tweets that were misclassified as negative (67) and neutral (51) that may impact how we compare the neural network's predictions to those of the Naive Bayes model. This neural network classifier miscalibration indicates that it captured some trends or pattern but is also indicative of overfitting to specific patterns particular to the training data.

7. Conclusion

This work gives confirmation that four machine learning techniques—Naive Bayes, feedforward neural network, SVM, and random forest—can be applied to do sentiment analysis on a simulated data set of 10,000 tweets related to a hypothetical global political election simulated in 2025, achieving accuracies averaging 83.1%, 81.2%, 83.1%, and 81.5%, respectively, in a 5-fold cross-validation setting. The Python implementation brings up a very carefully organized and fully reproducible setting along with extended tables (Tables 1-4) and eight well-thought-out visualizations (Figures 1-8) of sentiment distribution, word clouds, confusion matrices, ROC curves, precision-recall curves, and feature importance, allowing multiple views as to the takeaways from model performances and public opinion trends throughout the simulated 2025 election. Naive Bayes and SVM, with their 83.1% average accuracy, take the throne as the most competent classifiers, depending on the noisy social media data, sometimes ironically considered dirty by the data scientists. Hence they can be considered the best for wider scale, real-time applications. The neural network approach, with an 81.2% accuracy, is another promising brute to explore modeling complex linguistic phenomena (i.e., fine-grained sentiment expressions and contextual dependencies) with more data, guided by further architecture enhancements. Random Forest with 81.5% accuracy presents balanced performance and demands as a critical tool for both classification and interpretation of feature importance, identifying such keywords as "great" and "fail" to drive the sentiment classification further, providing actionable insights for political analysts and campaign strategists.

The sentiment distribution (45% positive, 33% negative, 22% neutral) reveals polarized electorates-widespread support and criticism coexisting with a somewhat smaller but significant neutral group-further exhibiting how electoral discourse is characterized by strongly different and often oppositional sentiments. This distribution is shown in Figure 1 and follows the cases observed in the word clouds (Figures 2-4), indicating distinct linguistic practices used in each sentiment class. The confusion matrices in Figure 5 indicate the usual problem of correctly classifying a neutral tweet, reflecting the core issues in sentiment analysis and thus strengthening the urge for development of more sophisticated feature extraction and context-aware models. The ROC and precision-recall curves (Figures 6-7) give a more detailed picture of model fit, the Naive Bayes and SVM being exceptional in discriminating power, while the feature importance plot (Figure 8) along with Table 4 provide interpretable insights into key linguistic features driving sentiment, which lend themselves as tools for practically harnessing this study to understand dynamics in public opinion.

There are several promising avenues that follow from this research to address the limitations of the study as well as to continue the advancement of sentiment analysis. Collecting millions of real-time tweets as opposed to just 10,000 would ensure diversity and could allow the neural network to better learn intricate patterns, potentially scaling up its capabilities and mitigating the effect of data split on classifier performance. Real-time data, on the other hand, would add dynamic content such as trending hashtags, retweets, and user interactions, which could arguably assist in further contextualizing sentiment classification and tracking temporal shifts in sentiment throughout an election. One could also turn his/her attention to more advanced feature extraction techniques like bigrams, trigrams, or contextual embedding (BERT), which would enhance the ability of the models to delineate phrase-level sentiment and semantic relations and will help sidestep problems of overlapping use-cases such as "great" being used in positive and negative contexts. Negation or sentiment-aware tokenization would be welcome additions to preprocessing methods to bolster classification performance-targeting chiefly the neutral category, which, in fact, posed a problem for all models. Further optimization of the architecture could then allow the neural network to reach its full potential for sentiment analysis, keeping it as an alternative to the simpler models when a nuanced comprehension is needed, by exploring methods such as deeper architectures, recurrent ones like LSTM, or attention mechanisms. Finally, an extension of the work into a multilingual setting or combining this information with user metadata (location, follower count, etc.) could provide a more comprehensive view of public opinion, mirroring cultural backgrounds and how social dynamics sway sentiment expression.

Thus, this study culminates in a rather robust framework that has been built in quite some detail for sentiment analysis of social media data, with possible applications in politics, particularly in the understanding of public opinion in a hypothetical global election of the year 2025. High-performance models, exhaustive visualizations, and actionable insights-amalgamated into one offering-capitalize on this study as an asset for researchers, political analysts, and data scientists working on societal trends, upset electoral sentiment, or working toward the inception of an automated system for real-time opinion mining. Addressing the limitations identified here, and furthering some of the future directions suggested, will thus give later researchers the capacity to improve sentiment analysis with regard to its accuracy, scale, and interpretability relevant to the changing landscape of social media.

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Appendix

Appendix A: Main Implementation Code

The full code for data simulation, preprocessing, feature extraction, model training, and evaluation.

```
# Install required libraries
!pip install emoji textblob nltk scikit-learn tensorflow seaborn wordcloud vaderSentiment
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, KFold
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_recall_fscore_support, confusion_matrix
from sklearn.utils.class_weight import compute_class_weight
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Input
from tensorflow.keras.callbacks import EarlyStopping
import nltk
import emoji
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import re
# Download NLTK resources
nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('stopwords')
nltk.download('wordnet')
# Preprocessing function
def preprocess_text(text):
text = emoji.demojize(text)
text = re.sub(r'http\S+|@\w+|#\w+|[^\w\s]|\d', '', text.lower())
tokens = word_tokenize(text)
stop_words = set(stopwords.words('english')) - {'not', 'no'}
tokens = [t for t in tokens if t not in stop_words]
```

```
lemmatizer = WordNetLemmatizer()
tokens = [lemmatizer.lemmatize(t) for t in tokens]
return ' '.join(tokens)
# Simulate a more complex dataset
np.random.seed(42)
n_tweets = 10000
sentiments = np.random.choice(['positive', 'negative', 'neutral'], size=n_tweets, p=[0.45, 0.33, 0.22])
positive_phrases = ["great effort", "amazing work", "hopeful future", "strong support", "excellent choice"]
negative_phrases = ["great failure", "failed policy", "disappointing result", "weak effort", "awful campaign"]
neutral_phrases = ["election update", "voting process", "campaign event", "political debate", "neutral stance"]
ambiguous_phrases = ["interesting choice", "unexpected outcome", "mixed feelings", "close race", "great challenge", "strong debate"]
sarcastic_phrases = ["great job not", "amazing fail", "hopeful disaster", "strong weakness", "excellent mess"]
tweets = []
for i, sentiment in enumerate(sentiments):
if sentiment == 'positive':
phrase = np.random.choice(positive_phrases + ambiguous_phrases + sarcastic_phrases,
p=[0.14, 0.14, 0.14, 0.14, 0.14, # positive_phrases (5 * 0.14 = 0.70)
0.025, 0.025, 0.025, 0.025, 0.025, 0.025, # ambiguous_phrases (6 * 0.025 = 0.15)
0.03, 0.03, 0.03, 0.03, 0.03]) # sarcastic_phrases (5 * 0.03 = 0.15)
tweet = f"Tweet {i} about election: {phrase}!"
elif sentiment == 'negative':
phrase = np.random.choice(negative_phrases + ambiguous_phrases + sarcastic_phrases,
p=[0.14, 0.14, 0.14, 0.14, 0.14, # negative_phrases (5 * 0.14 = 0.70)
0.025, 0.025, 0.025, 0.025, 0.025, 0.025, # ambiguous_phrases (6 * 0.025 = 0.15)
0.03, 0.03, 0.03, 0.03, 0.03]) # sarcastic_phrases (5 * 0.03 = 0.15)
tweet = f"Tweet {i} about election: {phrase}."
else:
phrase=np.random.choice(neutral_phrases + ambiguous_phrases + sarcastic_phrases,
p=[0.14, 0.14, 0.14, 0.14, 0.14, # neutral_phrases (5 * 0.14 = 0.70)
0.025, 0.025, 0.025, 0.025, 0.025, 0.025, # ambiguous_phrases (6 * 0.025 = 0.15)
0.03, 0.03, 0.03, 0.03, 0.03]) # sarcastic_phrases (5 * 0.03 = 0.15)
tweet = f"Tweet {i} about election: {phrase}."
tweets.append(tweet)
# Create DataFrame
data=pd.DataFrame({'tweet': tweets, 'sentiment': sentiments})
# Add more complex noise
def add_noise(text):
if np.random.random() < 0.9: # 90% chance of adding noise
noise = np.random.choice(["...", "??", "!!!", "meh", "umm", "lol", "idk", "not sure", "maybe good", "kinda bad", "pretty okay", "so so", "random stuff"])
text = text + " " + noise
if np.random.random() < 0.5: # 50% chance of adding ambiguous words
ambiguous_word = np.random.choice(["really", "actually", "possibly", "somewhat", "very", "not bad", "quite good", "whatever"])
text = text + " " + ambiguous_word
return text
data['tweet'] = data['tweet'].apply(add_noise)
# Preprocessing
data['cleaned_tweet'] = data['tweet'].apply(preprocess_text)
# TF-IDF Vectorization
X = data['cleaned_tweet']
y = data['sentiment']
vectorizer=TfidfVectorizer(max_features=500, ngram_range=(1, 1))
X_tfidf = vectorizer.fit_transform(X)
# Define label mapping
label_map = {'positive': 0, 'negative': 1, 'neutral': 2}
# Compute class weights for imbalanced classes
y_encoded = np.array([label_map[label] for label in y])
class_weights = compute_class_weight(class_weight='balanced', classes=np.unique(y_encoded), y=y_encoded)
class_weight_dict = {i: weight for i, weight in enumerate(class_weights)}
# Use k-fold cross-validation
kf = KFold(n_splits=5, shuffle=True, random_state=42)
nb_scores, nn_scores, svm_scores, rf_scores = [], [], [], []
for fold, (train_idx, test_idx) in enumerate(kf.split(X_tfidf)):
print(f"\nFold {fold + 1}/5")
X_temp, X_test = X_tfidf[train_idx], X_tfidf[test_idx]
y_temp, y_test = y.iloc[train_idx], y.iloc[test_idx]
# Split training data into train and validation for Neural Network
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=0.2, stratify=y_temp, random_state=42)
# Encode labels for Neural Network
y_train_enc = np.array([label_map[label] for label in y_train])
y_val_enc = np.array([label_map[label] for label in y_val])
y_test_enc = np.array([label_map[label] for label in y_test])
# Naive Bayes
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
nb_pred = nb_model.predict(X_test)
# Neural Network with adjusted regularization and architecture
nn_model = Sequential([
Input(shape=(X_train.shape[1],)),
Dense(256,activation='relu',
kernel_regularizer=tf.keras.regularizers.l2(0.01)),
Dropout(0.3),
Dense(128,activation='relu',
kernel_regularizer=tf.keras.regularizers.l2(0.01)),
Dropout(0.3),
Dense(3, activation='softmax')])
nn_model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
nn_model.fit(X_train.toarray(), y_train_enc, validation_data=(X_val.toarray(), y_val_enc),
epochs=20,batch_size=64,verbose=0,
callbacks=[early_stopping],
class_weight=class_weight_dict)
```

```
nn_pred_probs=nn_model.predict(X_test.toarray(), verbose=0)
nn_pred = np.argmax(nn_pred_probs, axis=1)
nn_pred_labels = [list(label_map.keys())[p] for p in nn_pred]
# SVM
svm_model = LinearSVC(C=0.5)
svm_model.fit(X_train, y_train)
svm_pred = svm_model.predict(X_test)
# Random Forest
rf_model = RandomForestClassifier(n_estimators=50, random_state=42)
rf_model.fit(X_train, y_train)
 rf_pred = rf_model.predict(X_test)
 # Evaluate
def evaluate_model(y_true, y_pred, model_name):
accuracy = accuracy_score(y_true, y_pred)
precision, recall, f1, _ = precision_recall_fscore_support(y_true, y_pred, average='weighted')
print(f"\n{model_name} Results:")
print(f"Accuracy: {accuracy:.3f}")
print(f"Precision: {precision:.3f}")
print(f"Recall: {recall:.3f}")
print(f"F1-Score: {f1:.3f}")
cm = confusion_matrix(y_true, y_pred, labels=['positive', 'negative', 'neutral'])
print(f"{model_name} Confusion Matrix:")
print(cm)
return accuracy, precision, recall, f1
nb_metrics = evaluate_model(y_test, nb_pred, f"Naive Bayes (Fold {fold + 1})")
nn_metrics = evaluate_model(y_test, nn_pred_labels, f"Neural Network (Fold {fold + 1})")
svm_metrics = evaluate_model(y_test, svm_pred, f"SVM (Fold {fold + 1})")
rf_metrics = evaluate_model(y_test, rf_pred, f"Random Forest (Fold {fold + 1})")
nb_scores.append(nb_metrics)
nn_scores.append(nn_metrics)
svm_scores.append(svm_metrics)
rf_scores.append(rf_metrics)
# Average scores across folds
def average_metrics(scores, model_name):
avg_accuracy = np.mean([s[0] for s in scores])
avg_precision = np.mean([s[1] for s in scores])
avg_recall = np.mean([s[2] for s in scores])
avg_f1 = np.mean([s[3] for s in scores])
print(f"\nAverage {model_name} Results (5-Fold CV):")
print(f"Accuracy: {avg_accuracy:.3f}")
print(f"Precision: {avg_precision:.3f}")
print(f"Recall: {avg_recall:.3f}")
print(f"F1-Score: {avg_f1:.3f}")
average_metrics(nb_scores, "Naive Bayes")
average_metrics(nn_scores, "Neural Network")
average_metrics(svm_scores, "SVM")
average_metrics(rf_scores, "Random Forest")
```

Appendix B: Confusion Matrices Visualization Code

This script generates heatmaps for the confusion matrices.

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
import pandas as pd
import numpy as np
# Example data preparation - replace with your actual data
# Generate sample data if real data isn't available
np.random.seed(42)
X = np.random.rand(100, 5) # 100 samples, 5 features
y = np.random.randint(0, 3, 100) # 3 classes (0, 1, 2)
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Example predictions - replace with your actual model predictions
nb_pred = np.random.randint(0, 3, len(y_test)) # Naive Bayes predictions
nn_pred = np.random.randint(0, 3, len(y_test)) # Neural Network predictions
svm_pred = np.random.randint(0, 3, len(y_test)) # SVM predictions
rf_pred = np.random.randint(0, 3, len(y_test)) # Random Forest predictions
# Label mapping - replace with your actual class labels
label_map = {
 0: "Class 0",
 1: "Class 1",
 2: "Class 2"}
# Create confusion matrices
cm_nb = confusion_matrix(y_test, nb_pred)
cm_nn = confusion_matrix(y_test, nn_pred) # Using y_test instead of y_test_enc
cm_svm = confusion_matrix(y_test, svm_pred)
cm_rf = confusion_matrix(y_test, rf_pred)
# Plot confusion matrices
plt.figure(figsize=(20, 5))
plt.subplot(1, 4, 1)
sns.heatmap(cm_nb, annot=True, fmt='d', cmap='Blues',
xticklabels=label_map.values(),
yticklabels=label_map.values())
plt.title('Naive Bayes Confusion Matrix')
plt.subplot(1, 4, 2)
sns.heatmap(cm_nn, annot=True, fmt='d', cmap='Blues',
xticklabels=label_map.values(),
yticklabels=label_map.values())
plt.title('Neural Network Confusion Matrix')
plt.subplot(1, 4, 3)
sns.heatmap(cm_svm, annot=True, fmt='d', cmap='Blues',
xticklabels=label_map.values(),
yticklabels=label_map.values())
plt.title('SVM Confusion Matrix')
plt.subplot(1, 4, 4)
sns.heatmap(cm_rf, annot=True, fmt='d', cmap='Blues',
xticklabels=label_map.values(),
yticklabels=label_map.values())
plt.title('Random Forest Confusion Matrix')
plt.tight_layout()
plt.savefig('confusion_matrices.png',dpi=300,
bbox_inches='tight')
plt.show()
```

Appendix C: ROC Curves Visualization Code

This script generates ROC curves for all models.

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
import tensorflow as tf
import numpy as np
```

```
# Check if required variables exist
try:
# Verify all required variables are defined
required_vars = ['nb_model', 'nn_model', 'X_test_hybrid', 'y_test_enc', 'label_map']
 missing_vars = [var for var in required_vars if var not in globals()]
if missing_vars:
print(f"Error: Missing variables: {', '.join(missing_vars)}. Run the main implementation code (Appendix A in your thesis) in Google Colab first to define nb_model, nn_model, X_test_hybrid, y_test_enc, and label_map. Ensure you execute all cells in the main code before running this visualization.")
print("Error: The following variables are not defined: {', '.join(missing_vars)}. Please run the main implementation code (Appendix A in your thesis) in Google Colab first to define nb_model, nn_model, X_test_hybrid, y_test_enc, and label_map. Ensure you execute all cells in the main code before running this visualization.")
# Generate placeholder ROC curves with dummy data
print("Generating placeholder ROC curves with dummy data for visualization purposes...")
plt.figure(figsize=(10, 8))
colors = ['#1f77b4', '#ff7f0e', '#2ca02c']
dummy_fpr = np.linspace(0, 1, 100)
for i, label in enumerate(['Positive', 'Negative', 'Neutral']):
dummy_tpr = dummy_fpr ** (1.0 / (i + 1)) # Simulate different curves
dummy_auc = auc(dummy_fpr, dummy_tpr)
plt.plot(dummy_fpr, dummy_tpr, color=colors[i], label=f'Dummy Naive Bayes {label} (AUC = dummy_auc:.2f})')
plt.plot(dummy_fpr, dummy_tpr * 0.9, color=colors[i], linestyle='--', label=f'Dummy Neural Network {label} (AUC = {dummy_auc * 0.9:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Placeholder ROC Curves (Dummy Data)')
plt.legend(loc='lower right')
plt.grid(True)
plt.savefig('roc_curves_placeholder.png', dpi=300)
plt.show()
raise NameError("Placeholder plot generated. Run the main code for actual ROC curves.")
# Validate variable types and shapes
if not hasattr(nb_model, 'predict_proba'):
raise AttributeError("nb_model does not have predict_proba method. Ensure it's a trained MultinomialNB model.")
if not hasattr(nn_model, 'predict'):
raise AttributeError("nn_model does not have predict method. Ensure it's a trained Keras model.")
if not isinstance(X_test_hybrid, np.ndarray):
raise TypeError("X_test_hybrid must be a numpy array.")
if not isinstance(y_test_enc, (list, np.ndarray)):
raise TypeError("y_test_enc must be a list or numpy array.")
if not isinstance(label_map, dict):
raise TypeError("label_map must be a dictionary.")
# Convert y_test_enc to one-hot encoding
y_test_one_hot = tf.keras.utils.to_categorical(y_test_enc)
# Ensure shapes match
if y_test_one_hot.shape[0] != X_test_hybrid.shape[0]:
raise ValueError("Mismatch between y_test_one_hot and X_test_hybrid sample sizes.")
# Get probabilities
nb_probs = nb_model.predict_proba(X_test_hybrid)
nn_probs = nn_model.predict(X_test_hybrid, verbose=0)
# Validate probability shapes
if nb_probs.shape != nn_probs.shape or nb_probs.shape[1] != y_test_one_hot.shape[1]:
raise ValueError("Probability arrays have incorrect shapes.")
# Plot ROC curves
plt.figure(figsize=(10, 8))
colors = ['#1f77b4', '#ff7f0e', '#2ca02c'] # Colors for positive, negative, neutral
for i, label in enumerate(label_map.keys()):
fpr, tpr, _ = roc_curve(y_test_one_hot[:, i], nb_probs[:, i])
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, color=colors[i], label=f'Naive Bayes {label} (AUC = {roc_auc:.2f})')
fpr, tpr, _ = roc_curve(y_test_one_hot[:, i], nn_probs[:, i])
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, color=colors[i], linestyle='--', label=f'Neural Network {label} (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Naive Bayes and Neural Network')
plt.legend(loc='lower right')
plt.grid(True)
plt.savefig('roc_curves.png', dpi=300)
plt.show()
except NameError as e:
print(f"Error: {e}. Running the main code is required to get actual results.")
except (AttributeError, TypeError, ValueError) as e:
print(f"Error: {e}. Verify that all models are trained correctly and variables are in the expected format.")
except Exception as e:
print(f"An unexpected error occurred: {e}. Ensure all required libraries (tensorflow, sklearn, matplotlib) are installed and the main code ran without errors.")
```

Appendix D: Precision-Recall Curves Visualization Code

This script generates precision-recall curves for all models.

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import precision_recall_curve
from sklearn.preprocessing import label_binarize
# Sample data generation - replace with your actual data
np.random.seed(42)
y_test = np.random.randint(0, 3, 100) # 3 classes (0, 1, 2), 100 samples
nb_probs = np.random.rand(100, 3) # Naive Bayes probabilities
nn_probs = np.random.rand(100, 3) # Neural Network probabilities
# Binarize the output (convert to one-hot encoding)
y_test_one_hot = label_binarize(y_test, classes=[0, 1, 2])
# Label mapping - replace with your actual class names
label_map = {
0: "Class 0",
1: "Class 1",
2: "Class 2"}
```

```
# Plot Precision-Recall curves
plt.figure(figsize=(10, 8))
for i, label in enumerate(label_map.values()): # Using.values() for cleaner labels
# Naive Bayes curve
precision,recall,_= precision_recall_curve(y_test_one_hot[:, i], nb_probs[:, i])
plt.plot(recall, precision, label=f'Naive Bayes - {label}')
# Neural Network curve
precision,recall,_= precision_recall_curve(y_test_one_hot[:, i], nn_probs[:, i])
plt.plot(recall, precision, linestyle='--', label=f'Neural Network - {label}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curves by Class')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left') # Legend outside plot
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('precision_recall_curves.png', dpi=300, bbox_inches='tight')
plt.show()
```

Appendix E: Word Cloud (Positive Tweets)

This script generates a word cloud for positive tweets.

```
import pandas as pd
from wordcloud import WordCloud
import matplotlib.pyplot as plt
# 1. Try loading the dataset (REPLACE 'your_file.csv' with your actual file)try:
data = pd.read_csv('your_file.csv') # Change to your file (e.g., 'tweets.csv')
print("File loaded successfully!")
except FileNotFoundError:
print("Error: File not found. Using example data instead.")
# Fallback: Create dummy data (for testing)
data = pd.DataFrame({
'sentiment': ['positive', 'negative', 'positive'],
'cleaned_tweet': ['happy good joy', 'sad bad angry', 'love great awesome'] })
# 2. Check if required columns exist
required_columns = ['sentiment', 'cleaned_tweet']
if not all(col in data.columns for col in required_columns):
print(f"Error: DataFrame must contain these columns: {required_columns}")
exit()
# 3. Generate word cloud for positive tweets
positive_tweets=''.join(data[data['sentiment']== 'positive']['cleaned_tweet'].dropna())
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(positive_tweets)
# 4. Plot and save the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Positive Tweets')
plt.savefig('wordcloud_positive.png') # Saves in the current directory
plt.show()
```

Appendix F: Word Cloud (Negative Tweets)

This script creates a word cloud for negative tweets.

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt
# Assuming data is defined
negative_tweets=''.join(data[data['sentiment']== 'negative']['cleaned_tweet'])
wordcloud=WordCloud(width=800,height=400, background_color='white').generate(negative_tweets)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Negative Tweets')
plt.savefig('wordcloud_negative.png')
plt.show()
```

Appendix G: Word Cloud (Neutral Tweets)

This script generates a word cloud for neutral tweets.

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt
# 1. Check if 'data' exists and has neutral tweets try:
neutral_tweets=data[data['sentiment']== 'neutral']['cleaned_tweet'].dropna()
if len(neutral_tweets) == 0:
raise ValueError("No neutral tweets found.")
except NameError:
print("Error: 'data' is not defined. Load your dataset first.")
exit()
except ValueError as e:
print(f"Warning: {e} Using example text instead.")
neutral_tweets = ["neutral content example"] # Fallback dummy text
# 2. Generate word cloud (join tweets if they exist)
text = ' '.join(neutral_tweets)
wordcloud=WordCloud(width=800,height=400, background_color='white').generate(text)
# 3. Plot and save
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Neutral Tweets')
plt.savefig('wordcloud_neutral.png')
plt.show()
```

Appendix H: Sentiment Distribution Plot

This script plots the sentiment distribution.

```
import matplotlib.pyplot as plt
import seaborn as sns
# Assuming data is defined
sentiment_counts = data['sentiment'].value_counts()
plt.figure(figsize=(8, 6))
sns.barplot(x=sentiment_counts.index, y=sentiment_counts.values)
plt.title('Sentiment Distribution')
plt.xlabel('Sentiment')
plt.ylabel('Number of Tweets')
plt.savefig('sentiment_distribution.png')
plt.show()
```

Appendix I: Feature Importance Plot

This script plots the top 10 features from Random Forest.

```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import RandomForestClassifier
# Sample data generation - replace with your actual data
```

```
np.random.seed(42)
# 1. Create sample vectorizer and feature names
sample_texts = ["This is a sample text", "Another example text", "Machine learning is fun"] * 10
vectorizer = TfidfVectorizer(max_features=20) # Using TF-IDF vectorizer
X_text = vectorizer.fit_transform(sample_texts)
# 2. Create sample VADER features
vader_features = np.random.rand(len(sample_texts), 3) # Random VADER scores
# 3. Combine features (text + VADER)
X_train_hybrid=np.hstack([X_text.toarray(), vader_features])
# 4. Create sample target and model
y_train = np.random.randint(0, 2, len(sample_texts)) # Binary classification
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_hybrid, y_train)
# Get feature names and importances
feature_names = vectorizer.get_feature_names_out().tolist() + ['vader_pos', 'vader_neg', 'vader_neu']
importances = rf_model.feature_importances_
# Select top 10 features
top_indices = np.argsort(importances)[-10:]
top_features = [feature_names[i] for i in top_indices]
top_importances = importances[top_indices]
# Plot feature importances
plt.figure(figsize=(10, 6))
sns.barplot(x=top_importances,y=top_features, palette="viridis")
plt.title('Top 10 Feature Importances (Random Forest)')
plt.xlabel('Importance Score')
plt.ylabel('Feature Names')
plt.tight_layout()
plt.savefig('feature_importance.png',dpi=300, bbox_inches='tight')
plt.show()
```