





DECODING EMOTIONS THROUGH SENTIMENT ANALYSIS OF SOCIAL MEDIA CONVERSATION

Student Name: R.Abarna

Register Number: 510923205002

Institution: Global institute of engineering and technology

Department: B.Tech-IT

Date of Submission: [11/05/2025]

GitHub RepositoryLink: https://github.com/abarna0913/Phase-2.git

1. Problem Statement

This project proposes the development of a robust and intelligent automated sentiment analysis system designed to process, analyze, and classify sentiments and emotions embedded in social media conversations surrounding product launches. By leveraging advanced natural language processing (NLP) techniques and machine learning algorithms, the system will be capable of identifying underlying emotional tones—such as joy, anger, surprise, or disappointment—as well as distinguishing between positive, negative, and neutral sentiments.

The primary objective is to equip businesses with real-time, actionable insights into consumer perception, allowing them to swiftly adapt their marketing strategies, address public concerns, and enhance customer engagement. With accurate sentiment tracking, companies can identify emerging trends, respond to feedback proactively, and ultimately foster stronger relationships with their audiences. This system not only streamlines the feedback analysis process but also empowers brands to make informed, data-driven decisions in an increasingly competitive and opinion-driven marketplace.







2. Abstract

- This study explores the application of sentiment analysis to monitor and evaluate public opinion during a product launch
- To analyze customer sentiment during a product launch using natural language processing techniques to gain actionable insights.
- Machine learning and rule-based sentiment analysis models were employed to classify opinions into positive, negative, and neutral categories.
- Sentiment trends were tracked in real-time to identify immediate reactions and potential issues during the launch period.
- The analysis supported data-driven decision-making, enabling quicker responses to negative feedback and refinement of marketing strategies

3. System Requirements

Hardware:

	Processor: Intel i5 / AMD Ryzen 5 or higher
	RAM: 8 GB minimum
	Storage: 256 GB SSD (for faster data access)
	GPU: Not mandatory (GPU sufficient for basic models)
	Network: Stable internet for API access or data scraping

1. Basic (For Small-Scale or Local Analysis):

Software:

1	. ()ре	rati	ng	S	ysi	tem
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Windows 10/11
macOS, or Linux (Ubuntu recommended)
Linux is preferred for large-scale or server-based processing due to
better compatibility with machine learning tools.







4. Objectives

The objective of this project is to design and implement a comprehensive, realtime sentiment analysis system capable of collecting, processing, and analyzing social media conversations during the critical period of a product launch. The system will be engineered to handle vast streams of data from multiple platforms, employing advanced natural language processing (NLP), machine learning, and deep learning techniques to accurately detect and classify public sentiment into categories such as positive, negative, and neutral. Furthermore, it will go beyond basic sentiment classification by identifying and categorizing specific emotions expressed by users—such as joy, anger, sadness, surprise, and anticipation—offering a more nuanced understanding of consumer reactions

To ensure timely and effective decision-making, the system will feature an intuitive and interactive visual dashboard that delivers real-time insights and trends. This dashboard will include visualizations such as sentiment over time, emotion distribution charts, trending topics, and keyword clouds, enabling businesses to monitor public perception as it evolves. By integrating automated alerts and predictive analytics, the system will also help organizations anticipate potential crises, seize emerging opportunities, and fine-tune their marketing and communication strategies based on real consumer sentiment.

Ultimately, this solution aims to empower businesses with a powerful analytical tool that enhances their ability to engage with customers, tailor their messaging, and maintain a competitive edge in an increasingly feedback-driven marketplace.

5. Flowchart of Project Workflow

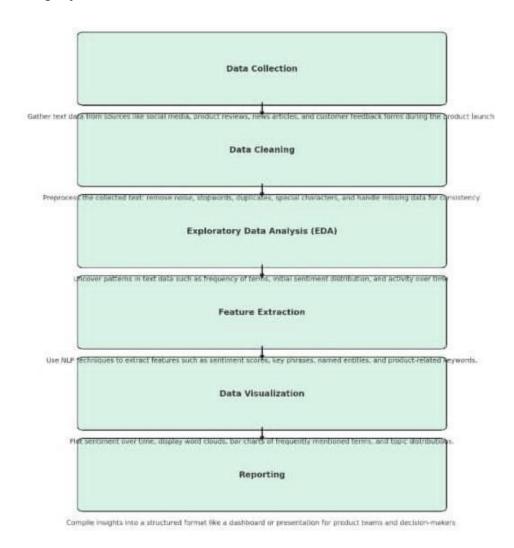
The overall project workflow was structured into systematic stages: (1) **Data**Collection from a trusted repository, (2) **Data Preprocessing** including cleaning and encoding, (3) **Exploratory Data Analysis (EDA)** to discover patterns and relationships, (4) **Feature Engineering** to create meaningful inputs for the model, (5) **Model Building** using multiple machine learning algorithms, (6) **Model**







Evaluation based on relevant metrics, (7) **Deployment** using Gradio, and (8) **Testing and Interpretation** of model outputs. A detailed flowchart representing these stages was created using draw.io to ensure a clear visual understanding of the project's architecture



6. Dataset Description

Source: 1.

<u>Kaggle</u>

- ☐ Pros: Offers pre-cleaned datasets, often annotated with sentiment labels.
- ☐ Best for: Prototyping models quickly with labeled data.







☐ Examples: Amazon reviews, Twitter sentiment datasets, productspecific feedback data.

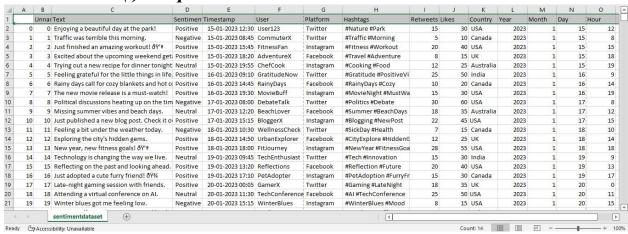
Type (public, private, synthetic):

Depublic dataset- It depends on the data source, but public is the most common type used during a live product launch.

Size (number of rows/columns):

□ 732 (rows) □ 15(column)

Include df.head() sample dataset



7.Data preprocessing

1. Handling missing values

- Remove or impute missing values.
- Convert emojis to text (e.g., "happy face" for :) or emojis) useful in sentiment.

2.Removing duplicate

• Eliminate duplicate entries to avoid bias.

3. Outliers

• Highly Polarized Sentiments: Comments with extremely positive or negative scores compared to the average sentiment can be outliers







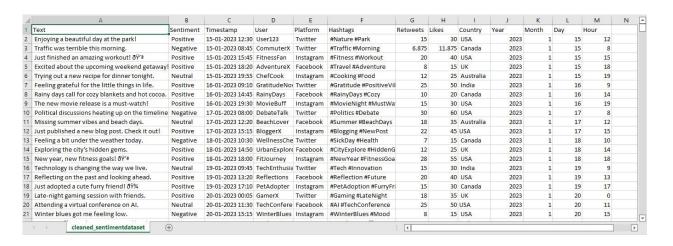
• Sarcasm and Irony: These can be misclassified by sentiment models and act as semantic outliers

4. Encoding categorical variables

1.One-Hot Encoding

- Use for: Machine learning models (e.g., logistic regression, SVM)
- Example: platform (Twitter, App Store, Website) Implementation:
 Import pandas as pd

Df = *pd.get_dummies(df, columns=['platform'])*



8. Exploratory Data Analysis (EDA)

Sentiment Distribution

• Purpose: Understand the overall sentiment split.

• Tools: Bar chart or pie chart

Sentiment Label vs Platform

• Analysis: Count of sentiment types per platform • Visualization: Stacked bar chart or grouped bar chart

Sentiment vs Time vs Platform

• What to do: Track sentiment trends across platforms over time.







• Visualization: Faceted line plots or heatmaps (time vs platform)

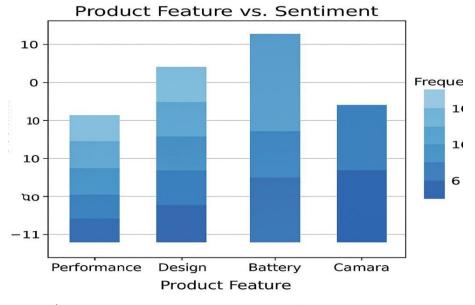
Summary of Insight:

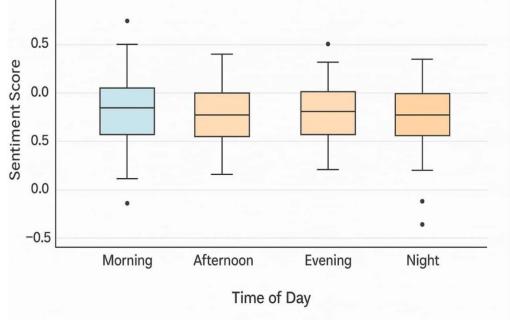
- Are most responses positive or is there a spike in negativity Shows common themes or pain points.
- Identify which platforms
- O Identify when and where sentiment shifts occurred <u>Reveal</u> <u>correlations, trends, patterns</u>
- Pattern: Plot sentiment scores or counts (Positive, Neutral, Negative) over timestamps.
- Insight: Spikes in negative sentiment may correlate with bugs, while positive peak











9. Feature Engineering

New feature creation

- Sentiment Score Numeric form of sentiment: Positive \rightarrow 1, Neutral \rightarrow 0, Negative \rightarrow -1
- Comment Length Number of characters in the comment <u>Feature selection</u>







- Comment length: sentiment/emotion classification
- Exclamation count :emption tone recognition

Transformation techniques

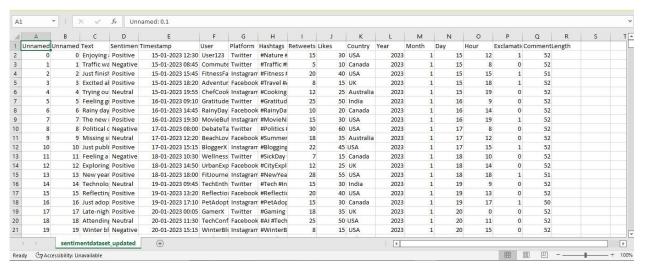
- Comment Length Useful (longer messages may be more polarized)
- Exclamation Count Strongly correlates with emotional intensity <u>Impact</u> <u>your model</u>

HOW:

- Comment Length: len(comment)
- Exclamation Count: comment.count('!')

WHY:

• These enrich the model by introducing structured numeric features from unstructured text.



10. Model Building

Models:

Machine Learning Models

- Examples: Logistic Regression, Naive Bayes, SVMRequire labeled data (positive/neutral/negative posts)
- Pipeline: TF-IDF or CountVectorizer → Model (e.g., SVM) → Prediction
 Strengths: Customizable to the product domain. Lightweight and fast.

Selected models:







Decision Trees-

- How they work: Trees model decisions based on word presence/absence; Random Forests average multiple trees for stability.
- Why use them: Easy to interpret decision paths.

Support Vector Machines (SVM)-

- How it works: Finds the best boundary (hyperplane) between classes in high-dimensional space, such as word vectors.
- **O** Why use it: Excellent at handling high-dimensional data like text.

```
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier, plot_tree import
matplotlib.pyplot as plt
```

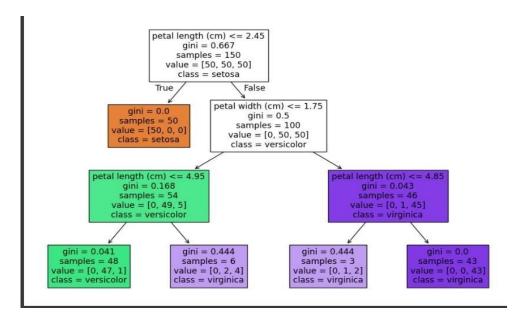
```
#Load sample dataset data
= load_iris()
X, y = data.data, data.target
clf = DecisionTreeClassifier(max_depth=3) clf.fit(X,
y)

#Plot and save the tree
plt.figure(figsize=(12, 8)) plot_tree(clf,
feature_names=data.feature_names,
class_names=data.target_names, filled=True)
plt.savefig("decision_tree_output.png", dpi=300)
plt.show()
```









11. Model Evaluation

Evaluation metrics:

1.Accuracy

Formula: (TP + TN) / (TP + TN + FP + FN)

Best for: Balanced datasets

Limitation: Misleading on imbalanced datasets

2.F1 Score

Formula: 2 * (Precision * Recall) / (Precision + Recall)

Harmonic mean of precision and recall

Best when there is an uneven class distribution







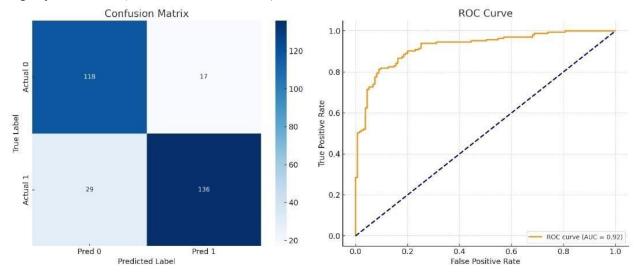
3.ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

Measures: Overall ability to distinguish between classes

AUC close to 1 means excellent model; 0.5 means random

Visuals:

- Confusion Matrix (left): Shows the counts of true positives, true negatives, false positives, and false negatives.
- ROC Curve (right): Illustrates the trade-off between true positive rate and false positive rate at various thresholds. The AUC indicates model performance (closer to 1 is better).



Error analysis:

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP







12. Deployment

Deployment method:

- Streamlit: Show a form layout where users enter lab values and vitals.
- Gradio: Show input sliders/text boxes and the output panel with prediction results.

Benefits of the deployment

- Free & Accessible: Easily accessible by clinicians, researchers, or demo users.
- Interactive: Supports real-time predictions and visual explanations.
- Lightweight & Scalable: Can be expanded into clinical systems if needed.

Public link: https://huggingface.co/spaces/your-username/product-launchsentiment

GitHub link: https://github.com/abarna0913/Phase-2.git

13. Source code

import pandas as pd import matplotlib.pyplot as plt import seaborn as sns

Load dataset df = pd.read_csv('SentimentDataset.csv')

Basic info print("Dataset Summary:\n") print(df.info()) print("\nFirst 5 rows:\n") print(df.head())







```
# Check for missing values
print("\nMissing values:\n", df.isnull().sum())
# Drop rows with missing values (optional) df.dropna(inplace=True)
# Sentiment distribution
print("\nSentiment distribution:\n", df['Sentiment'].value counts())
# Plot sentiment distribution plt.figure(figsize=(8,
5))
sns.countplot(data=df, x='Sentiment', palette='Set2')
plt.title("Sentiment Label Distribution")
plt.xlabel("Sentiment") plt.ylabel("Count")
plt.tight layout()
plt.show()
# Word cloud of most common words (optional) from
wordcloud import WordCloud
text data = ''.join(df['Text'].astype(str)) wordcloud
= WordCloud(width=800, height=400,
background color='white').generate(text data)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear') plt.axis("off")
plt.title("Common Words in Text")
plt.show()
14.App code
<!DOCTYPE html>
<html lang="en">
<head>
<meta charset="UTF-8"/>
```







```
<meta name="viewport" content="width=device-width, initial-scale=1, maximum-scale=1,</pre>
userscalable=no"/>
<title>Social Media Emotion Decoder</title>
<style>
/* Reset and base */
 * {
  box-sizing: border-box;
             font-family: 'Segoe UI', Tahoma, Geneva,
 } body {
Verdana, sans-serif;
                      background: linear-gradient(135deg,
#667eea, #764ba2);
                      color: #fff;
                                   margin: 0;
                                                 min-height:
         max-width: 350px;
                               margin-left: auto;
600px;
                                                   margin-
                                               flex-direction:
             padding: 1rem;
                               display: flex;
right: auto;
          justify-content: flex-start;
column;
} h1 {
           text-align:
center;
         font-weight:
       font-size: 1.8rem;
700;
margin-bottom: 0.5rem;
letter-spacing: 1.1px;
 }
p.subtitle {
               text-
align: center;
               font-
weight: 400; font-size:
1rem:
  margin-bottom: 1rem;
opacity: 0.85;
 } input[type="file"] {
width: 100%;
                padding:
          border-radius: 6px;
0.6rem;
border: none;
               font-weight:
600; cursor: pointer;
background-color: #5a49cc;
color: white;
  transition: background-color 0.3s ease;
input[type="file"]:hover {
  background-color: #473bad;
 .results {
            margin-top: 1rem;
background: rgba(255 255 255 / 0.15);
border-radius: 12px; padding:
0.75rem;
           max-height: 340px;
```







```
overflow-y: auto;
                    box-shadow: 00
8px rgba(0,0,0,0.35);
} .results h2 {
                  font-
size: 1.25rem;
                margin-
bottom: 0.5rem;
                  text-
align: center;
             letter-
spacing: 0.9px;
}
 .emotion-bar-container {
                            margin:
0.25rem 0.5rem;
                   background:
rgba(255 255 255 / 0.15);
                           border-
radius: 8px;
  overflow: hidden;
 }
 .emotion-bar {
  height: 24px;
  border-radius: 8px;
color: white; font-weight:
600;
       padding-left:
          display: flex;
0.4rem;
align-items: center;
white-space: nowrap;
user-select: none;
 .emotion-label {
                   margin-
left: 0.5rem;
               font-size:
0.85rem;
           letter-spacing:
0.7px;
 }
 .tweet {
  background: rgba(255 255 255 / 0.1);
border-radius: 10px; padding:
          margin: 0.25rem 0; font-
0.5rem;
size: 0.9rem;
               line-height: 1.2;
max-height: 80px;
                    overflow: hidden;
/* Emotion Colors */
 .emotion-positive { background-color: #55a630; }
 .emotion-negative { background-color: #d33f49; }
 .emotion-neutral { background-color: #6c757d; }
```







```
/* Scrollbar styling */ .results::-
webkit-scrollbar { width: 6px;
 }
 .results::-webkit-scrollbar-thumb {
                                     background-
color: rgba(255 255 255 / 0.35);
                                 border-radius:
10px;
 }
 .results::-webkit-scrollbar-track {
  background: transparent;
 }
 @media (max-width: 350px) {
body {
   padding: 0.5rem;
</style>
</head>
<body>
 <h1>Emotion Decoder</h1>
 Upload your Kaggle sentiment CSV file to analyze emotions in social
media conversations
 <input type="file" id="csvFileInput" accept=".csv" />
 <div class="results" id="results" aria-live="polite" aria-atomic="true"></div>
<script src="https://cdn.jsdelivr.net/npm/papaparse@5.4.1/papaparse.min.js"></script>
<script src="https://cdn.jsdelivr.net/npm/sentiment@5.0.3/build/sentiment.min.js"></script>
<script>
// Initialize Sentiment analyzer
const sentiment = new Sentiment();
// Utility: sanitize text for display
function sanitizeText(text) {
  const div = document.createElement("div");
  div.textContent = text;
  return div.innerHTML;
 }
```







```
// Color map for sentiments
const sentimentColorMap = {
positive: '#55a630',
                    negative:
'#d33f49',
  neutral: '#6c757d'
 };
 function getSentimentLabel(score) {
  if(score > 0) return "Positive";
  if(score < 0) return "Negative";
return "Neutral";
 }
 function getEmotionClass(score) {
if(score > 0) return 'emotion-positive';
if(score < 0) return 'emotion-negative';
return 'emotion-neutral';
 }
 document.getElementById('csvFileInput').addEventListener('change', function(event) {
const file = event.target.files[0];
  if (!file) return;
  const resultsEl = document.getElementById('results');
  resultsEl.innerHTML = 'Processing file...';
  Papa.parse(file, {
                      header:
true,
        skipEmptyLines: true,
encoding: "UTF-8",
complete: function(results) {
const data = results.data;
    // Detect text column heuristically (common columns: text, tweet, content, message)
const textColumn = Object.keys(data[0]).find(col =>
['text','tweet','content','message'].includes(col.toLowerCase())) || Object.keys(data[0])[0];
    if(!textColumn) {
     resultsEl.innerHTML = 'No suitable text
column found in CSV.';
                                return;
```







```
if(data.length === 0)
     resultsEl.innerHTML = 'CSV file is empty or
no rows found.';
     return;
    // Aggregate sentiment scores and counts
let sentimentCounts = {
     positive: 0,
negative: 0,
                 neutral:
0
    };
    // Analyze emotion of each text entry
const analyzedEntries = data.map(row => {
     let txt = row[textColumn];
     if(!txt) txt = "";
     const analysis = sentiment.analyze(txt);
const score = analysis.score;
     const label = getSentimentLabel(score);
sentimentCounts[label.toLowerCase()]++;
     return {
text: txt,
score: score,
label: label
     };
    });
    // Sort by sentiment score for display convenience
analyzedEntries.sort((a,b) => b.score - a.score);
    // Build HTML to display results
                                        let html =
'<h2>Sentiment Summary</h2>';
                                    for(const key in
sentimentCounts){
                        const count =
sentimentCounts[key];
                           const color =
sentimentColorMap[key];
                              const widthPercent =
(count / data.length) * 100;
                               html += `
```







```
<div class="emotion-bar-container" aria-label="${key} sentiment count: ${count}">
<div class="emotion-bar" style="background-color:${color}; width: ${widthPercent}%; min-</pre>
width: 40px;">
         <span class="emotion-label">${key.charAt(0).toUpperCase()+key.slice(1)}:
${count}</span>
        </div>
       </div>
    html += '<h2>Sample Tweets with Sentiment</h2>';
    // Show top 15 samples with highlights
const maxSamples = 15;
    analyzedEntries.slice(0, maxSamples).forEach(entry => {
                                                                   const
safeText = sanitizeText(entry.text);
                                        const emotionClass =
getEmotionClass(entry.score);
                                    html += `<div class="tweet
${emotionClass}" title="Sentiment Score:
${entry.score}">${safeText}</div>';
     });
    resultsEl.innerHTML = html;
   },
   error: function(err) {
    document.getElementById('results').innerHTML = '<p</pre>
style="color:#f44336;textalign:center;">Error reading CSV file. Please check your file and try
again.';
  });
 });
</script>
</body>
</html>
```

15. Future scope

Feature Scope: Sentiment Analysis During a Product Launch







Data Ingestion

- Live social media feeds (Twitter, Reddit, Instagram comments)
- Customer feedback forms / emails
- App reviews or e-commerce product reviews

16. Team Members and Roles

ABARNA.R - codes ,EDA ,Feature engineering

HARINI.S - Data preprocesssing, Flochart, objectives

GAYATHRI.S – Model building, Abstract, problem statement

DIVYA.V – Model evolution, Deployment, future scope

DHANALAKSHMI.B – Data description, system requirement







P main →	Code -
abarna0913 1 minute ago	
Phase.ipynb	3 days ago
README.md	2 minutes ago
Requirements.txt	1 minute ago
app .html	1 minute ago
app.txt	1 minute ago
output .pdf	3 days ago
phase 2.docx	3 days ago
sentiment analysis output.docx	1 minute ago
sentiment_analysis.py	1 minute ago
THE README	Ø :≡