Phase-2 Submission

Student Name: Sri kanth T

Register Number: AU410723104085

Institution: Dhanalakshmi College of Engineering

Department: computer science engineering

Date of Submission: 07-May-25

GitHub Repository link: https://github.com/srikanth-thangamuthu/NM_Srikanth

---

Project Title: Decoding Emotions Through Sentiment Analysis of Social Media Conversation

1. Problem Statement

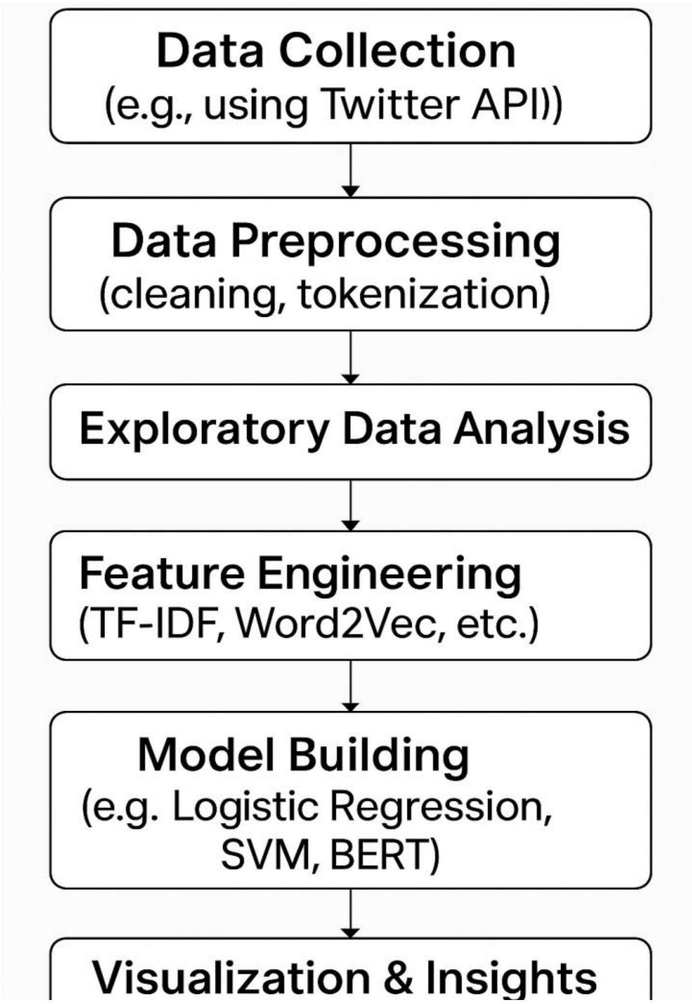
With the exponential growth of social media platforms like Twitter, Facebook, and Instagram, people now express their thoughts, opinions, and emotions online more than ever. These platforms have become a rich repository of user-generated content, which provides unique opportunities to understand public sentiment across various domains such as politics, mental health, marketing, and customer service.

2. Project Objectives

1. *To collect a diverse dataset of social media text data such as tweets or Facebook comments.*
2. *To preprocess the textual data by cleaning, normalizing, and tokenizing the content.*
3. *To build models capable of performing sentiment classification with high accuracy and robustness.*
4. *To visualize emotional trends across time, location, or topics to better understand public sentiment.*
5. *To address challenges such as sarcasm detection, handling class imbalance, and dealing with multilingual content*

3. Flowchart of the Project Workflow

- *Data Collection: Using APIs like Twitter API or extracting data from public datasets on Kaggle.*
- *Data Preprocessing: Cleaning text by removing noise (URLs, hashtags, mentions), normalizing, and tokenizing.*
- *Exploratory Data Analysis: Identifying patterns in data, distribution of sentiments, and word usage.*
- *Feature Engineering: Creating numerical representations of text using techniques like TF-IDF, Word2Vec, or BERT embeddings.*
- *Model Building: Training machine learning models such as Logistic Regression, SVM, or deep learning models like LSTM and BERT.*
- *Model Evaluation: Assessing models using metrics such as accuracy, recall, F1-score, and confusion matrix.*
- *Visualization and Insights: Plotting sentiment trends, keyword importance, and evaluating emotional responses across different dimensions.*



4. Data Description

Dataset Source: *Data is collected from the Twitter API, Reddit threads, or publicly available sentiment datasets on platforms like Kaggle.*

Data Type: *Unstructured text data containing user-generated content.*

Features: *Tweet/comment text, timestamps, user metadata (optional), sentiment labels.*

Target Variable*: Sentiment classification—commonly Positive, Negative, and Neutral.*

Nature of Data: *Can be static (archived datasets) or dynamic (real-time data from social APIs).*

5. Data Preprocessing

Text Cleaning: *Remove punctuation, numbers, stop words, URLs, hashtags, and emojis.*

Text Normalization: *Lowercasing, correcting spelling errors, and expanding contractions.*

Tokenization and Lemmatization: *Breaking text into individual words and reducing them to their root form.*

Handling Imbalanced Classes: *Apply oversampling (e.g., SMOTE) or under sampling techniques if sentiment categories are not evenly distributed.*

6. Exploratory Data Analysis (EDA)

- *Analyze most frequently occurring words across sentiment classes.*
- *Generate word clouds to visualize dominant words in positive, negative, and neutral texts.*
- *Assess the distribution of sentiments to understand biases in the data.*
- *Study trends over time or across hashtags to identify sentiment shifts.*

7. Feature Engineering

Text Vectorization: *Convert text into numerical format using TF-IDF, Bag of Words, or advanced embeddings like Word2Vec or GloVe.*

Contextual Embeddings: *Use pre-trained language models like BERT to capture contextual relationships in sentences.*

Linguistic Features: *Add parts of speech tags, sentiment lexicons, or n-gram frequency counts.*

8. Model Building

Choose appropriate models such as:

- *Logistic Regression and SVM for baseline performance*
- *Random Forest for robustness and interpretability*
- *LSTM and BERT for deep learning-based performance*
- *Fine-tune models using cross-validation and hyperparameter tuning.*
- *Evaluate performance using metrics:*
- *Accuracy*
- *Precision, Recall, and F1-score*
- *Confusion Matrix and ROC/AUC*

9. Visualization of Results and Model Insights

Confusion Matrix: *Visual representation of prediction performance.*
ROC/AUC Curve: *To analyze model performance at various classification thresholds.*
Sentiment Over Time: *Line plots to visualize how sentiment changes over time.*
Keyword Contribution: *Identify key terms that contribute most to each sentiment class.*

10. Tools and Technologies Used

Programming Language: *Python*
NLP Libraries: *NLTK, spaCy, TextBlob, HuggingFace Transformers*
Data Handling: *pandas, numpy*
Modeling: *scikit-learn, TensorFlow, Keras*
Visualization: *matplotlib, seaborn, plotly*
IDEs: *Google Colab, Jupyter Notebook*
Version Control: *GitHub for tracking project development*

11. Team Members and Contributions

Name	Role	Responsibilities
Umesh	*Presentation Designer*	*Designed and structured the project presentation for clear and effective delivery.*
Srikanth	*Content Researcher*	*Researched sentiment analysis techniques and contributed to writing project content.*
Yashwanth	*Content Researcher*	*Helped gather insights and develop detailed write-ups for each section of the project.*
Ravikumaar	*Technical Support & Review*	*Assisted with reviewing the technical workflow, validating data processing steps, and ensuring overall quality control.*