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Emotion Detection in Customer Feedback UsingAdvanced Sentiment Analysis

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ABSTRACT :

In today's business landscape, understanding customer feedback is key to enhancing satisfaction and loyalty. This project advances traditional sentiment analysis by detecting specific emotions—joy, anger, sadness, surprise, and fear—using NLP and machine learning. By analyzing feedback from reviews and social media in real time, our system helps businesses promptly address concerns, improve service, and make data-driven decisions. Robust preprocessing ensures accurate detection, even with slang or sarcasm, allowing companies to proactively enhance the customer experience.

Keywords: Feedback, Sentiment, Emotion

Introduction :

In today's business environment, customer feedback plays a critical role in shaping company strategies and improving customer experiences. Traditional methods of sentimentanalysis focus on categorizing feedback aseither positive, negative, or neutral. However, this oversimplified binary classification fails to capture the full range of emotions customersexpress. Nuanced emotions like joy, anger, surprise, or sadness provide deeper insights into customer satisfaction, loyalty, and pain points. Additionally, feedback often contains complex language structures such as slang, sarcasm, and domain-specific jargon, which are poorlyhandled by basic models. Without proper understanding of these nuances, businesses struggle to respond to customer needs effectively, resulting in missed opportunities for enhancing satisfaction and preventing customer churn. Problem: Existing sentiment analysis tools lack the ability to accurately detect nuanced emotions and handle complex textual features (sarcasm, slang), leading to limited actionable insights from customer feedback.

Literature Review :

Sentiment analysis has advanced from basic polarity detection to more sophisticated models like RNNs and LSTMs, enabling a deeper understanding of emotions beyond positive, negative, or neutral labels. Emotion detection, asan extension, identifies specific emotions such as joy, anger, and sadness. Transformer models like BERT have significantly enhanced this capability by grasping the context of words, offering businesses richer insights into customerfeedback. However, challenges remain in handling slang, sarcasm, and industry-specificjargon. Transformer-based models like GPT-3, when fine-tuned with domain-specific data,have shown improved performance in detecting these nuances. Real-time emotion detection is increasingly adopted in customer service, allowing industries to respond instantly to customer sentiments, which boosts personalization and satisfaction. Looking ahead, multimodal emotion detection—incorporatingtext, speech, and facial cues—holds promise for a more comprehensive understanding of emotions, though text-based analysis remains central for now.

Methods and Algorithms :

Data Handling:

- Pandas: Used for reading and manipulating the dataset from a CSV file.

Text Preprocessing:

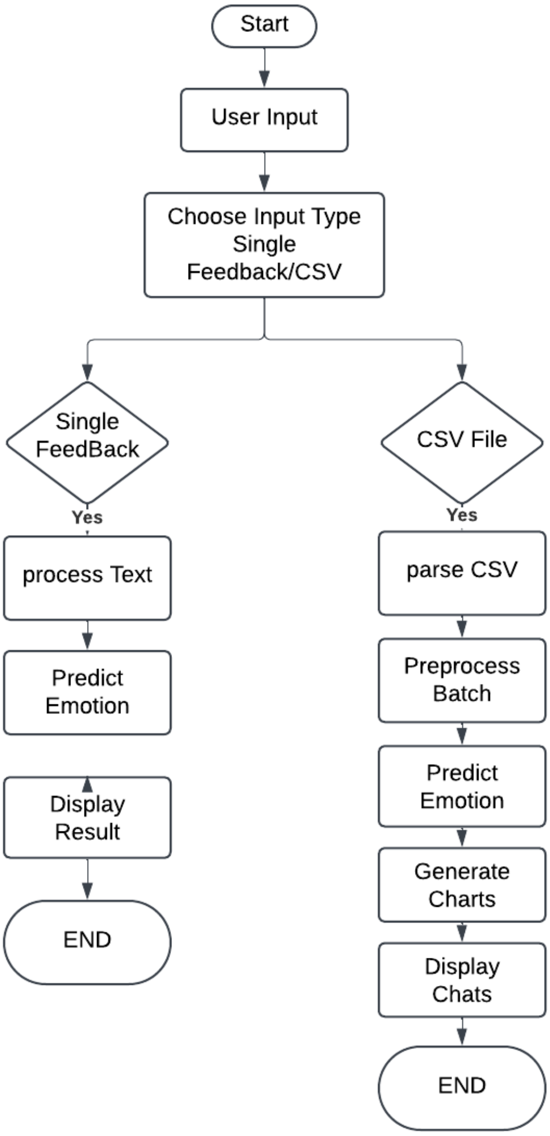
- Regular Expressions (re): Cleans text by removing non-word characters.

Lowercasing:

- Standardizes text to lowercase.
- Tokenization: Splits text into individual words.
- Stopwords Removal: Filters out common words using NLTK's stopwords. Machine Learning:
- train_test_split(): Divides the data into trainingand testing sets.

- TfidfVectorizer: Converts text data into numerical format using TF-IDF to highlight important words.
- MultinomialNB: A Naive Bayes classifier usedfor text classification based on categorical data..

Flow Chart :



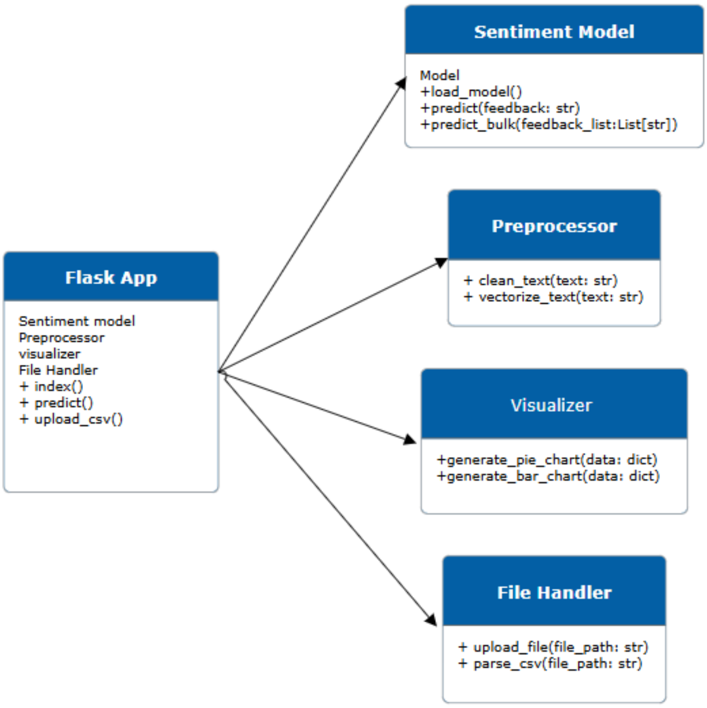
Architecture :

Model Architecture:

Input Layer: The processed feedback text is transformed into TF-IDF vectors, representing the frequency and significance of words.
Multinomial Naive Bayes Classifier: The model processes the TF-IDF features to predict one of the five sentiment emotions based on thefeedback input.
o Output Layer: The model outputs the predicted emotion class for each feedback entry.

Web Application Architecture:

Frontend: The user interacts with the applicationthrough an HTML interface, allowing for input of individual feedback or uploading of CSV files.
Backend: Flask serves as the backend, processing inputs and managing the interaction with the sentiment analysis model. It routes the input to the model for prediction and returns the results to the user. o Visualization Component: The application includes a visualization component using Matplotlib to generate charts displaying the distribution of predicted emotionsfor batch CSV input, enhancing user understanding of the results.



Future Scope :

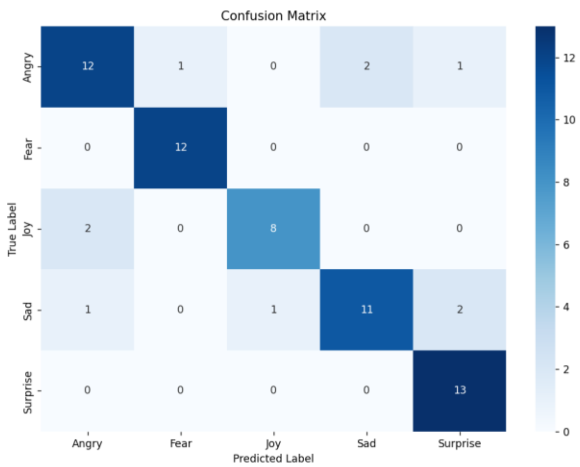
The Feedback Emotion Classifier project has significant potential for future enhancements, including: 1. Expanded Emotion Classification: Incorporating additional emotions using advanced models like RNNs or transformers. 2. Multilingual Support: Enabling analysis in multiple languages to reach a broader audience.

3. Real-Time Analysis: Implementing live feedback analysis from platforms like social media for immediate insights. 4. Integration with CRM Systems: Connecting with customer relationship tools to provide comprehensivesentiment insights. 5. User Customization: Allowing users to define their own sentimentcategories for tailored analysis. 6. Improved Visualizations: Developing more interactive charts and dashboards for better data interpretation. 7. Continuous Model Improvement: Regularly updating the model with new data to enhance accuracy. 8. Cloud Deployment: Utilizing cloud services for improved scalability and accessibility.

Results :

Accuracy: The Model have 85.45% accuracy

- Precision, Recall, and F1-Score: The over allPrecision is 0.85, Recall is 0.85 and F1-Score is 0.84 based on the model evaluation
- Confusion Matrix: The confusion matrix isgiven below



Conclusion :

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9. REFERENCES :

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