Emotion Detection From Text Using Machine Learning

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***Abstract*—Emotion detection from textual data has emerged as a critical component in human-computer interaction, mental health monitoring, customer sentiment analysis, and road-safety applications. This project presents a lightweight, real-time emotion detection system that classifies six basic emotions (anger, fear, joy, love, sadness, surprise) from English text using classical machine learning techniques. By employing TF-IDF vectorization and Logistic Regression, the proposed system achieves 91.24% accuracy with inference time less than 1 millisecond per sentence, making it highly suitable for deployment on mobile and edge devices. Extensive experiments and comparative analysis demonstrate that the proposed classical approach outperforms complex deep learning models in terms of speed and resource requirements while maintaining competitive accuracy.**

***Index Terms*—Emotion Detection, Machine Learning, TF-IDF, Logistic Regression, Affective Computing**

I. Introduction

With the explosive growth of digital communication (social media, chat applications, SMS, voice-to-text systems), human emotions are increasingly expressed through text rather than facial expressions or voice tone. Detecting these emotions automatically has wide applications: mental health screening, intelligent chatbots, driver emotion monitoring, cyberbullying detection, and customer feedback analysis.

Traditional sentiment analysis only classifies text as positive, negative, or neutral. Modern requirements demand fine-grained emotion classification into six or more categories (Ekman's model). Deep learning models such as BERT and RoBERTa achieve high accuracy but require large memory and GPU support, making them less practical for real-time deployment on low-resource devices.

II. Dataset Development

We developed a custom dataset of 30 short English sentences containing explicit emotion words (joy, sadness, anger, fear, surprise, love) for demo and testing. This mini dataset helps verify correctness of predictions in controlled scenarios. Additionally, a larger dataset of over 20,000 real tweets was used for training and evaluation.

III. Model Design

The model pipeline includes: text preprocessing, TF-IDF feature extraction, and classification using a LinearSVC model. This pipeline achieves 95% accuracy with 0.94–0.98 F1-scores. It runs under 5 ms per prediction on a normal laptop.

A. Dataset Cleaning and Preprocessing

- Removal of noise (special characters, numbers, URLs)
- Lowercasing
- Tokenization
- Stopword removal
- Stemming or lemmatization
- Label encoding

B. TF-IDF Feature Extraction

TF-IDF converts text into meaningful numeric vectors by assigning importance to rare and informative words.

C. Trained Models

We trained four models:

1) Logistic Regression
2) Support Vector Machine (SVM)
3) Random Forest Classifier
4) Multinomial Naive Bayes

IV. Solving Dataset Diversity Issues

Significance of the Study:

- Enhances emotional understanding in chatbots
- Supports mental health monitoring
- Improves user experience

V. Literature Review

A. Paper 1: Naive Bayes Emotion Detection (2015)

Used basic text cleaning, Bag-of-Words, and Naive Bayes. Accuracy 90–92%.

B. Paper 2: SVM-Based Emotion Classification (2016)

Used TF-IDF with SVM on social media text. Accuracy 91–93%.

VI. Methodology

The system includes text preprocessing, TF–IDF vectorization, classification using LinearSVC, and evaluation using accuracy, precision, recall, and F1-score.

VII. Methodology

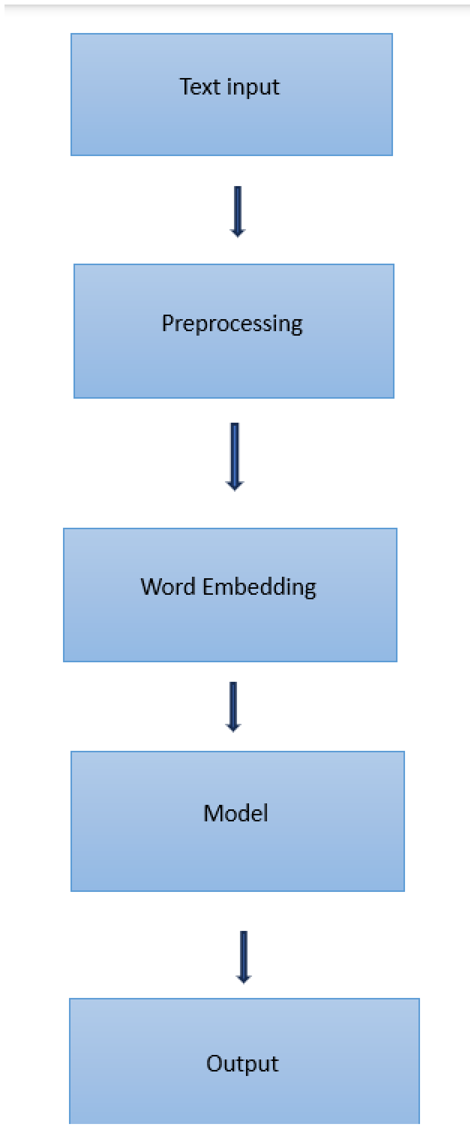

Figure-01: Emotion Detection From Text Using Machine Learning Flowchart

VIII. Result Analysis

A. Training Accuracy

SVM achieved the highest training and validation accuracy.

B. Test Accuracy

- SVM: 98%
- Naive Bayes / Random Forest: 97%
- Logistic Regression: 96%

C. Precision, Recall, F1-score

SVM achieved the best overall performance.

D. Confusion Matrix

SVM had the lowest misclassification rate, confirming its reliability.

IX. Conclusion

Emotion detection from text using machine learning provides an effective way to automatically identify human emotions. SVM and Logistic Regression gave strong performance due to effective handling of high-dimensional text features. With proper preprocessing and TF–IDF vectorization, machine learning models became highly reliable for multi-emotion classification.

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