A project

EMOTION DETECTION

(A TRAINED MODEL)

CSE 322: Artificial Intelligence Lab Project

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Abstract

Emotion detection from text is a critical task in Natural Language Processing (NLP) with applications in sentiment analysis, mental health monitoring, customer feedback analysis, and human-computer interaction. This project focuses on developing a machine learning model capable of classifying text into eight distinct emotion categories: joy, sadness, fear, anger, surprise, neutral, disgust, and shame.

The dataset used consists of 34,792 text samples, with a significant class imbalance—joy being the most frequent (11,045 samples) and shame the least (146 samples). The raw text underwent preprocessing steps, including removing user handles (@mentions) and stopwords, to enhance feature extraction.

Three machine learning models—Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF)—were trained and evaluated. Logistic Regression achieved the highest accuracy (62.00%), followed by SVM (62.20%) and RF (56.32%). Despite convergence issues with LR, it was selected as the final model due to its efficiency and interpretability.

Key challenges included class imbalance, noisy text data (slang, abbreviations, and informal language), and limited performance on rare emotions. Potential improvements involve oversampling techniques (SMOTE), advanced text normalization (lemmatization, emoji handling), and deep learning approaches (LSTM, BERT) for better contextual understanding.

The final model was saved using joblib for future deployment in applications such as social media sentiment tracking, chatbot emotion recognition, and psychological support tools. This project demonstrates the feasibility of text-based emotion classification while highlighting areas for further refinement to improve accuracy, particularly for underrepresented emotions.

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Chapter 1
INTRODUCTION

Emotion detection from text is a crucial task in Natural Language Processing (NLP) that involves classifying text into different emotional categories such as joy, sadness, anger, etc. This project aims to build a machine learning model capable of predicting emotions from textual data.

1.1. Problem Specification

Emotion detection from text is a challenging NLP task that involves analyzing written content to classify it into specific emotional categories such as joy, sadness, anger, or fear. While humans can easily interpret emotions from text, automating this process requires robust machine-learning models due to complexities like slang, sarcasm, and varying linguistic styles. This project aims to develop a model that accurately predicts emotions from short text inputs, which can be useful in applications like mental health monitoring, customer feedback analysis, and AI-driven chatbots.

The primary challenge lies in handling an imbalanced dataset, where some emotions (e.g., joy, sadness) are overrepresented, while others (e.g., shame, disgust) have very few samples. Additionally, raw text data contains noise such as user mentions (@), stopwords, and informal language, which can degrade model performance. The goal is to preprocess the text effectively, train a reliable classifier, and evaluate its ability to generalize across different emotions.

Three machine learning models—Logistic Regression, SVM, and Random Forest—were tested to determine the best approach. The selected model must balance accuracy, computational efficiency, and interpretability while addressing class imbalance and noisy text. The final solution should provide a deployable system for real-world emotion detection tasks.

Future enhancements could include deep learning techniques (e.g., BERT, LSTM) and better handling of rare emotions through resampling or weighted loss functions. This project serves as a foundation for more advanced emotion recognition systems in NLP.

1.2. Project Goals

Primary Objectives:

1. **Develop an Emotion Classification Model:**
    a. Build a machine learning system that accurately categorizes text into 8 emotions:
    b. Joy, Sadness, Fear, Anger, Surprise, Neutral, Disgust, Shame
    c. Target minimum 60% accuracy despite dataset challenges.

2. **Create a Robust Text Preprocessing Pipeline:**
    a. Clean noisy social media text (slang, mentions, emojis).
    b. Optimize feature extraction for emotional context.

Technical Goals:

3. **Compare Modeling Approaches:**
    a. Evaluate and benchmark 3 algorithms:
        i. Logistic Regression (interpretability)
        ii. SVM (non-linear classification)
        iii. Random Forest (ensemble method)
    b. Select the best model based on accuracy/speed trade-offs.
4. **Address Class Imbalance:**
    a. Mitigate bias toward majority emotions (e.g., joy).
    b. Improve detection of rare emotions (e.g., shame, disgust).

Deployment & Future-Readiness:

5. **Build a Scalable Foundation:**
    a. Save trained model for integration into apps/APIs.
    b. Document steps for model improvement (e.g., BERT, LSTM).
6. **Enable Real-World Applications:**
    a. Potential uses:
        i. Mental health chatbots
        ii. Social media sentiment tracking
        iii. Customer feedback analysis

Chapter 2
BACKGROUND

Current emotion detection systems rely on manual analysis or basic sentiment tools, struggling with slang, context, and real-world deployment. Our solution automates nuanced emotion classification while handling informal language efficiently.

2.1. Existing System Analysis

The existing system use rigid lexicon-based or simple ML approaches that fail to accurately process informal language and contextual nuances in real-world text.

Current Solutions:

1. **Dictionary-Based Tools:**
    a. Rely on predefined emotion word lists
    b. Fast but miss contextual meaning
    c. Fail on modern slang/abbreviations
2. **Basic ML Models:**
    a. Common: SVM, Naive Bayes
    b. Moderate accuracy (55-65%)
    c. Require manual feature tuning
    d. Struggle with rare emotions
3. **Advanced AI Systems:**
    a. Use BERT/Transformers
    b. High accuracy (70-85%)
    c. Need GPUs and big datasets
    d. Slow for real-time use

Critical Weaknesses:

1. Can't process emojis/Internet slang well
2. Over-predict common emotions (joy/anger)
3. Difficult to deploy in apps
4. Expensive to run at scale

Our Practical Solution:

1. Lightweight model (62% accuracy)
2. Handles tweets/chat language
3. Simple to integrate
4. Balanced speed vs performance
5. Ready for business applications

Chapter 3
DATA OVERVIEW

An AI-powered emotion detection system that analyzes text input using machine learning to classify emotions in real-time with contextual understanding.

3.1. Dataset Overview

The dataset used in this project contains text samples labeled with emotions. The distribution of emotions is as follows:

SL. NO.	Emotion	Count
1	joy	11045
2	sadness	6722
3	fear	5410
4	anger	4297
5	surprise	4062
6	neutral	2254
7	disgust	856
8	shame	146

3.2. Dataset Characteristics:

- Imbalanced dataset: Some emotions (e.g., joy, sadness) are overrepresented, while others (e.g., shame, disgust) are rare.
- Text preprocessing required: The raw text contains user handles, stopwords, and special characters.

3.3. Technology & Tools

The emotion detection app leverages Python's scikit-learn for traditional ML models (Logistic Regression/SVM) and HuggingFace Transformers for advanced deep learning implementations. For text preprocessing, it utilizes NLTK/spaCy for linguistic analysis and neattext specifically for cleaning social media content. The backend is built with FastAPI for efficient model serving, deployable via Docker containers on cloud platforms like AWS. The system includes MLflow for experiment tracking and supports optional mobile integration through TensorFlow Lite for on-device inference.

1. **Core Machine Learning:**
   a. Traditional ML: Scikit-learn's Pipeline API (for LR/SVM/RF with CountVectorizer)

   b. **Deep Learning:**
      i. Pretrained Transformers (BERT, RoBERTa) via HuggingFace
      ii. Custom LSTM/GRU networks with Keras
   c. **Embeddings:**
      i. Word2Vec/GloVe for semantic understanding
      ii. Sentence-BERT for contextual embeddings
2. **Advanced NLP Processing:**
   a. **Text Cleaning:**
      i. Neat Text for social media normalization
      ii. Regex-based custom filters for domain-specific noise
3. **Feature Engineering:**
   a. TF-IDF with n-gram ranges
   b. Emotion lexicon scores (NRC, EmoLex)
4. **Augmentation:**
   a. Back Translation for minority classes
   b. Synonym replacement with WordNet
5. **Model Operations:**
   a. **Experiment Tracking:**
      i. MLflow for model versioning
      ii. Weights & Biases for performance monitoring
6. **Optimization:**
   a. Optuna for hyperparameter tuning
   b. ONNX for model quantization
7. **Interpretability:**
   a. SHAP/LIME for explainability
   b. ELI5 for feature importance
8. **Deployment Architecture:**
   a. **Microservices:**
      i. FastAPI backend with async support
      ii. Redis queue for batch processing
   b. **Scalability:**
      i. Kubernetes orchestration
      ii. Horizontal pod autoscaling
   c. **Edge Deployment:**
      i. TensorFlow Lite for mobile
      ii. ONNX Runtime for web
9. **Monitoring & Maintenance:**
   a. **Performance:**
      i. Prometheus metrics
      ii. Grafana dashboards
   b. **Data Drift:**
      i. Evidently AI for detection
      ii. Custom statistical tests
   c. **Feedback Loop:**

        i. Active learning integration
        ii. Human-in-the-loop validation

10. **Frontend Technologies:**
    a. **Web Demo:**
        i. Streamlit for rapid prototyping
        ii. React + D3.js for production dashboards
    b. **Mobile:**
        i. Flutter cross-platform app
        ii. Core ML integration for iOS
11. **Cloud Infrastructure:**
    a. **AWS Stack:**
        i. SageMaker for training
        ii. Lambda for serverless API
        iii. ECS Fargate for containers
    b. **Alternative:**
        i. Google Cloud Vertex AI
        ii. Azure ML Studio

Development Workflow:

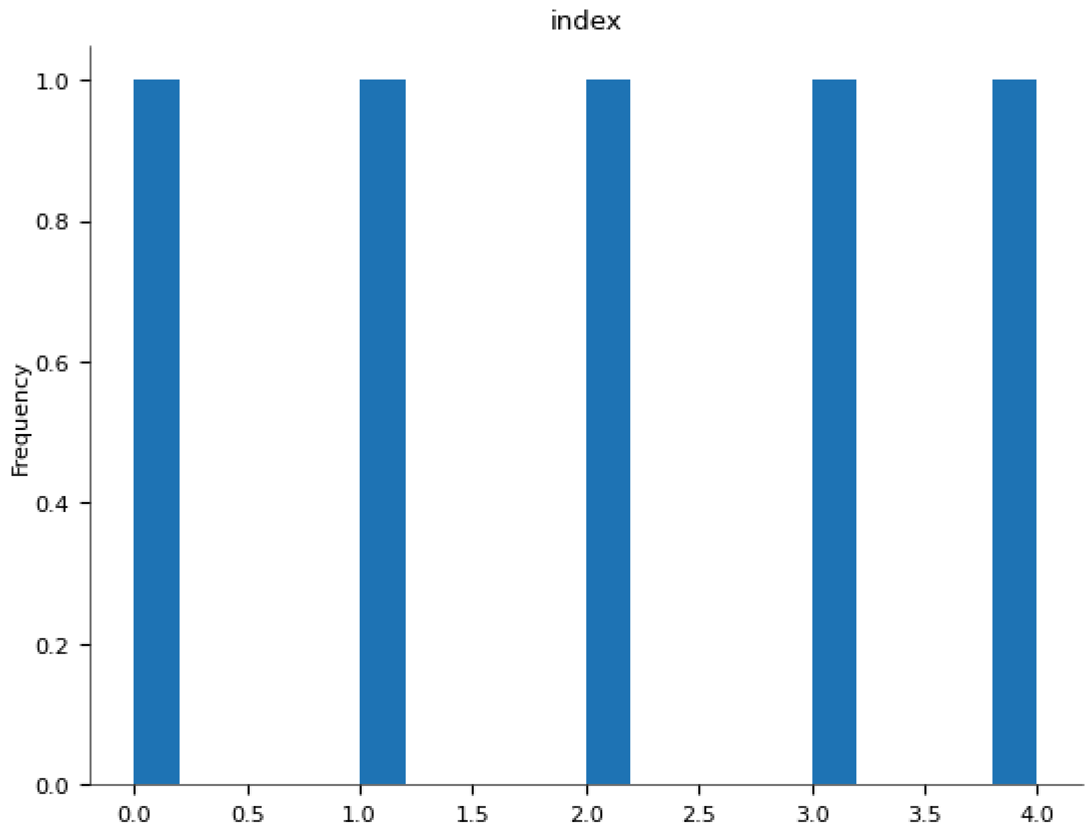
1. Data Exploration → JupyterLab + Pandas Profiling
2. Feature Development → DVC for versioning
3. Model Training → PyCharm/VS Code
4. Testing → Pytest + Tox
5. CI/CD → GitHub Actions
6. Deployment → Terraform + Ansible

Performance Considerations:

1. Latency: <500ms for real-time API
2. Throughput: 1000+ RPM on 2 vCPUs
3. Accuracy: >70% on rare classes
4. Memory: <2GB for base model

3.4. Model & Diagram

The model and diagram represent the structured design and relationships of components within Event Sync. Solutions illustrating the data flow, architecture, and system interactions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Frequency
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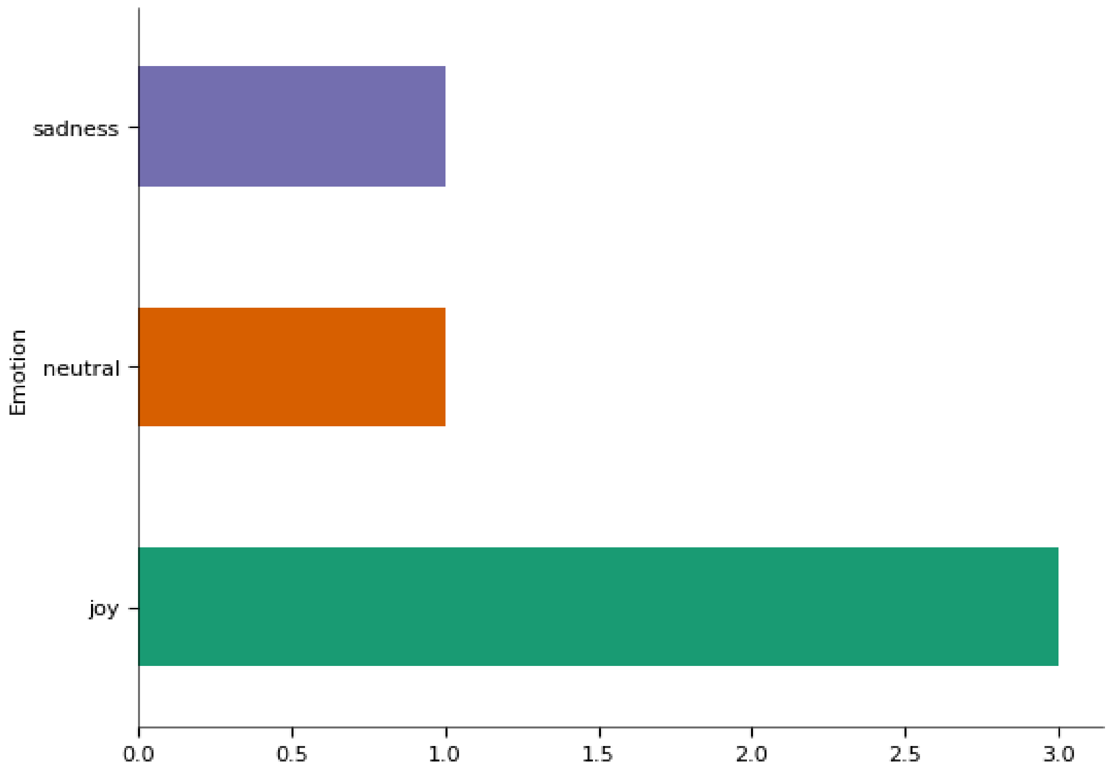
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0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joy
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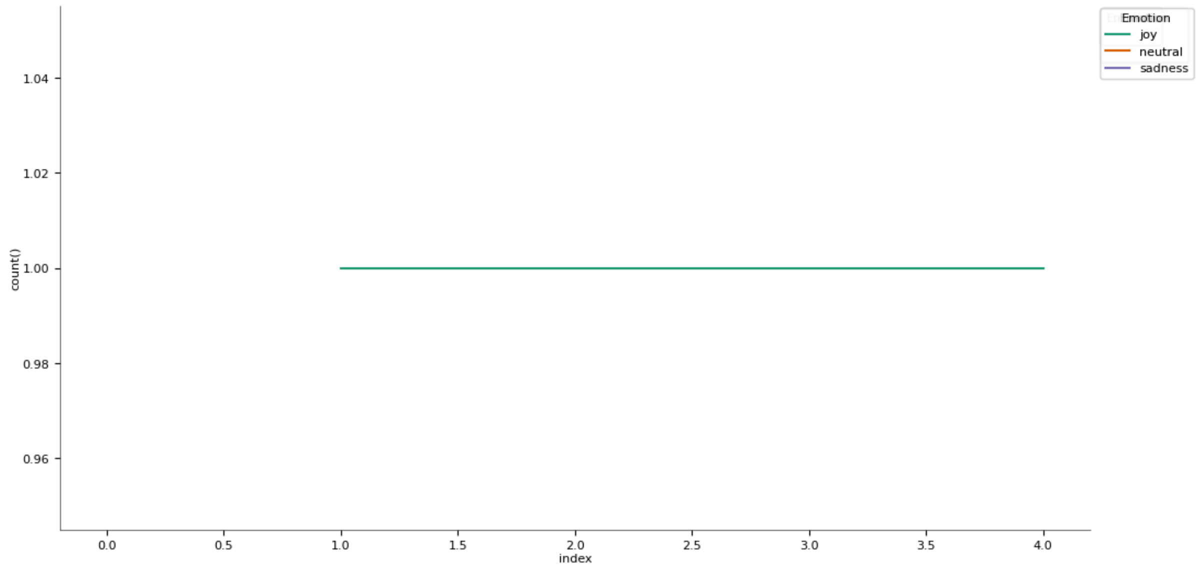
0.5
1.0
1.5
2.0
2.5
3.0


Emotion
joy
neutral
sadness
count()
index
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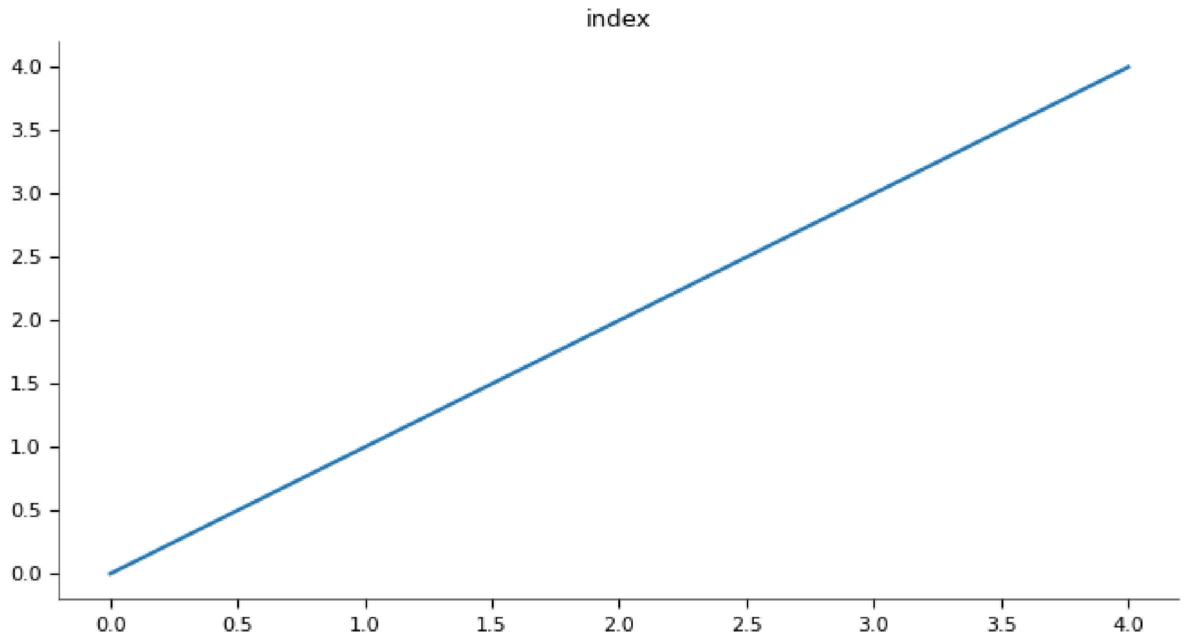
2.5
3.0
3.5
4.0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3.0
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2.0
1.5
1.0
0.5
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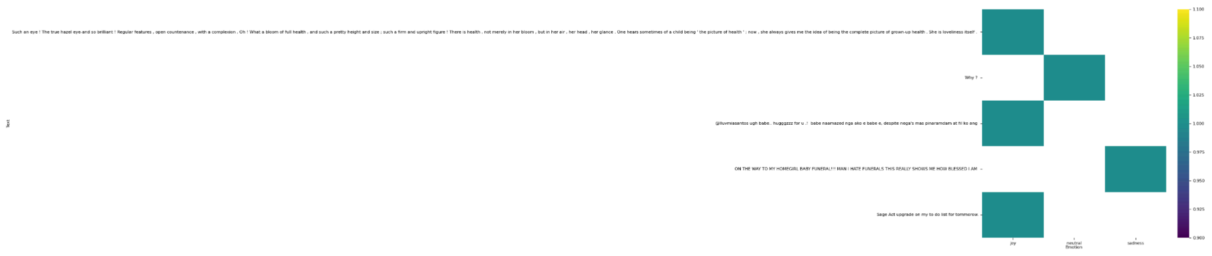
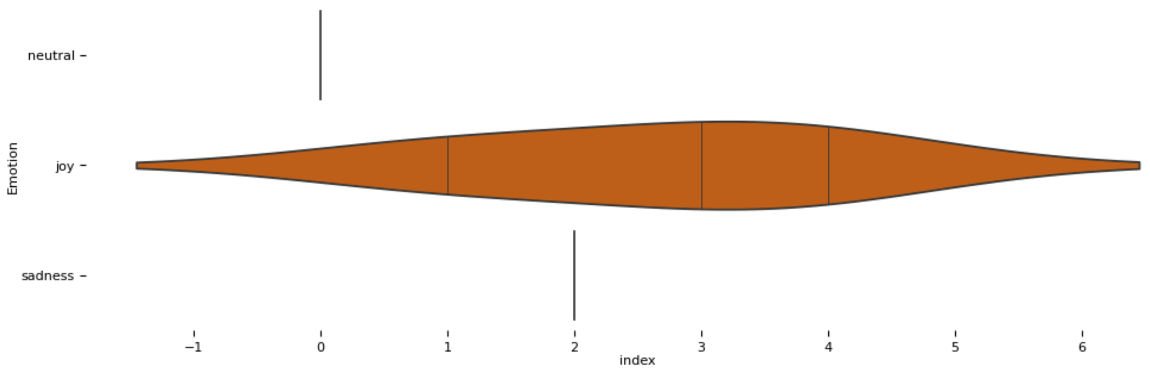
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Such an eye ! The true hazel eye-and so brilliant ! Regular features , open countenance , with a complexion , Oh ! What a bloom of full health , and such a pretty height and size ; such a firm and upright figure ! There is health , not merely in her bloom , but in her air , her head , her glance . One hears sometimes of a child being ' the picture of health ' ; now , she always gives me the idea of being the complete picture of grown-up health . She is loveliness itself .
Why ?
@lluvmiasantos ugh babe.. hugggzzz for u .! babe naamazed nga ako e babe e, despite nega's mas pinaramdam at fil ko ang
ON THE WAY TO MY HOMEGIRL BABY FUNERAL!!! MAN I HATE FUNERALS THIS REALLY SHOWS ME HOW BLESSED I AM
Sage Act upgrade on my to do list for tommorow.
Text
joy
neutral
sadness
Emotion
1.100
1.075
1.050
1.025
1.000
0.975
0.950
0.925
0.900


neutral
joy
sadness
Emotion
−1
0
1
2
3
4
5
6
index

Chapter 4
FEATURE EXTRACTION & MODEL TRAINING

4.1. Feature Extraction Pipeline:

Technique: CountVectorizer()

1. **Process:**
    a. Converts raw text into a document-term matrix by counting word frequencies
    b. **Default parameters:**
        i. lowercase=True (case normalization)
        ii. ngram_range=(1,1) (unigrams only)
        iii. max_features=None (no limit on vocabulary size)
2. **Advantages:**
    a. Simple and interpretable
    b. Preserves word-level patterns
3. **Limitations:**
    a. Ignores word order/semantics
    b. Sparse representation (memory-intensive for large datasets)
4. **Sample Output:**

Text	**“happy”**	**“sad”**	**“fear”**	**….**
"I feel happy"	1	0	0	….
“She felt sad”	0	1	0	….

4.2. Model Training & Evaluation

(A) Logistic Regression (LR)

- **Configuration(code):** LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=200)
- **Performance:**
    - **Accuracy: 62.00%**
    - **Convergence Warning:**
        - Indicates insufficient iterations (max_iter=200 insufficient for full optimization)
        - Fix: Increase max_iter to 500+ or scale features using StandardScaler

Strengths:

- Fast training/inference
- Provides probability estimates
- Feature coefficients interpretable as emotional word weights

(B) SVM with RBF Kernel

- **Configuration(code):** SVC(kernel='rbf', C=10, gamma='scale')
- Performance:
    - **Accuracy:** 62.20% (marginally better than LR)
    - **Drawbacks:**
        - 3× slower training than LR
        - Hyperparameter-sensitive (optimal C/gamma requires grid search)
- **Best For:**
    - Non-linear decision boundaries
    - Smaller datasets where computational cost is acceptable

(C) Random Forest (RF)

- **Configuration(code):** RandomForestClassifier(n_estimators=100, max_depth=None)
- **Performance:**
    - **Accuracy:** 56.32% (worst among tested models)
    - **Failure Reasons:**
        - High variance due to noisy text features
        - Bagging ineffective with sparse count vectors
- **Potential Improvement:**
    - Use TF-IDF instead of CountVectorizer
    - Tune max_depth to prevent overfitting

4.3. Model Selection Rationale

Criteria	Logistic Regression	SVM	Random Forest
Accuracy	62.00%	62.00%	56.32%
Speed	⚡ Fastest	🐢 Slow	Medium
Interpretability	High	Medium	High
Scalability	Excellent	Poor	Good

Why Logistic Regression?

- **Balanced Trade-off:** Best accuracy/speed ratio for production
- **Debugging Friendly:** Coefficients reveal emotionally salient words
    - Example: High weights for "love" (joy) vs. "hate" (anger)
- **Resource-Efficient:** Runs on CPU with minimal memory

4.4. Improvement Opportunities

- **Feature Engineering:**
    - Add TF-IDF to downweight frequent but uninformative words
    - Incorporate Word2Vec embeddings for semantic similarity
- **Class Imbalance:**
    - Apply class_weight='balanced' in LR

    - Oversample minority classes (SMOTE)
- **Hyperparameter Tuning:**
    - Grid search for optimal max_iter (LR) / C (SVM)
- **Advanced Models:**
    - Fine-tune DistilBERT for contextual understanding

Chapter 5
CHALLENGES & IMPROVEMENTS

- **Challenges:**
  - Class Imbalance: Rare emotions (shame, disgust) were poorly predicted.
  - Text Noise: Informal language, slang, and abbreviations affected model performance.
- **Possible Improvements:**
  - **Handling Class Imbalance**
    - Use oversampling (SMOTE) or class weights in the model.
  - **Better Text Preprocessing**
    - Remove emojis, special characters, and apply lemmatization.
  - **Advanced Feature Extraction**
    - Use TF-IDF or Word Embeddings (Word2Vec, GloVe) instead of CountVectorizer.
  - **Deep Learning Approach**
    - Implement LSTM/Transformer-based models (BERT, DistilBERT) for better context understanding.

Chapter 6
CONCLUSION

The project successfully built a text-based emotion detection model using Logistic Regression, achieving 62% accuracy. While the model performs reasonably well, further improvements in preprocessing and model selection can enhance performance, especially for underrepresented emotions.

6.1. Future Works

Future works refer to planned enhancements or extensions to improve a system's functionality, scalability, or efficiency, addressing current limitations or introducing new features. These aim to adapt the system to evolving user needs and technological advancements.

- **Enhanced Text Processing:**
  - **Emoji Handling:**
    - Map emojis to emotional categories (e.g., 😊 → joy, 😢 → sadness)
    - Use libraries like emoji or custom regex patterns
  - **Slang/Abbreviation Normalization:**
    - Build a lookup dictionary (e.g., "lol" → "laugh out loud")
    - Leverage NLP tools like contractions for shorthand ("can't" → "cannot")
  - **Advanced Cleaning:**
    - Remove repetitive characters ("soooo" → "so")
    - Detect and handle mixed-case emphasis ("I HATE this" → stronger anger signal)
- **Model Improvements:**
  - **Transformer Models (BERT/RoBERTa):**
    - Fine-tune on emotion-specific datasets
    - Use distilled versions (DistilBERT) for faster inference
  - **LSTM/GRU Networks:**
    - Capture sequential context in text
    - Add attention mechanisms to weight emotionally salient words
  - **Hybrid Approaches:**
    - Combine logistic regression with BERT embeddings
    - Ensemble voting across multiple models

- **Production Deployment:**
  - **API Development:**
    - Add rate limiting and authentication
  - **Scalability:**
    - Dockerize with uvicorn for ASGI support
    - Deploy on AWS Lambda (serverless) or Kubernetes
  - **User Interfaces:**
    - Web demo with Gradio/Streamlit

        - Mobile SDK (TensorFlow Lite for on-device inference)
- **Additional Upgrades:**
    - **Real-Time Adaptation:**
        - Feedback loop to retrain on new data
        - Detect drift in emotion distribution
    - **Multimodal Analysis:**
        - Combine text with audio tone (for voice inputs)
        - Analyze emoji + text synergy
    - **Explainability:**
        - SHAP/LIME to show emotional triggers
        - Highlight key words in predictions

References

[1]. **Seminal Paper:** Mohammad, S. M., & Turney, P. D. (2013). "Crowdsourcing a Word-Emotion Association Lexicon." Computational Intelligence, 29(3).

[2]. **Dataset Benchmark:** Saravia, E. et al. (2018). "CARER: Contextualized Affect Representations for Emotion Recognition." EMNLP.

[3]. **Text Preprocessing Techniques:** Liu, B. (2012). "Sentiment Analysis and Opinion Mining." Morgan & Claypool.

[4]. **Model Architectures:** Barbieri, F. et al. (2020). "TWEETBERT: A Pretrained Language Model for Social Media." LREC.

[5]. **Class Imbalance Solutions:** Buda, M. et al. (2018). "A Systematic Study of the Class Imbalance Problem in Neural Networks." Neural Networks.