





# DECODING EMOTIONS THROUGH SENTIMENT ANALYSIS OF SOCIAL MEDIA CONVERSATION

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**Github Repository Link:** 

https://github.com/dhanalakshmi166/github\_EBPL\_DS-decoding-social-media.git

#### 1. Problem Statement

When a new product is launched, understanding public reaction is crucial for assessing the success of marketing strategies, identifying potential issues, and shaping future decisions. Traditional feedback methods such as surveys are slow and limited in reach. Twitter, being a fast-paced and widely used platform, offers







real-time insights into consumer sentiment. However, the massive volume and unstructured nature of tweets present a challenge in extracting meaningful emotional feedback. This project aims to develop a system that performs real-time sentiment and emotion analysis on Twitter data to decode public reaction to a product launch, enabling companies to respond swiftly and make informed decisions.

#### 2. Abstract

In the digital age, social media platforms like Twitter serve as powerful mediums for public expression, particularly during high-profile events such as product launches. This project focuses on analyzing public reaction to a product launch by extracting, processing, and interpreting tweets related to the event. Using natural language processing (NLP) techniques and sentiment analysis, the system categorizes user opinions into sentiments such as positive, negative, or neutral. The methodology includes real-time tweet collection using scraping tools, data cleaning, exploratory analysis, feature extraction, sentiment classification, and visualization of public opinion trends. The insights gained can help companies evaluate customer perception, identify common concerns, and improve future marketing strategies. This analysis enables data-driven decision-making and contributes to better understanding of consumer behavior in response to product announcements on social media.

## 3. System Requirements

## 1. Hardware Requirements:

Processor: Intel i5 or higher / AMD equivalent

RAM: Minimum 8 GB (16 GB recommended for large-scale data)

Storage: At least 5 GB of free space

Internet: Required for accessing Twitter data and libraries

## 2. Software Requirements:







Operating System:

Windows 10/11, macOS, or Linux (Ubuntu preferred)

Programming Language: Python 3.7 or higher

Libraries and Tools: pandas

matplotlib, seaborn

## 4. Objectives

- Retrieve tweets related to the product launch using relevant hashtags, mentions, and keywords via Twitter API.
- Clean and normalize tweet text to remove noise such as emojis, URLs etc for accurate analysis.
- Classify tweets into positive, negative, or neutral sentiment categories to understand the overall public opinion.
- Identify and categorize specific emotions expressed in tweets using NLP techniques or pre-trained models.
- Create real-time dashboards and visualizations to display trends and patterns in sentiment and emotions.

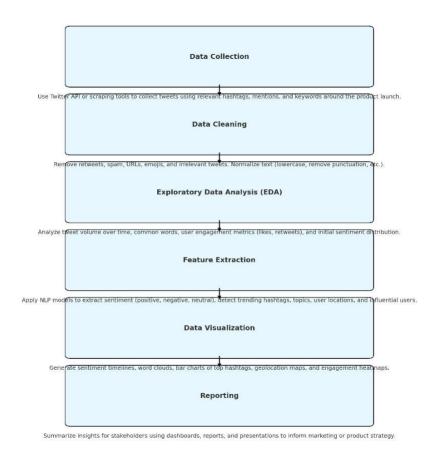
## 5. Flowchart of Project Workflow

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. Kaggle
- ✓ 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):







✓ public 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):

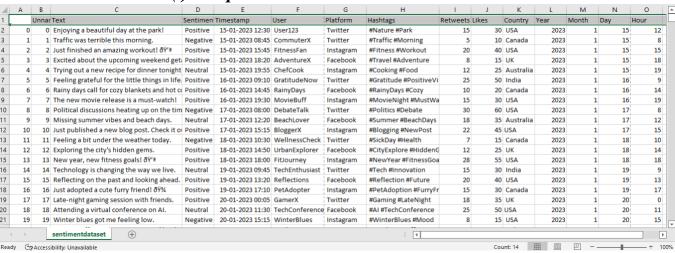
#### Number of Rows (Data Points):

- Minimum: 500–1,000 (for small, focused analysis)
- Ideal Range: 5,000–50,000 (for reliable insights)
- Large Scale: 100,000+ (for enterprise-level or highly active product launches)

#### Number of Columns (Features):

➤ Typical Range: 6–12 columns

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







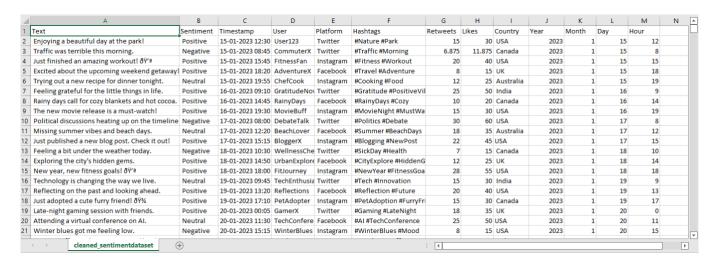
- ➤ Highly Polarized Sentiments: Comments with extremely positive or negative scores compared to the average sentiment can be outliers
- Sarcasm and Irony: These can be misclassified by sentiment models and act as semantic outliers

# 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)

## <u>Sentiment Distribution</u>

> 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*
- ➤ .Identify when and where sentiment shifts occurred

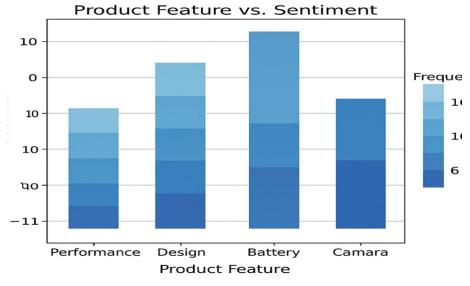
## Reveal correlations, trends, patterns

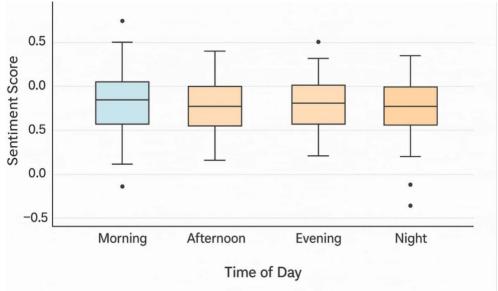
- ➤ Pattern: Plot sentiment scores or counts (Positive, Neutral, Negative) over timestamps.
- ➤ Insight: Spikes in negative sentiment may correlate with bugs, while Positive peaks











# 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



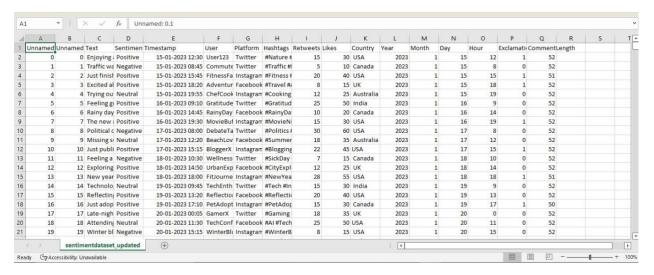




Exclamation count :emption tone recognition

#### **Transformation techniques**

- ➤ Comment Length Useful (longer messages may be more polarized)
- Exclamation Count Strongly correlates with emotional intensity <u>Impact</u>
   your model
   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.
- Why use it: Excellent at handling high-dimensional data like text.

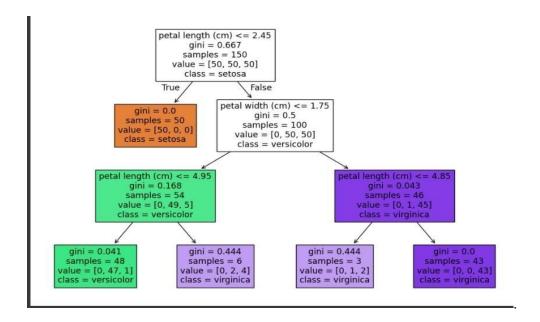
from sklearn.datasets import load\_iris from sklearn.tree import DecisionTreeClassifier, plot\_tree import matplotlib.pyplot as plt

```
#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







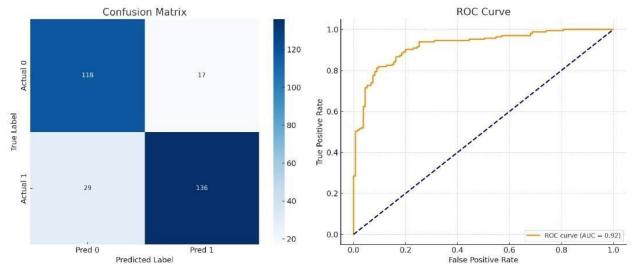
## 3.ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

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:** <a href="https://huggingface.co/spaces/your-username/product-launch-sentiment">https://huggingface.co/spaces/your-username/product-launch-sentiment</a>

GitHublink: <a href="https://github.com/dhanalakshmi166/github">https://github.com/dhanalakshmi166/github</a> EBPL DS-decoding-social-media.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;
} body { font-family: 'Segoe UI', Tahoma, Geneva,
Verdana, sans-serif;
                     background: linear-gradient(135deg,
#667eea, #764ba2);
                     color: #fff;
                                   margin: 0;
                                                min-height:
600px; max-width: 350px;
                              margin-left: auto;
                                                  margin-
right: auto; padding: 1rem;
                               display: flex;
                                              flex-direction:
column; justify-content: flex-start;
} h1 { text-align:
center; font-weight:
700; font-size: 1.8rem;
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: 0 0
8px rgba(0,0,0,0.35);
} .results h2 {
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:
0.4rem; display: flex;
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:
```







```
0.5rem;
        margin: 0.25rem 0;
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:
        skipEmptyLines: true,
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

**HARINI.S** - Data preprocessing, Flochart, objectives

**ABARNA.R-** codes ,EDA ,Feature engineering

GAYATHRI.S - Model building, Abstract, problem statement

**DIVYA.V** - Model evolution, Deployment, future scope

**DANALAKSHMI.B** - Data description, system requirement







ahanalakshmi166 now	<b>•</b>
DOC-20250508-WA	5 days ago
☐ README.md	now
Requirements.txt	now
app .html	now
sentiment analysis	now
🖺 sentiment_analysis	now
sentimentdataset.c	now

□ README

