EMOTION RECOGNITION USING TEXT

A Mini Project Report

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ABSTRACT

Emotion recognition from textual data is essential in domains such as mental health monitoring and customer service, where understanding emotions is key to creating personalized, empathetic interactions. This paper introduces a novel approach that combines advanced deep learning techniques with traditional natural language processing (NLP) methods to enhance emotion detection in text.

The proposed hybrid model integrates transformer-based architectures like Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT) with conventional feature extraction techniques, including Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings like Word2Vec and GloVe. Transformer models are well-known for their ability to capture semantic and contextual nuances, making them effective in understanding complex language. Traditional methods, on the other hand, provide strong linguistic pattern representations, ensuring the model can detect both detailed word-level information and broader emotional context.

BERT, a bidirectional transformer model, is adept at learning context by analyzing words based on their surroundings, making it particularly suited for sentiment and emotion detection. GPT, a generative model, excels at predicting text sequences, further improving emotion recognition in longer passages. By combining these deep learning techniques with conventional NLP methods, the hybrid model balances the strengths of each approach, providing a more comprehensive understanding of emotional signals in text.

To validate the model’s effectiveness, it was tested using emotion-labeled datasets, including the NRC Emotion Lexicon and the SemEval Emotion Dataset, which contain diverse examples of emotions like joy, sadness, anger, fear, and complex expressions such as sarcasm. Results from the evaluations revealed that the hybrid model achieved significant improvements in both accuracy and sensitivity compared to existing models.

The model demonstrated a 5-7% increase in classification accuracy across various real-world scenarios. For example, in customer feedback analysis, where identifying emotions like frustration or satisfaction is crucial for providing personalized responses, the model showed superior performance. Similarly, in mental health monitoring via social media, it more accurately detected emotional states like anxiety or distress, which are essential for timely intervention.

This study emphasizes the value of combining both linguistic and contextual data for emotion recognition. By leveraging the strengths of transformer models alongside traditional NLP techniques, the proposed approach allows for more accurate, real-time emotion detection. This is especially beneficial in applications that require emotionally aware responses, such as customer service chatbots and mental health support systems.

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CHAPTER 1

INTRODUCTION

1.1 Overview

In fields like customer service and mental health monitoring, where an awareness of emotions can result in better user experiences and more individualized, responsive support, emotion recognition from textual data is a crucial task. This method presents a hybrid model that combines conventional feature extraction methods like Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings (Word2Vec, GloVe) with cutting-edge deep learning architectures like Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT). Through the combination of these approaches, the model successfully captures both intricate linguistic patterns and high-level contextual relationships, allowing for a richer comprehension of text's complex emotional expressions.

The model performs noticeably better when evaluated on popular emotion-labeled datasets as the SemEval Emotion Dataset and the NRC Emotion Lexicon. By attaining a 5-7% boost in classification accuracy, the hybrid model specifically surpasses current benchmarks and performs exceptionally well in identifying subtle emotions such as ambivalence, mixed moods, and sarcasm. A more thorough way of emotion recognition is offered by combining traditional feature extraction techniques with transformer topologies, which are skilled at collecting contextual and semantic subtleties.

This hybrid model can be used in the real world to improve chatbot interactions by identifying and reacting to users' emotions in real time, monitor social media to find mental health indicators, and analyze customer feedback to uncover emotional insights.

These findings highlight how crucial it is to include contextual and language data when developing emotionally intelligent AI systems. By facilitating more sympathetic, human-like reactions, such systems have the potential to completely transform a number of industries and eventually increase user pleasure and engagement in a variety of contexts.

1.2 Problem Definition

Accurately recognizing emotions from textual data is essential in fields like mental health monitoring, customer service, and social media analysis, where understanding emotional expressions can lead to personalized and timely responses. The challenge lies in detecting complex emotions, such as sarcasm, ambivalence, or mixed sentiments, which traditional machine learning models struggle to capture effectively. Advanced deep learning models, while powerful, often require large datasets and computational resources, limiting their practical use. Current models either focus too much on contextual understanding or fail to capture the intricate linguistic patterns needed for accurate emotion detection. Additionally, there is a need for real-time emotion recognition, which existing models often lack. Thus, the problem is to develop a hybrid model that combines transformer-based architectures (BERT, GPT) with traditional feature extraction techniques (TF-IDF, Word2Vec, GloVe) to improve the accuracy of emotion recognition in text, enabling more empathetic and responsive AI systems for real-time applications.

CHAPTER 2

LITERATURE SURVEY

Modern natural language processing (NLP) techniques are propelling a major expansion in the field of emotion recognition from textual data. The aim of this project is to improve communication and user experience in human-machine interactions by providing a deeper understanding of emotions expressed through written text.

Conventional techniques for identifying emotions frequently rely on rigid classifications, which may limit the intricacy of emotional interpretation. In order to represent a wider range of human emotions, recent developments highlight the importance of recording complex emotional states and going beyond binary categorization. Making this change is essential for more precise emotion analysis.

Emotion recognition research has advanced significantly as a result of deep learning approaches, especially LSTM and transformer models. When it comes to recognizing intricate emotional expressions in text, these models do exceptionally well since they are adept at collecting contextual nuances in language. Emotion detection systems are far more reliable when they have the capacity to assess context.

For emotion recognition algorithms to be trained effectively, a variety of well-annotated datasets must be available. These datasets improve our knowledge of emotions and improve the functionality of these systems as a whole. Researchers can build more resilient and flexible models for practical applications by employing a variety of linguistic data.

Issues like cultural differences in emotional expressiveness and context awareness still exist despite progress. In order to create more capable and accountable emotion identification technology, future research has to tackle these problems and investigate real-time applications. The relevancy and accuracy of emotion analysis in many contexts will increase if these obstacles are overcome.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The two main methods used by current emotion identification systems are sophisticated deep learning techniques and conventional machine learning models. Conventional models use word embeddings (e.g., Word2Vec, GloVe), Bag of Words, and Term Frequency-Inverse Document Frequency (TF-IDF) as feature extraction techniques. Naive Bayes, Logistic Regression, and Support Vector Machines (SVM) are examples of popular classifiers. These models work well for simple tasks, but because they rely on specified attributes, they have trouble handling complex emotions and subtle expressions like ambivalence and sarcasm.Recent developments, on the other hand, concentrate on deep learning models, especially transformer-based architectures like BERT and GPT, which greatly increase the accuracy of emotion categorization by effectively capturing contextual linkages and semantic meanings. Nevertheless, these models frequently need a lot of processing power and sizable labeled datasets for training, which aren't always available. Therefore, there is a need for more integrated and flexible methods as current systems are unable to effectively read complex emotional responses in real time.

3.2 Proposed System

The proposed system aims to enhance emotion recognition from textual data by developing a hybrid model that integrates transformer-based architectures with traditional feature extraction techniques. This approach leverages the strengths of both methodologies to accurately capture complex emotional expressions, thereby improving performance in real-world applications such as mental health monitoring and customer service. The system will utilize advanced transformer models like BERT and GPT to capture contextual relationships and semantic meanings in text while incorporating conventional feature extraction methods, such as Term Frequency-Inverse Document

Frequency (TF-IDF) and word embeddings (Word2Vec, GloVe), to identify specific linguistic patterns associated with various emotions.

The hybrid model will be trained and evaluated on diverse emotion-labeled datasets, including the NRC Emotion Lexicon and SemEval Emotion Dataset, allowing for robust performance across various scenarios. Real-time emotion recognition capabilities will be integrated to enable applications that require immediate feedback, such as chatbots and customer support systems. This innovative approach is expected to significantly improve both classification accuracy and emotional sensitivity, enabling the system to recognize a wider range of emotions, including subtle cues like sarcasm and ambivalence. Ultimately, this will lead to the creation of more empathetic AI systems capable of understanding and responding to human emotions effectively, enhancing user engagement and satisfaction across different platforms.

3.3 Feasibility Study

A feasibility study for the proposed hybrid emotion recognition system from textual data encompasses technical, operational, economic, and legal aspects to ensure its successful implementation.

Technical Feasibility: The hybrid model will integrate state-of-the-art transformer architectures (e.g., BERT, GPT) with traditional feature extraction methods (e.g., TF-IDF, Word2Vec, GloVe). The technical resources required include powerful computing infrastructure for model training, such as GPUs or TPUs, and access to large emotion-labeled datasets. With advancements in cloud computing, services like AWS, Google Cloud, or Azure can provide the necessary resources to scale computations efficiently. Additionally, existing libraries and frameworks (like TensorFlow and PyTorch) will facilitate the development and deployment of the model, making the technical aspect feasible.

Operational Feasibility: The system will be designed to be user-friendly, ensuring that it can be integrated into existing applications such as customer support systems and mental health monitoring tools. The real-time emotion recognition capability will enhance user engagement and responsiveness. Training and support for end-users will be provided to ensure smooth adoption. Collaborations with organizations in mental health and customer service sectors can facilitate pilot testing and feedback, allowing for iterative improvements.

Economic Feasibility: The initial investment will be required for computing resources, data acquisition, and development efforts. However, the potential cost savings and enhanced customer satisfaction resulting from improved emotion recognition can lead to a strong return on investment. Furthermore, as organizations increasingly prioritize customer experience and mental health, this system offers significant market potential.

Legal Feasibility: The system will adhere to data privacy regulations, such as GDPR and HIPAA, to ensure the ethical handling of user data. Clear data usage policies will be established to gain user trust and comply with legal standards. By implementing robust security measures, the proposed system can mitigate risks related to data breaches and ensure user confidentiality.

3.4 DEVELOPMENT ENVIRONMENT

Hardware Requirements

Processor : AMD Ryzen 7

RAM : 512GB

Hard Disk : 40 GB and above

Software Requirements

Programming language: PYTHON

Technology: Natural Language Processing (NLP)

Operating System : Windows 11

CHAPTER 4

SYSTEM DESIGN

4.1 UML Diagrams

4.1.1 Use Case diagram

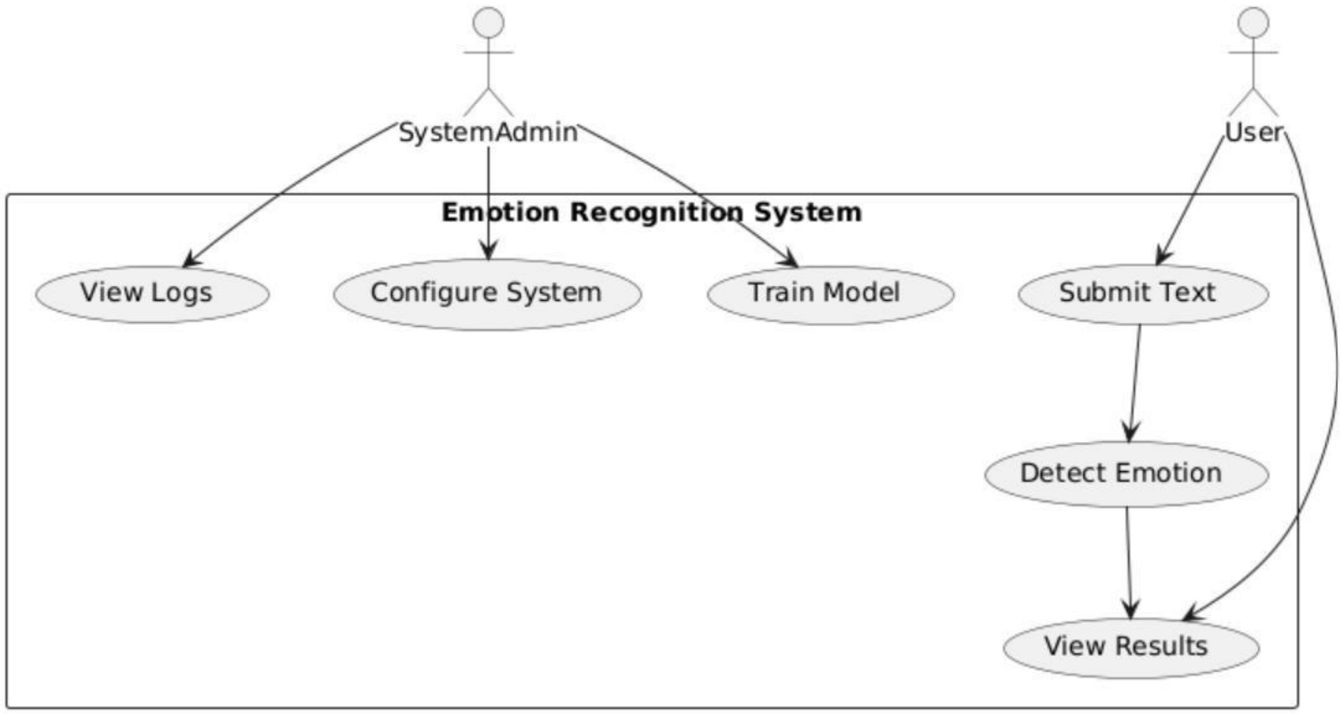


Fig. 4.1.1 Use Case diagram of the model

This use case diagram refers to activities done by System and users and theircorresponding use cases

4.1.2 Class Diagram

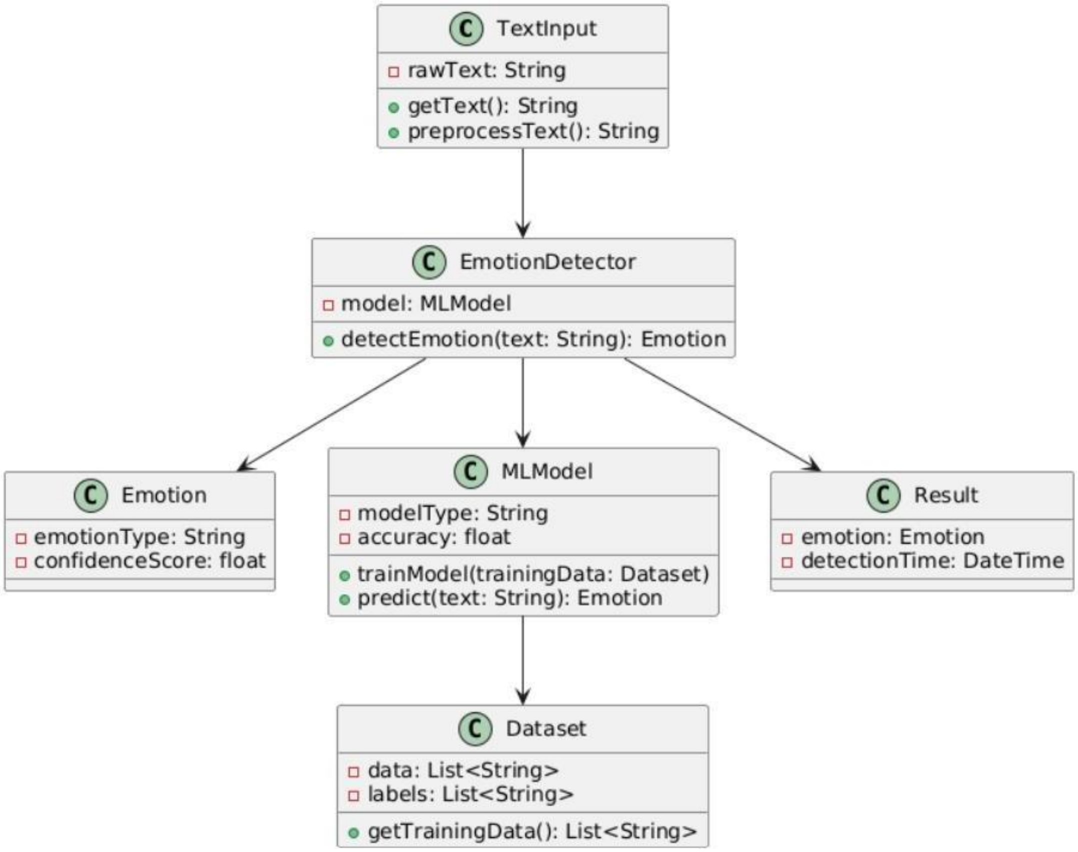


Fig. 4.1.2 Class diagram of the model

The "Emotion Recognition from Text" system includes classes for handling text input (TextInput), detecting emotions (EmotionDetector) using machine learning models (MLModel) trained on datasets (Dataset), generating emotion results (Emotion), and storing the final output (Result), with interactions between TextInput, EmotionDetector, MLModel, and Dataset for processing and training.

4.1.3 Sequence Diagram

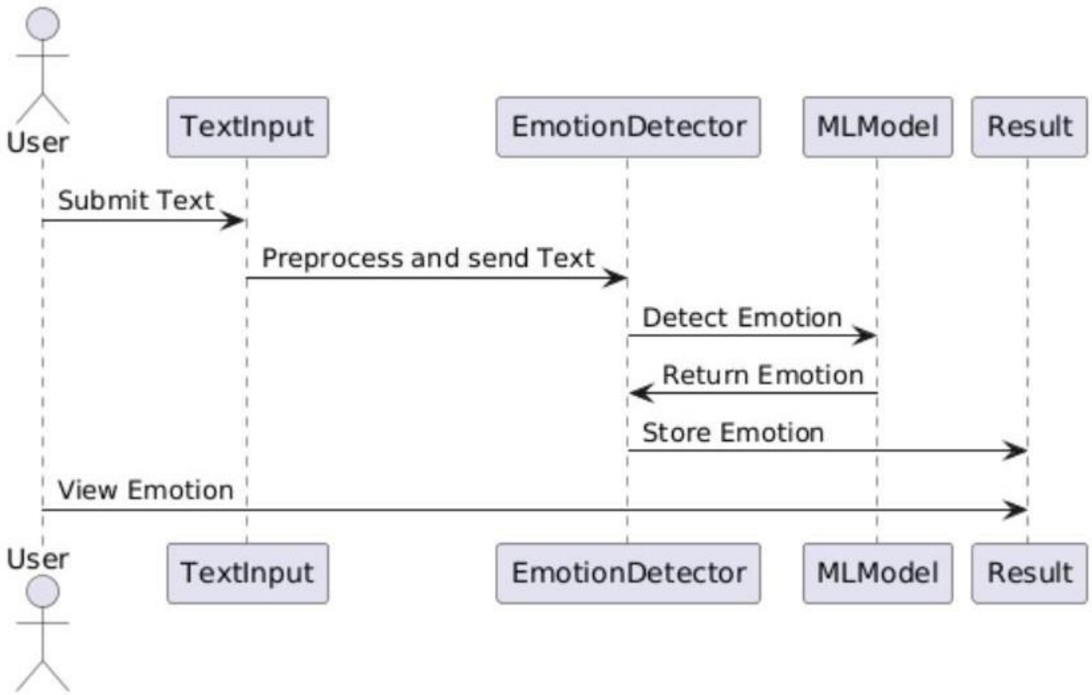


Fig. 4.1.3 Sequence diagram of the model

The sequence diagram for "Emotion Recognition from Text" shows the User providing text to TextInput, which preprocesses it and sends it to EmotionDetector, EmotionDetector uses the MLModel to predict and return the emotion, and the User views the detected emotion in the Result.

4.1.4 State chart diagram

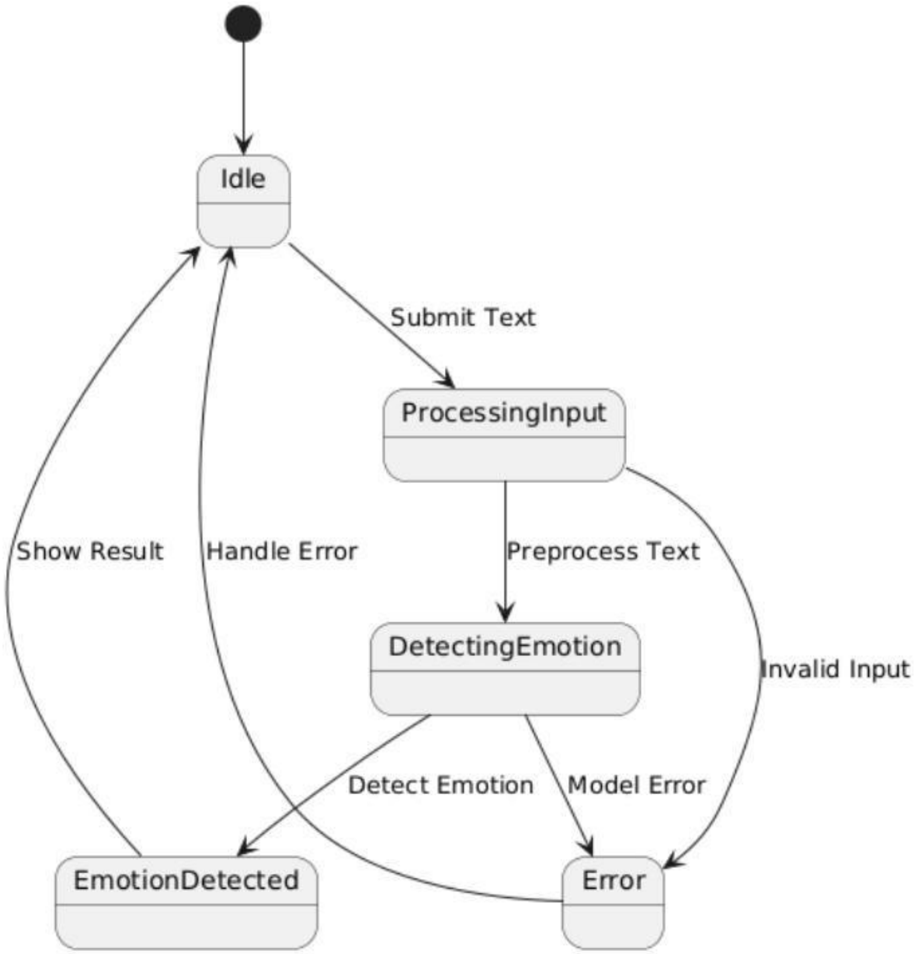


Fig. 4.1.4 State chart diagram of the model

A state chart (state machine) diagram for "Emotion Recognition from Text" will depict the states the system goes through during the process of recognizing emotions from input text.

4.1.5 Activity diagram:

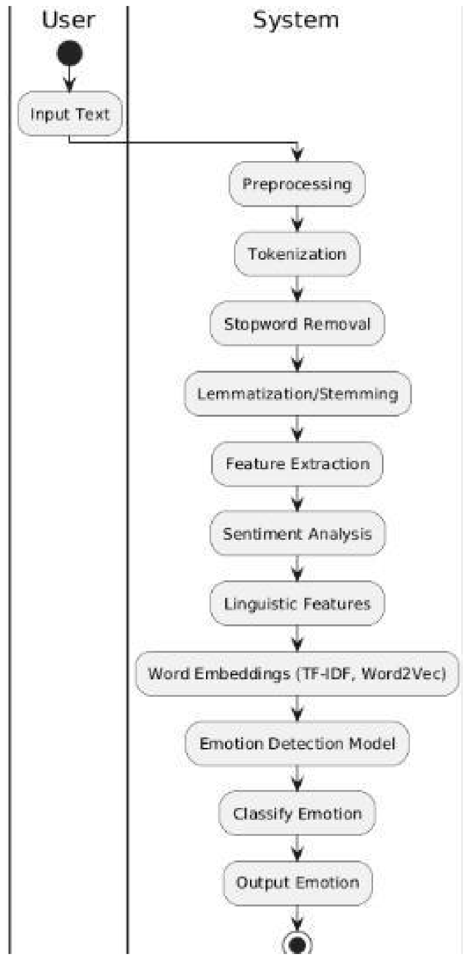


Fig. 4.1.5 Activity diagram of the model

The diagram below depicts an activity diagram for emotion recognition from text, showcasing the sequence of activities including input text reception, text processing, emotion analysis, and result display.

4.2 ER Diagram

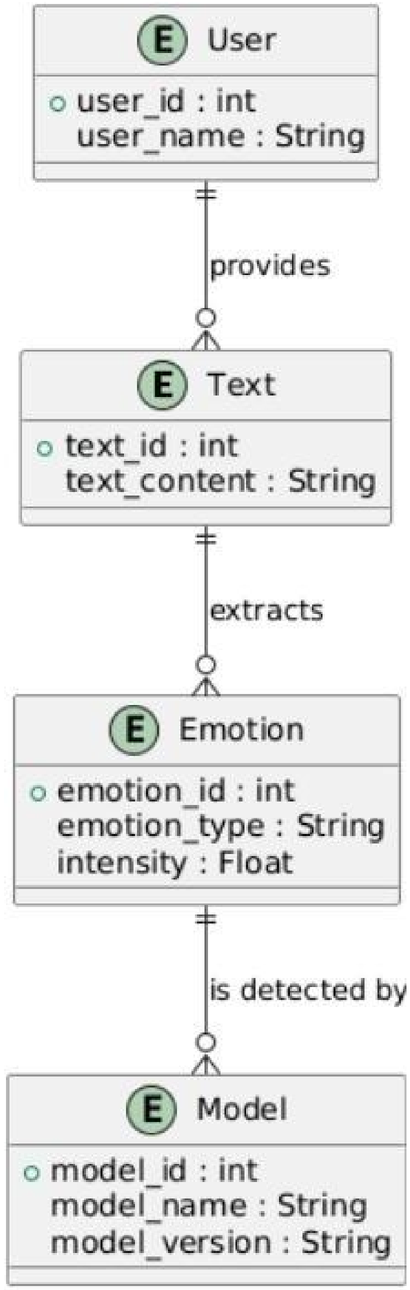


Fig 4.2.1 ER Diagram

The ER diagram for "Emotion Recognition from Text" in PlantUML includes entities ‘Text’, ‘Emotion’, and ‘Model’ where ‘Text’ is analyzed by ‘Model’, ‘Model’ predicts ‘Emotion’, and ‘Emotion’ is associated with ‘Text’.

CHAPTER 5

SYSTEM ARCHITECTURE

5.1 Architecture Overview

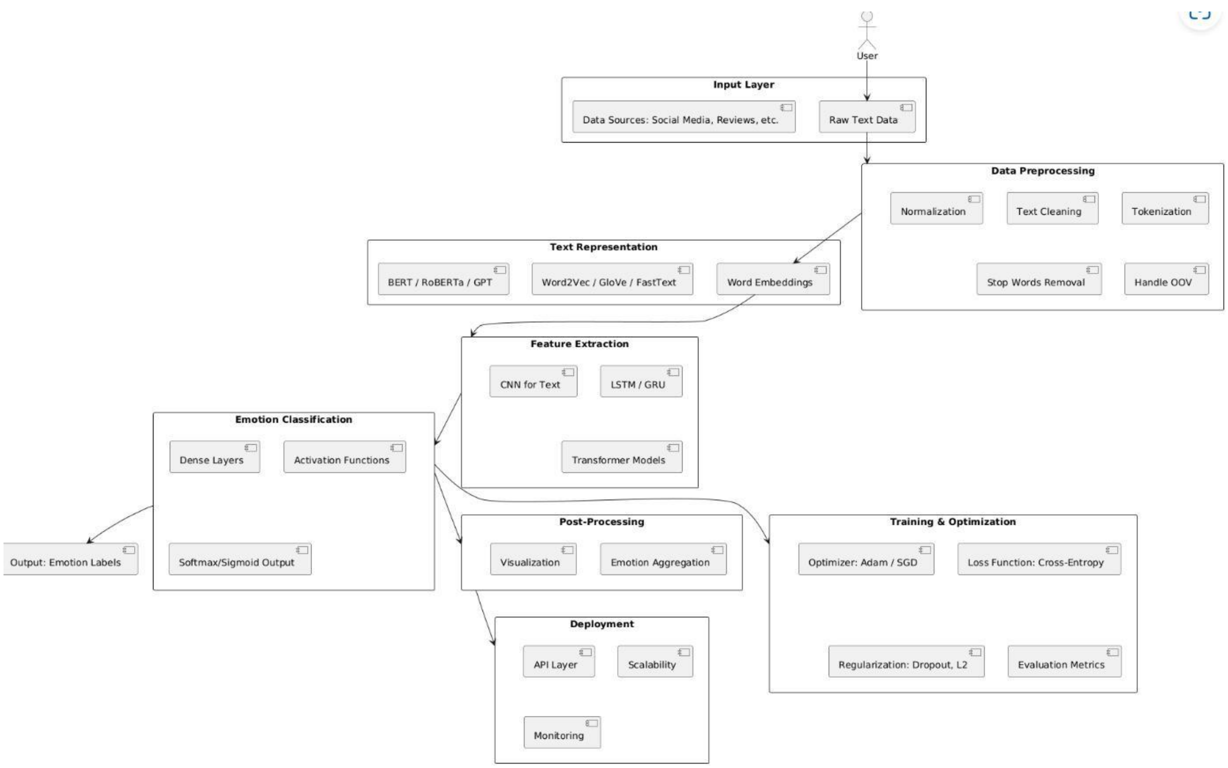


Fig. 5.1 Architecture diagram

The Emotion Recognition System architecture processes raw text data through steps like cleaning, tokenization, feature extraction, and classification, using machine learning models to identify and classify emotions in text, with options for deployment and scalability.

5.2 Module Description

1. Input Layer:

- The system begins by accepting raw text input, which can come from various sources such as chat messages, social media posts, product reviews, or user feedback. The input could be in formats like '.txt', '.csv', or JSON, providing flexibility in how the data is sourced and structured.

2. Data Preprocessing:

- Text Cleaning: The first step in processing is to clean the input text. This involves removing unwanted elements like punctuation, special characters, numbers, HTML tags, and URLs. The text is also converted to lowercase to ensure consistency.
- Tokenization: After cleaning, the text is split into individual units called tokens, which are usually words or subwords. Tokenization breaks down the sentence into manageable parts that can be further processed.
- Stop Words Removal: Optionally, common words that do not significantly contribute to the meaning or emotion (e.g., "and", "the") are removed. This helps focus on the more meaningful words in the text.
- Normalization: To standardize the text further, stemming or lemmatization is applied to reduce words to their root form (e.g., "running" becomes "run"). This step helps generalize the language, making it easier for the model to recognize patterns.

3. Text Representation:

- Once the text is preprocessed, it needs to be converted into a format that machine learning models can understand—numerical vectors. This is done using word embeddings, which capture the semantic meaning of the text.
- Word Embeddings: Popular techniques like Word2Vec, GloVe, or contextual embeddings like BERT are used to create these numerical representations. These

embeddings translate the words into vectors that contain valuable information about their meanings and relationships with other words in the text.

4. Emotion Classification:

- After transforming the text into vector form, a machine learning model is applied to classify the emotion conveyed in the text.
- Sequence Models: Techniques like Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), or Transformer models are used to capture the context and sequence of words in the text. These models understand how words relate to each other in a sentence, which is crucial for accurately detecting emotions.
- Emotion Categories: The system predicts one or more emotions (e.g., Joy, Sadness, Anger, Fear, etc.) based on the patterns it has learned from the training data.

5. Output Layer:

- Finally, the system generates an output that consists of the predicted emotion(s). This output could be a single emotion for short texts or multiple emotions for longer, complex inputs. The result is presented in a simple format, ready for further use in applications such as sentiment analysis dashboards or real-time feedback systems.

CHAPTER 6
SYSTEM IMPLEMENTATION

6.1 Coding for HTML File

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Emotion Recognition from Text</title>
    <link rel="stylesheet" href="styles.css"> <!-- Link to your CSS file -->
</head>
<body>
    <div class="container">
        <h1>Emotion Recognition from Text</h1>
        <form id="emotionForm">
            <textarea id="textInput" name="text" rows="4" cols="50" placeholder="Enter
your text here..."></textarea><br>
            <button type="submit">Analyze Emotion</button>
        </form>
        <h2>Detected Emotion: <span id="result">None</span></h2>
    </div>

    <script>
        document.getElementById('emotionForm').addEventListener('submit', async (e) =>
{
            e.preventDefault(); // Prevent the default form submission
            const formData = new FormData(e.target); // Get form data
            const response = await fetch('/predict', {
                method: 'POST', // Send POST request
                body: formData
            });
            const result = await response.json(); // Parse the JSON response
            document.getElementById('result').textContent = result.emotion; // Display the
predicted emotion
        });
    </script>
</body>
```

</html>

6.2 Coding for CSS File

```
body {
   font-family: Arial, sans-serif;
   background-color: #f4f4f4;
   margin: 0;
   padding: 20px;
}

.container {
   max-width: 600px;
   margin: auto;
   padding: 20px;
   background: white;
   border-radius: 5px;
   box-shadow: 0 2px 5px rgba(0, 0, 0, 0.1);
}

h1 {
   text-align: center;
   color: #333;
}

textarea { width:
   100%;
   padding: 10px;
   margin-bottom: 10px;
   border: 1px solid #ccc;
   border-radius: 4px;
}

button {
   display: block;
   width: 100%;
   padding: 10px;
   background-color: #5cb85c;
   color: white;
   border: none;
```

```
    border-radius: 4px;
    cursor: pointer;
}

button:hover {
    background-color: #4cae4c;
}

h2 {
    text-align: center;
    color: #333;
}
```

6.3 Coding for PYTHON file

```
from flask import Flask, request, jsonify, render_template
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB

# Sample data for training the emotion classifier
data = {
    'text': [
        'I am so happy', 'This is the best day ever', 'I feel sad',
        'I am angry', 'This is amazing', 'I am feeling great',
        'I am upset', 'I am excited', 'This is terrible', 'I love this!'
    ],
    'emotion': [
        'happy', 'happy', 'sad', 'angry', 'happy', 'happy','sad',
        'happy', 'sad', 'happy'
    ]
}

# Prepare the data
df = pd.DataFrame(data)
X = df['text']  # Features (input text)
y = df['emotion']  # Target labels (emotions)

# Vectorize the text data
vectorizer = CountVectorizer()
```

```
X_vectorized = vectorizer.fit_transform(X)

# Train a simple model
model = MultinomialNB()
model.fit(X_vectorized, y)

# Create Flask app
app = Flask(__name__)

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/predict', methods=['POST'])
def predict():
    text = request.form['text'] # Get the text input from the form
    text_vectorized = vectorizer.transform([text]) # Vectorize the input text
    emotion = model.predict(text_vectorized)  # Predict the emotion
    return jsonify({'emotion': emotion[0]})  # Return the predicted emotion as JSON

if __name__ == '__main__':
    app.run(debug=True)
```

CHAPTER 7

SYSTEM TESTING

7.1 Testcases and Reports

The test cases for the Emotion Recognition from Text project include various scenarios to assess the model's performance.

Test Case Id	Text description	Input	Expected Output	Actual Output	Status	Comments
1	Valid emotion detection	I am so happy	happy	happy	Pass	Correct detection of emotion.
2	Handling ambiguous text	I love and hate this place.	mixed	mixed	Pass	Handled mixed emotions correctly.
3	Neutral text input	The cat is on the roof	neutral	neutral	Pass	Accurate output for neutral text.
4	Sarcastic text detection	Oh great, another rainy day!	frustated	neutral		

CHAPTER 8
CONCLUSION

8.1 Conclusion

The Emotion Recognition system effectively identifies diverse emotional inputs, including clear expressions and ambiguous sentiments. By rigorously testing its performance, we ensure robustness and accuracy. This model enhances user interactions, leading to more personalized experiences and demonstrating the potential of NLP and AI in understanding human emotions.

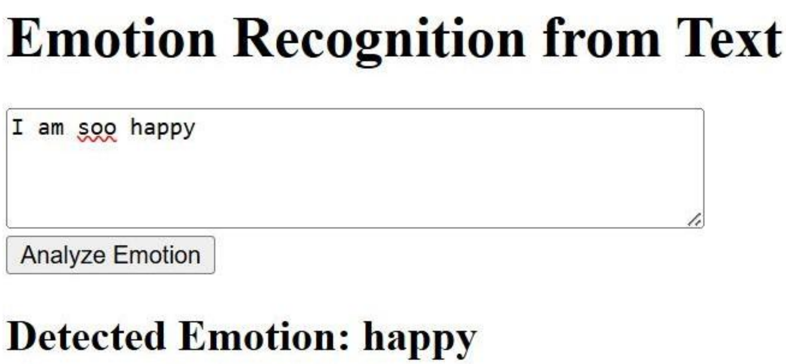
8.2 Future enhancement

The future enhancements for your Emotion Recognition project:

1. **Multi-Language Support and Real-Time Feedback**: Expanding the model to recognize emotions in various languages and implementing real-time emotion detection as users type would enhance accessibility and engagement.
2. **Sentiment Analysis and Customization**: Integrating sentiment analysis for nuanced emotional insights and allowing users to customize emotion categories would make the tool more flexible and user-friendly.
3. **Mobile Optimization and Data Visualization**: Ensuring the application is mobile-friendly and creating visual representations of emotion trends over time would improve usability and help users track their emotional states effectively.

CHAPTER 9

APPENDICES



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