Phase-2 Submission

Student Name: *RAJESHKUMAR N*

Register Number: *712523106014*

Institution: *ppg institute of technology*

Department: *B.E. Electronics and Communication Engineering*

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GitHub Repository Link:
https://github.com/raj75esh/NM_RAJESH_DS.git

1. Problem Statement

Social media is a major outlet for emotional expression, but the sheer volume of content makes manual analysis impractical. This project uses ***NLP-based multi-class classification*** *to detect emotions—like happiness, anger, sadness, fear, and neutrality—in social media posts.*

Type of Problem: *Multi-class Text Classification (Supervised Learning)*

Why It Matters:

- *Enables mental health monitoring*
- *Improves customer feedback insights*
- *Supports public sentiment analysis*
- *Enhances user safety and platform experience*

2. Project Objectives

The goal is to build an NLP-based system that classifies social media posts into

emotional categories like happiness, sadness, anger, fear, and neutrality.

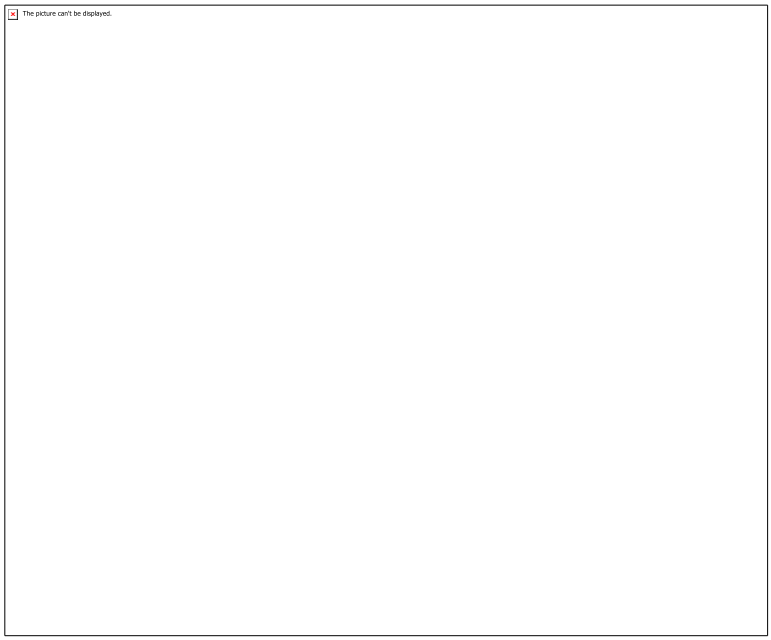
Key Technical Objectives:

- *Develop a multi-class classification model for emotion detection.*
- *Apply text preprocessing techniques (tokenization, stop-word removal, vectorization).*
- *Optimize model performance using accuracy, precision, recall, and F1-score.*
- *Ensure interpretability using tools like confusion matrices or SHAP/LIME.*
- *(Optional) Deploy a prototype for real-time emotion analysis.*

***Updated Goal Post Data Exploration**:*

Focus shifted from basic sentiment polarity to detailed emotion classification to capture richer, more actionable insights.

3. Flowchart of the Project Workflow



4. Data Description

The dataset used for this project is a collection of text-based social media posts, *specifically designed for* emotion classification. *It was sourced from* Kaggle, *titled* "Emotion Detection from Text", *which contains labeled examples of social media text mapped to emotional categories.*

- *Source: Kaggle (e.g., Emotion Detection from Text, CrowdFlower Emotion Dataset, or similar)*
- *Type of Data: Unstructured text data*
- *Number of Records: ~20,000+ text samples (varies depending on dataset used)*
- *Number of Features: 1 input feature (text), 1 target label (emotion)*
- *Dataset Nature: Static – does not update in real-time*
- *Target Variable: Emotion labels such as happy, sad, angry, fear, surprise, neutral, etc.*
- *Learning Type: Supervised Learning (Multi-class classification)*

5. Data Preprocessing

Handling Missing Values: All rows with missing text or emotion labels were removed to ensure data completeness.

- ***Removing Duplicates:*** *Duplicate text entries were identified and dropped to avoid data redundancy.*
- ***Outlier Treatment:*** *Extremely short texts (e.g., less than 3 words) were considered outliers and removed, as they provide little semantic value.*
- ***Data Type Conversion:*** *Text data was converted to string format, and emotion labels were cast as categorical variables for consistency.*

- ***Text Cleaning and Preparation:*** *Text was cleaned by removing URLs, punctuation, and converting to lowercase, followed by tokenization, stop word removal, and lemmatization.*
- ***Categorical Encoding:*** *Emotion categories were encoded using* ***Label Encoding*** *to prepare them for supervised learning algorithms.*
- ***Text Vectorization and Normalization:*** *TF-IDF vectorization transformed text into numerical format, providing normalized feature values suitable for model input.*

6. Exploratory Data Analysis (EDA)

- ***Univariate Analysis***

Emotion Distribution: Count plot shows imbalance—some emotions (e.g., joy, sad) are more common than others like fear or surprise.

Text Length: Histogram reveals most social media posts are short (under 30 words), aligning with platform norms.

- ***Bivariate/Multivariate Analysis***

Boxplot (Text Length vs Emotion): Emotions like anger and fear often correspond to longer posts, while happy and neutral are shorter.

Word Frequency Patterns: Emotion-specific words like "sorry", "love", "hate", and "great" are commonly tied to respective sentiments.

Correlation Matrix (TF-IDF features): Reveals low multicollinearity, but some overlap in terms used across emotions.

- ***Insights Summary***

Class Imbalance: May lead to biased model predictions—should address using oversampling or class weighting.

Feature Influence: Text length and word usage are key predictors; they help differentiate emotions and improve classification accuracy.

7. Feature Engineering

Text Length & Word Count: *The number of words and characters in posts helps capture emotional intensity, with longer texts indicating stronger emotions like anger or fear.*

- ***Sentiment Polarity Score:*** *Using tools like VADER or TextBlob to assign a positive/negative sentiment, complementing the multi-class emotion classification.*
- ***POS Ratios:*** *The ratio of adjectives, nouns, and verbs to identify emotion-specific language patterns (e.g., joy vs. anger).*
- ***Top-N Keywords (TF-IDF):*** *Extract important keywords using TF-IDF to focus on words strongly linked to specific emotions (e.g., love for joy).*
- ***Text Length Binning:*** *Categorizing text length into bins (short, medium, long) to help capture emotion intensity patterns.*
- ***PCA for Dimensionality Reduction:*** *Reduce feature space with PCA to improve efficiency and reduce overfitting.*
- ***Temporal Features:*** *Extract date and time features (e.g., day of the week) to capture patterns in emotion based on timing.*

8. Model Building

Models Chosen*:*

- ***Logistic Regression****: Simple, interpretable, and effective for text classification.*
- ***Random Forest****: Robust, handles complex data relationships well, and avoids overfitting.*
- ***Data Split****:*
- *Split data into* ***training*** *and* ***testing*** *sets using* ***stratified sampling****.*

- ***Training***:
- *Use **TF-IDF** for text vectorization.*
- *Train both **Logistic Regression** and **Random Forest** models.*
- ***Evaluation Metrics***:
- *Evaluate using **accuracy, precision, recall**, and **F1-score**.*
- ***Model Comparison***:
- *Compare both models, selecting the one with the best **F1-score** for emotion classification.*

9. Visualization of Results & Model Insights

***Confusion Matrix**: Shows actual vs predicted emotions, highlighting misclassifications. High diagonal values indicate correct predictions.*

- ***ROC Curve**: Evaluates model performance by plotting True Positive Rate vs False Positive Rate. A higher AUC indicates better model performance.*
- ***Feature Importance Plot**: Displays which features (e.g., specific words) are most influential in predicting emotions.*
- ***Residual Plot**: Visualizes prediction errors; random scatter around zero indicates a well-fitting model.*
- ***Model Performance Comparison**: Compares models (e.g., Logistic Regression vs. Random Forest) on metrics like accuracy, precision, and F1-score to select the best performer.*

10. Tools and Technologies Used

- ***Programming Language**: Python*
- ***IDE/Notebook**: Google Co lab, Jupiter Notebook*
- ***Libraries**: pandas, NumPy, seaborn, matplotlib, scikit-learn, X Boost*
- ***Visualization Tools**: Portly, Tableau (optional for advanced visualizations)*

11. Team Members and Contributions

TEAM MEMBER	ROLE	RESPONSIBILITIES
SUBASH S	*Team Lead, Model Development*	*Responsible for developing and training machine learning models for fake news detection.*
RAJESHKUMAR N	*Data Cleaning, Feature Engineering*	*Handled data preprocessing, cleaning, and feature extraction for model training.*
KAMALESH S	*EDA, Data Visualization*	*Conducted exploratory data analysis to understand data distribution and patterns.*
PRASANNA S D	*Documentation and Reporting*	*Managed project documentation, including technical reports and presentation materials.*
SANJAY E	*NLP Implementation, Model Evaluation*	*Implemented NLP algorithms for text processing and analysis.*