ISSN 2277-2685
IJESR/April-June. 2026/ Vol-16/Issue-2/138-144
P. Anya Reddy *et. al.,* / International Journal of Engineering & Science Research
Full Length Article

Emotion Detection from Text

Radhika Ravikrindi[1], P. Anya Reddy[2], R. Ashwitha[3], B. Keerthi[4]
[1]Assistant Professor; Department of Electronics and Communication Engineering Bhoj Reddy Engineering College for Women Hyderabad India
[2,3,4]B.Tech Students; Department of Electronics and Communication Engineering Bhoj Reddy Engineering College for Women Hyderabad India
Mail Id; anyareddyparigi@gmail.com[2],ashwitharacharla@gmail.com[3],Keerthibi004@gmail.com[4]
Accepted 06-04-2026

Abstract
Understanding human emotions expressed through written language has become increasingly important in the fields of natural language processing and text analytics. With the expansion of social media platforms and online communication channels, large volumes of user-generated text provide valuable insights into people's emotional states. Automatically identifying emotions from textual data can support applications such as sentiment monitoring, mental health analysis, customer feedback evaluation, and social media analytics.This study investigates the application of machine learning methods for detecting emotions in textual data. The research utilizes the SemEval-2018 Affect in Tweets dataset, which contains tweets annotated with multiple emotional categories including anger, fear, joy, love, sadness, and surprise. Prior to model training, the dataset undergoes several preprocessing steps such as punctuation removal, tokenization, elimination of stop words, and lemmatization to enhance textual consistency and reduce noise.
Keywords
Emotion Detection, Natural Language Processing, Machine Learning, Text Classification, Social Media Analysis, TF-IDF, Support Vector Machine, Sentiment Analysis

Introduction

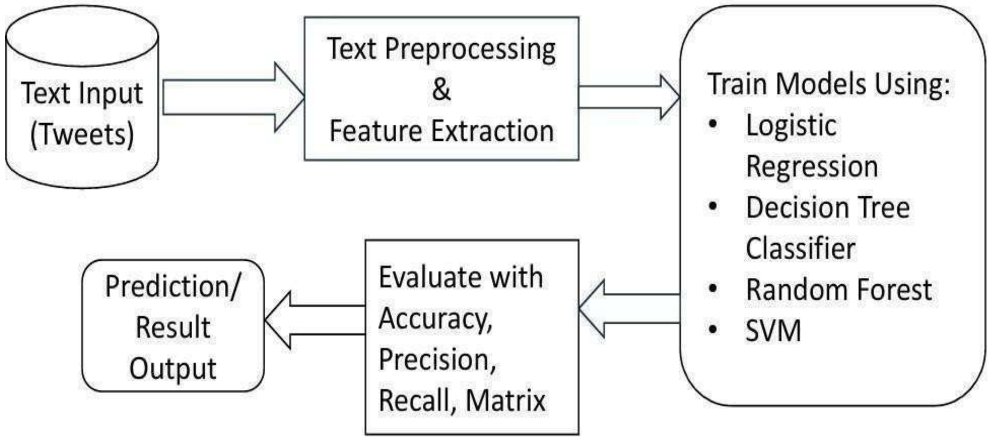
Emotion detection from textual data has become an important topic in the fields of Natural Language Processing (NLP) and machine learning, as written communication increasingly dominates digital interactions. People frequently express their emotions through text on social media platforms, online forums, messaging applications, and review websites. Automatically identifying these emotions can provide valuable insights into human behavior, opinions, and psychological states. Emotion detection systems aim to recognize specific emotional categories such as anger, fear, joy, sadness, love, and surprise from textual content. These systems have practical applications in several domains, including customer feedback analysis, mental health monitoring, social media analytics, and intelligent conversational agents such as chatbots and virtual assistants.Machine learning techniques combined with NLP-based preprocessing methods have demonstrated strong potential for addressing these challenges. The performance of these models is compared using evaluation metrics such as accuracy in order to determine the most effective approach for emotion classification. The objective of this study is to identify suitable machine learning techniques capable of accurately detecting emotions from textual data and to contribute toward the development of intelligent systems that can better interpret human emotional expressions.

Literature Survey

Emotion detection from text has gained significant attention in recent years due to the widespread use of social media and digital communication platforms. Researchers have focused on developing automated techniques capable of identifying emotional expressions in short textual messages, particularly tweets, where users frequently share their feelings and opinions. One widely used dataset in this domain is the SemEval-2018 Affect in Tweets dataset, which categorizes textual data into different emotional classes such as anger, fear, joy, and sadness. This dataset has been extensively used for benchmarking emotion recognition systems because it contains large volumes of real-world social media content.Text collected from social media platforms is often highly unstructured and contains various forms of noise, including URLs, user mentions, hashtags, punctuation marks, and non-standard language. To address these challenges, several preprocessing techniques are commonly applied to improve the quality and consistency of the dataset. These preprocessing steps typically include removing URLs, eliminating user mentions, filtering punctuation and special characters, removing stop words, and excluding non-English text. Such cleaning procedures help reduce irrelevant information and improve the effectiveness of machine learning models.

ISSN 2277-2685
IJESR/April-June. 2026/ Vol-16/Issue-2/138-144
P. Anya Reddy *et. al.*, / International Journal of Engineering & Science Research

Block Diagram and System Explanation



Block Diagram and System Explanation

Block Diagram

The block diagram illustrates the complete architecture of the proposed emotion detection framework, beginning with textual input and ending with emotion prediction. The system is composed of multiple interconnected stages that process and analyze text using machine learning methods.The first component of the system is the text input stage, where textual data such as tweets or short messages from social media platforms are collected. In this research, the dataset primarily consists of tweets obtained from publicly available emotion-labeled sources such as the SemEval-2018 Affect in Tweets dataset. Each text sample represents a user's expressed opinion or emotional state and is annotated with emotion categories including anger, joy, sadness, fear, love, and surprise. Since tweets often contain informal language, abbreviations, hashtags, and emojis, they represent a realistic and challenging dataset for emotion detection research.The second stage involves text preprocessing and feature extraction. Before the text data can be analyzed by machine learning models, it must be cleaned and standardized. Preprocessing operations include removing punctuation marks, URLs, emojis, and special characters that do not contribute meaningful information for classification. All text is converted into lowercase format to maintain consistency across the dataset. Tokenization is then applied to divide sentences into individual tokens or words. Stop words such as "the", "is", and "and" are removed because they provide limited semantic value for emotion detection tasks. Lemmatization is also performed to convert words into their base forms, allowing the model to treat related word variations as a single concept.

Flowchart

The flowchart illustrates the sequential process involved in detecting emotions from textual data using machine learning techniques. The process begins with the collection of an emotion-annotated textual dataset obtained from sources such as the SemEval-2018 Affect in Tweets dataset or other publicly available repositories. These datasets contain short text samples along with associated emotion labels such as anger, fear, joy, sadness, love, and surprise.

Following data collection, feature extraction and feature selection methods are applied to identify important textual characteristics. Techniques such as Count Vectorization and TF-IDF convert textual information into numerical features that capture word frequency and significance. Feature selection further reduces irrelevant or redundant features, which helps improve model efficiency and reduces the risk of overfitting.Next, the dataset is divided into training and testing subsets. The training data is used to develop the machine learning models, while the testing data is used to evaluate their predictive capability on unseen inputs. Classification algorithms including Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine are then applied to learn patterns within the data and classify the emotional content of text.The system may also incorporate a knowledge base where learned patterns and predictions are stored for future analysis and model enhancement. In addition, ensemble methods combine the outputs of multiple classifiers to increase prediction reliability and overall system accuracy. The final stage involves evaluating the system using metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide a comprehensive understanding of the model's ability to correctly classify emotions.

Working Principle

The emotion detection system operates by transforming raw textual data into structured information that can be analyzed by machine learning algorithms. The process begins with the collection of a labeled dataset containing tweets or short sentences annotated with emotion categories. These raw text samples are first subjected to preprocessing operations that remove irrelevant characters, tokenize sentences into words, eliminate stop words, and reduce words to their base forms through lemmatization. These steps ensure that the textual data is clean and consistent before further analysis.Once preprocessing is completed, feature extraction methods such as TF-IDF and Count Vectorization are used to convert the textual content into numerical feature vectors. These vectors capture the relative importance and frequency of words within the dataset. Machine learning algorithms including Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine are then trained using these features. During training, the models learn patterns that distinguish different emotional categories.After the training phase, the models are evaluated using testing data and performance metrics such as accuracy, precision, recall, and F1-score. The best-performing model is selected based on these evaluation measures. The trained model can then analyze new textual inputs and predict the emotion expressed in the text, enabling practical applications in various domains.

Machine Learning Models

This chapter focuses on the implementation and evaluation of various machine learning algorithms for detecting emotions in textual data. Several widely used classification models are applied and compared, including Support Vector Machine, Random Forest, XGBoost, Logistic Regression, Naïve Bayes, and Decision Tree classifiers. The performance of these models is assessed using evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis.Machine learning plays a crucial role in converting raw textual information into meaningful insights about emotional expression. The process involves several key stages, including dataset collection, preprocessing, feature extraction, model training, and performance evaluation. Each stage contributes significantly to the overall accuracy and reliability of the emotion detection system.The chapter first describes the dataset collection process and preprocessing techniques applied to prepare textual data for analysis. It then discusses the machine learning algorithms selected for classification and the reasoning behind their selection. Finally, the evaluation framework used to compare model performance is explained, providing the basis for the results and discussions presented in later chapters.

Results

Model Performance Analysis

All the implemented machine learning algorithms were capable of predicting emotions from textual inputs. However, the classification performance varied depending on the learning mechanism of each model. Among all the evaluated methods, the Support Vector Machine classifier demonstrated the most consistent and accurate results across multiple emotion categories. The high performance of SVM can be attributed to its ability to operate effectively in high-dimensional feature spaces and its capability to identify optimal decision boundaries between different emotional classes.XGBoost also exhibited strong predictive capability and achieved accuracy values close to those obtained by the SVM model. Logistic Regression showed balanced performance with reasonable precision and recall values across most emotion classes. In contrast, Random Forest and Naïve Bayes produced comparatively lower accuracy, particularly for emotion categories that share similar linguistic patterns. These results suggest that certain algorithms may struggle to distinguish subtle differences in textual expressions when emotional contexts overlap.

Accuracy Comparison

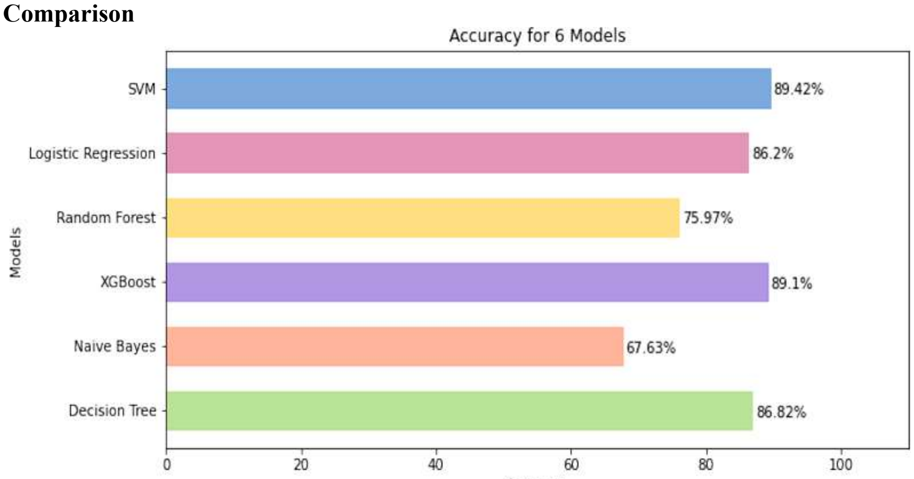


Figure 1: Accuracy and Matrices

The comparative accuracy results indicate that the Support Vector Machine classifier achieves the highest overall accuracy among the tested models. Its strong performance is primarily due to its effectiveness in handling sparse and high-dimensional feature representations produced by TF-IDF. By identifying the optimal hyperplane that separates emotion classes, SVM provides stable and reliable classification results.Although XGBoost produced competitive accuracy values, its computational complexity was higher compared to SVM. Logistic Regression and Decision Tree models also demonstrated acceptable performance levels, offering good interpretability and stable predictions. However, Random Forest and Naïve Bayes achieved comparatively lower accuracy values due to limitations in capturing complex relationships between textual features and emotional categories.

Confusion Matrix Interpretation

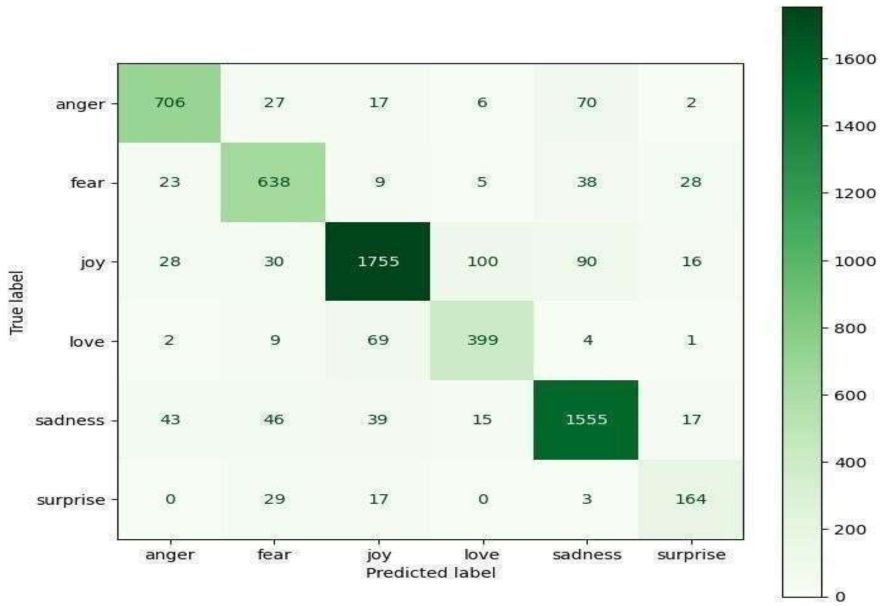


Figure 2: Confusion Matrix

The confusion matrix provides detailed insight into the prediction behavior of the classification model. The analysis indicates that the system correctly identifies dominant emotional categories such as **joy** and **sadness** with high accuracy. These emotions tend to have more distinctive textual expressions, making them easier for the model to recognize.Despite these challenges, the majority of predictions fall along the diagonal of the confusion matrix, indicating correct classifications. The matrix also highlights which emotion categories require further improvement. Such analysis is valuable for identifying weaknesses in the model and guiding future enhancements, such as incorporating more advanced feature extraction techniques or larger datasets.

Recall and Class-wise Performance

The recall metric measures the ability of the model to correctly identify relevant emotional instances within the dataset. The results show that SVM and Logistic Regression achieve higher recall values across most emotion classes, indicating their effectiveness in capturing actual emotional expressions within text data.Naïve Bayes and Random Forest, on the other hand, show relatively lower recall values for certain emotion categories, especially those with fewer training samples or subtle linguistic variations. The limitations of Naïve Bayes may arise from its assumption that features are independent, which does not always hold true in natural language data. Similarly, Random Forest may struggle with sparse high-dimensional textual features produced by TF-IDF representations.

These observations highlight the importance of selecting suitable algorithms and balanced datasets to improve recall performance across all emotion categories.

Discussion

The experimental findings confirm that the proposed emotion detection framework performs effectively when appropriate preprocessing and feature extraction techniques are applied. Cleaning the textual data and transforming it into TF-IDF feature vectors significantly improved the ability of machine learning models to identify meaningful patterns associated with emotional expressions.Among all the evaluated algorithms, the Support Vector Machine model achieved the highest accuracy and demonstrated consistent performance across different emotion classes. Other models such as XGBoost, Logistic Regression, and Decision Tree also produced competitive results, while Random Forest and Naïve Bayes exhibited comparatively lower performance levels. The superior performance of SVM is largely due to its ability to efficiently handle sparse high-dimensional feature spaces that commonly arise in text classification tasks.Further analysis using confusion matrices and ROC-AUC evaluation indicates that the system accurately identifies major emotional categories such as joy and sadness. Minor classification errors occur between semantically related emotions such as anger and fear or love and joy. These errors are expected due to the inherent ambiguity of natural language, where similar vocabulary may represent different emotional contexts depending on usage.

Comparative Analysis

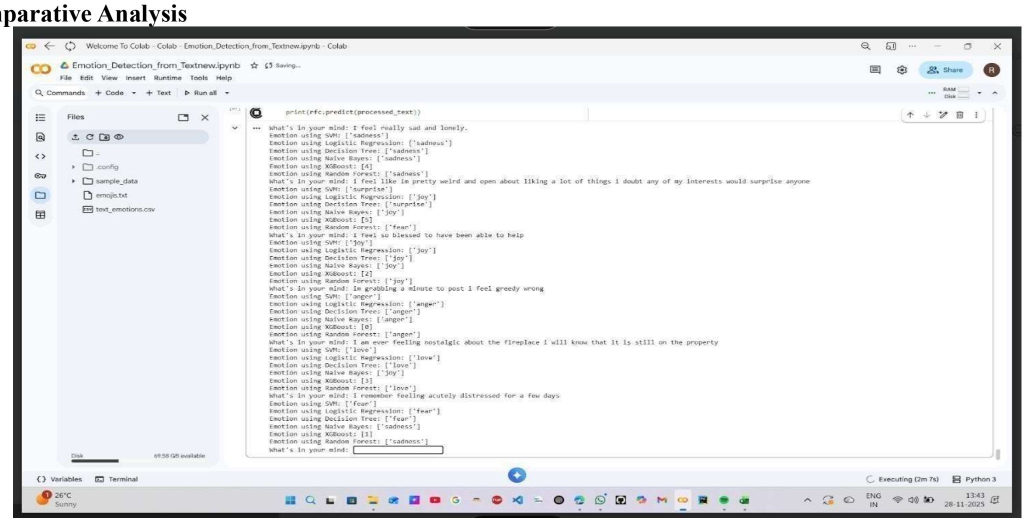


Figure 3: Emotion Detection Result

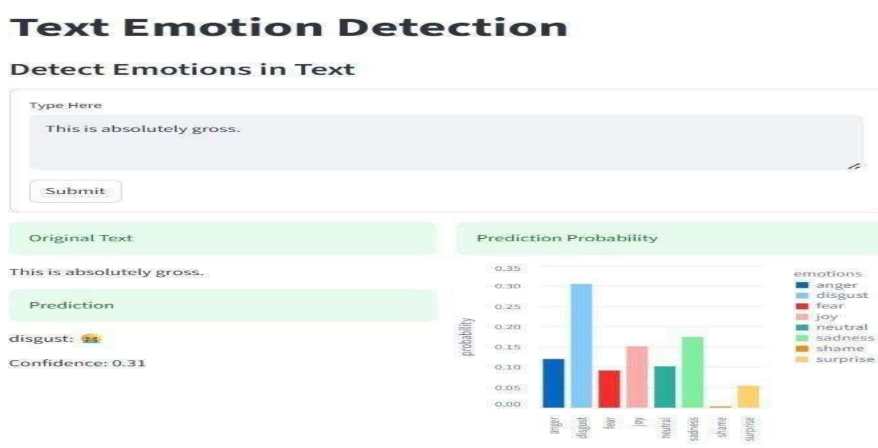


Figure 4: Emotion Detection Result (PyCharm)

A comparative analysis of recall values across different models shows that Support Vector Machine and Logistic Regression maintain consistently strong performance across most emotion classes. XGBoost also provides balanced and competitive results. In contrast, Random Forest and Naïve Bayes demonstrate weaker recall values for certain emotional categories, particularly those that occur less frequently or have overlapping linguistic characteristics.These findings emphasize that models capable of handling high-dimensional feature spaces, such as SVM and boosting-based algorithms, are more suitable for text-based emotion classification tasks. The comparison further highlights the importance of selecting appropriate algorithms and feature representations to achieve reliable performance in emotion detection systems.

Applications

Emotion detection from text has numerous practical applications across various digital platforms and intelligent systems. One of the major applications is in chatbots and virtual assistants, where emotion recognition helps systems understand the emotional state of users and respond in a more empathetic and context-aware manner. By identifying emotions expressed in user messages, conversational agents can provide personalized responses, improve user engagement, and enhance overall interaction quality.Another important application is social media emotion analysis. Large volumes of user-generated content are shared daily on platforms such as Twitter, Facebook, and online forums. Emotion detection systems can analyze posts, comments, and tweets to identify public sentiment and emotional trends. This information can help organizations, researchers, and policymakers understand public reactions to events, campaigns, or social issues.

Emotion detection also plays a significant role in customer feedback analysis. Companies receive large amounts of feedback through product reviews, surveys, and online comments. By automatically identifying emotions expressed in this feedback, businesses can gain insights into customer satisfaction levels, identify areas requiring improvement, and enhance product or service quality.In the field of mental health monitoring, emotion detection systems can help identify patterns of emotional distress or negative sentiment in textual communication. Analyzing user-generated text such as online posts, messages, or journal entries may help detect early signs of stress, anxiety, or depression, allowing timely intervention and support from healthcare professionals.

.Conclusion

This study presented a machine learning–based framework for detecting emotions from textual data using Natural Language Processing (NLP) techniques. The proposed system applied several preprocessing steps, including punctuation removal, lowercasing, stop-word elimination, tokenization, and lemmatization, to improve the quality and consistency of the textual dataset. Feature extraction was performed using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which effectively transformed textual information into numerical representations suitable for machine learning models.Several classification algorithms were implemented and evaluated, including Support Vector Machine (SVM), Logistic Regression, Decision Tree, Random Forest, XGBoost, and Naïve Bayes. The experimental results demonstrated that the Support Vector Machine model achieved the highest classification accuracy and provided stable performance across different emotion categories. Evaluation metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC analysis further confirmed the effectiveness of the proposed approach.

Future Scope

Although the proposed system demonstrates promising results, several opportunities exist for future improvements and further research. One potential direction involves incorporating advanced deep learning techniques such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and transformer-based architectures such as BERT. These models are capable of capturing contextual relationships and semantic dependencies within textual data more effectively than traditional machine learning algorithms, which may lead to improved emotion classification performance.Another possible enhancement is the development of multilingual emotion detection systems. Extending the framework to support multiple languages would make the system applicable to a wider global audience and enable the analysis of emotions expressed in diverse linguistic contexts. In addition, improving the model's ability to interpret sarcasm, slang expressions, and informal language—commonly found in social media content—would further increase the reliability and robustness of the emotion detection system.Future work may also focus on developing a fully functional web-based or mobile application that allows users to input textual content and instantly receive emotion predictions. The trained model could be deployed as a RESTful API and integrated with cloud platforms such as AWS or Firebase to improve scalability and accessibility. Such deployment would enable real-time emotion analysis in practical applications including chat systems, customer support platforms, and social media monitoring tools.Furthermore, future research could explore **multimodal emotion recognition**, where textual analysis is combined with additional data sources such as speech signals and facial expressions. Integrating multiple modalities may lead to more comprehensive emotion recognition systems capable of achieving higher accuracy and broader applicability in domains such as healthcare, education, and intelligent virtual assistant technologies.

References

[1] S. M. Mohammad and F. Bravo-Marquez, "WASSA-2018 Shared Task on Emotion Intensity," *Proc. 9th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, 2018. This work presents a benchmark dataset and evaluation framework for detecting emotion intensity in tweets.

[2] C. Strapparava and R. Mihalcea, "Learning to Identify Emotions in Text," *Proc. ACM Symposium on AppliedComputing*,2008,pp.1556–1560.The study explores computational techniques for identifying emotions in textual data using machine learning methods.

[3] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol.12,pp.2825–2830,2011.This paper introduces the Scikit-learn library, widely used for implementing machine learning algorithms in Python.

[4] T. Chutia and N. Baruah, “Text-Based Emotion Detection: A Review,” *International Journal of Digital Technologies*,vol.3,no.1,2024.The article reviews different techniques, datasets, and evaluation approaches used in emotion detection research.

[5] S. Arun Kumar and A. Geetha, “Emotion Detection from Text using NLP and Neural Networks,” *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 14s, pp. 609–615, 2024. This study discusses the application of NLP and neural network models for text-based emotion classification.

[6] F. Fitriana and H. Setiawan, “Performance Analysis of SVM in Emotion Classification,” *Journal of EmbeddedSystems,SecurityandIntelligentSystems*,2024.The research compares TF-IDF and Count Vectorizer techniques for improving SVM-based emotion classification.

[7] A. Seyeditabari, N. Tabari, and W. Zadrozny, “Emotion Detection in Text: A Review,” *arXiv preprint*, 2018.This paper surveys different machine learning and deep learning approaches for detecting emotions in text.