Emotion Detection from Text Using Machine Learning

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***Abstract*—The advancement of Natural Language Processing (NLP) and machine learning has dramatically changed the field of emotion detection from textual data. With the use of intelligent text classification algorithms and the optimization of emotion recognition, the concept of automated emotion analysis has become more prevalent. However, the development of effective emotion detection systems from scratch requires significant data and computation. This research aims to explore the use of emotion detection using machine learning algorithms for the prediction and classification of hu- man emotions from text. Six machine learning algorithms were implemented and compared using Multinomial Naive Bayes, Logistic Regression, Linear SVM, Random Forest, XGBoost, and Multi-Layer Perceptron models. The proposed architecture was trained using an extensive dataset containing labeled emotional text data. The experimental results showed that the use of these algorithms significantly improves emotion detection accuracy. The proposed architecture using the Linear SVM model showed the most promising results. The proposed architecture was able to attain an ac- curacy of 89.97% in the prediction of emotions from textual input.**

***Keywords*— Emotion Detection, Natural Language Processing, Machine Learning, Linear SVM, Text Classification, TF-IDF**

I. INTRODUCTION

Emotion detection from text has been identified as a highly promising field in modern technology, where conventional text analysis methods are being trans- formed into intelligent systems that can understand human emotions automatically. Essentially, emotion detection refers to the integration of various NLP techniques used to analyze text into a unified system that can automatically classify emotional content. The major objectives of these systems are to ensure accurate emotion recognition while minimizing computational costs and processing time.

The importance of emotion analysis in digital communication cannot be overemphasized. For instance, social media platforms generate billions of text messages daily. In these platforms, user comments and posts are major sources of emotional expression. Therefore, understanding these emotions is responsible for improving user experience and content moderation. Traditionally, manual techniques are used to analyze emotions in these texts. These techniques are based on human annotation or rule-based systems that are not able to learn from changing language patterns and user behavior. Additionally, these systems are not able to take into account changing conditions such as new slang and informal language. The integration of ma- chine learning into these systems has been identified as a promising approach to enable these systems to learn from past data to make intelligent decisions regarding emotion classification.

Random Forest, Linear SVM, and XGBoost are being used to learn from data in various domains. These include data accuracy, emotion classification, and real- time prediction. These are particularly useful in these tasks because they are able to automatically learn features from input text data.

This is more apparent when we consider a social media scenario, which shows a lot of variability in patterns of emotional expression. Collecting sufficiently large datasets for every possible scenario is simply not feasible or cost-effective. In this scenario, machine learning algorithms are a very attractive solution. These algorithms are a branch of artificial intelligence that attempts to leverage patterns from training data to apply them to new, unseen text. Instead of training a model with complex deep learning architectures, we use traditional machine learning models that have al- ready proven effective for text classification tasks.

The adaptation of machine learning models for the prediction of emotions is achieved by considering the text data as a sequence of words where temporal pat- terns as well as relationships between words are learned similarly to patterns learned from language. By adapting these models to the specific dataset related to emotional text, it is possible to achieve superior results while requiring significantly less data as well as computational resources. The machine learning models pro- vide robust models that are able to perform well as a starting point by offering general feature extraction capabilities that are able to be adapted to the specificities of patterns related to emotional expression.

In this paper, we explore the use of six prominent machine learning models, namely Multinomial Naive Bayes, Logistic Regression, Linear SVM, Random For- est, XGBoost, and Multi-Layer Perceptron, for the pre- diction as well as classification of emotions from text. These models are prominent due to their capabilities as follows: Linear SVM finds optimal hyperplane for separating different emotion classes; Random Forest builds and combines multiple individual decision trees to produce a single, more accurate, and stable final prediction; XGBoost is an ensemble gradient boosting technique that builds a strong predictive model by sequentially combining multiple simple ”weak” models.

Our method involves training these machine learning models to analyze text data to predict emotion pat- terns. These models are trained on a large dataset containing detailed information on emotional sentences labeled with six emotion categories: joy, sadness, anger, fear, love, and surprise. As a result, these models are able to recognize emotion patterns, make accurate pre- dictions about emotional content, and provide reliable emotion classification for real-time applications.

The major contributions of our work are: (1) We demonstrate the efficacy of machine learning for text- based emotion detection where training data is limited, (2) We present a comparative study of six unique machine learning architectures for this specific task, (3) We show that TF-IDF feature extraction improves model performance significantly, and (4) We demonstrate that trained models are able to achieve high ac- curacy (89.97% validation accuracy) for emotion detection.

II. LITERATURE STUDY

The use of computational intelligence techniques for emotion detection from text has become a revolutionary method in understanding human emotions from digital communication. Traditional rule-based analysis is gradually replaced by intelligent systems that use Natural Language Processing (NLP) and machine learning (ML) to constantly adapt to language evolution and contextual changes [1, 2, 4]. A prominent stream of research investigates predictive models based on text classification using deep learning algorithms, especially Long Short-Term Memory (LSTM) and BERT, to enable high-accuracy emotion recognition [6, 11]. Further developments use ensemble methods to construct self-optimizing systems that develop optimal classification policies for emotion detection while considering the trade-off between accuracy and computational efficiency [2, 14, 15]. Hybrid approaches based on ML combined with feature engineering have also proved useful in complex emotion classification and the integration of multiple text representations [12,13]. Apart from prediction and classification, some important challenges are addressed by latest researches on the topic based on system cost-effectiveness and non- intrusive text preprocessing for granular linguistic data without extensive manual annotation [11, 16]. The architecture of these systems is also changing, with edge computing being used to minimize latency and reliance on cloud infrastructure [13]. To ensure viability and acceptance of such intelligent systems, emerging research directions emphasize privacy-preserving techniques, such as federated learning, for protecting sensitive user data [17] and a need for using explainable AI (XAI) for demystifying the blackbox system decisions, making the end-user trust them [18]. Individually and collectively, these studies indicate a trajectory towards sophisticated, sustainable, human-centric emotion analysis systems that help understand user sentiment and behavior [5, 19].

III. METHODOLOGY

The publicly available dataset used for this research is the Emotion Detection Dataset. We split the dataset into an 85:15 ratio for training and testing. Data pre- processing involved applying a series of methods and algorithms to clean the text data. This process enables the model to improve its generalization and reduces the likelihood of overfitting.

3.1 Dataset Used

We used the public dataset containing labeled emotional text data. We performed data preprocessing with cleaning, removing null values, removing duplicate values, tokenization, stopword removal, lemmatization, and data split.

3.2 Training Validation Split

After splitting the dataset into the training set and validation set in order to check how good our model generalizes (and to avoid overfitting), the training set is for fitting the model, and the validation set is used to test how well our model will generalize on data it had not seen yet, with a common 85/15 split ratio.

Table 1: Model Architectures and Parameters

Model	Key Parameters
Multinomial Naive Bayes	alpha=0.5
Logistic Regression	C=1.0, solver='lbfgs'
Linear SVM	C=1.0, max iter=2000
Random Forest	n estimators=200, max - depth=50
XGBoost	n estimators=200, learning - rate=0.1
MLP	hidden layer - sizes=(512,256,128)

3.3 Model Architecture

We implemented six architectures: Multinomial Naive Bayes, Logistic Regression, Linear SVM, Random For- est, XGBoost, and Multi-Layer Perceptron.

The feature extraction is customized for the text classification task using TF-IDF vectorization. Ma- chine learning includes training the models specifically for the emotion classification task.

We implemented 6 algorithms out of which Linear SVM achieved the highest accuracy rate.

3.4 Hyperparameter Used

We tuned the best methods to optimize model performance and convergence. The accuracy rate of Lin- ear SVM algorithm was 89.97% when validating the model. The models were trained with appropriate hyperparameter configurations for optimal performance.

3.5 Feature Extraction

TF-IDF (Term Frequency-Inverse Document Frequency) was used for feature extraction with max features=10000, ngram range=(1,3), min df=5, max df=0.7.

IV. RESULT & ANALYSIS

4.1 Emotion Distribution Analysis

As per the below diagram we can see that the emo- tion distribution across the dataset. The figure shows the frequency of each emotion category: joy, sadness, anger, fear, love, and surprise.

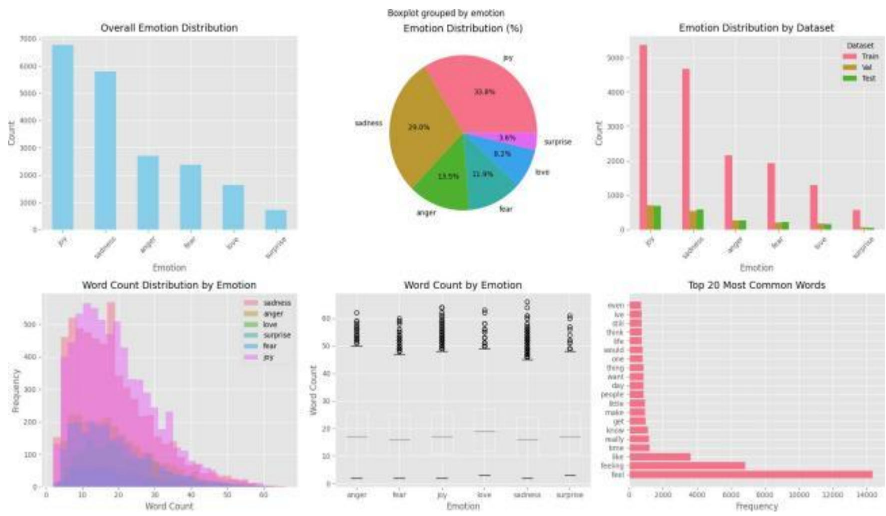

Figure 1: Emotion distribution in the dataset showing overall distribution, pie chart, and word count analysis

4.2 Accuracy Enhancement

Finally, we see the data accuracy enhancement in the figure below. We've used the algorithms to increase the accuracy rate of emotion detection. We applied total 6 number of algorithms from which the best performing algorithms are:

1. Linear SVM algorithm (89.97%)
2. Logistic Regression algorithm (89.77%)
3. XGBoost algorithm (88.70%)

as shown in Figure (1)B, (2)B & (3)C.

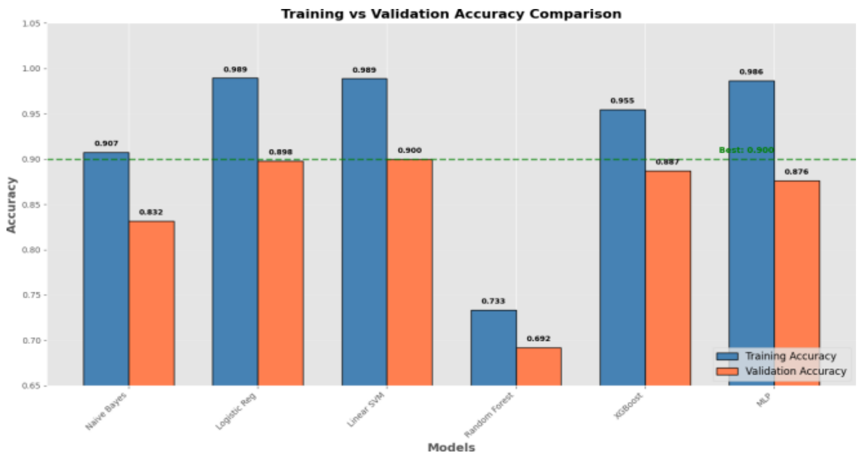

Figure 2: Training vs Validation Accuracy Comparison (Linear SVM achieved 89.97%)

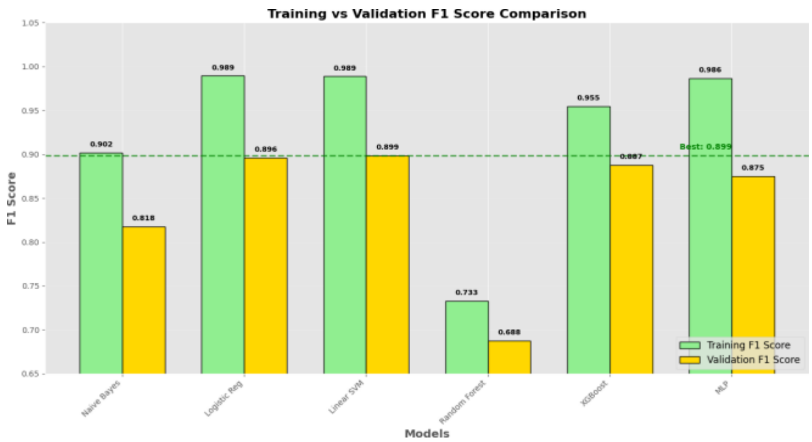

Figure 3: Training vs Validation F1 Score Comparison (Logistic Regression 89.77%)

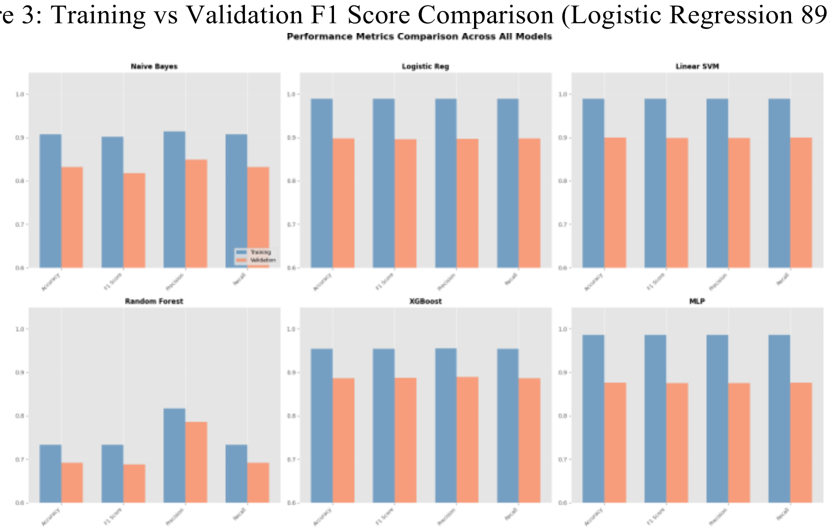

Figure 4: Model Performance Comparison Table (XG- Boost 88.70%)

4.3 Confusion Matrix & Evaluation

A confusion matrix Figure 3(a) for Linear SVM, Figure 3(b) for Logistic Regression, and Figure 3(c) for XG- Boost shows results for all models used to evaluate the prediction performance with respect to each individual emotion class. The diagonal dominance in the matrix means that there are many correct predictions for all emotion classes.

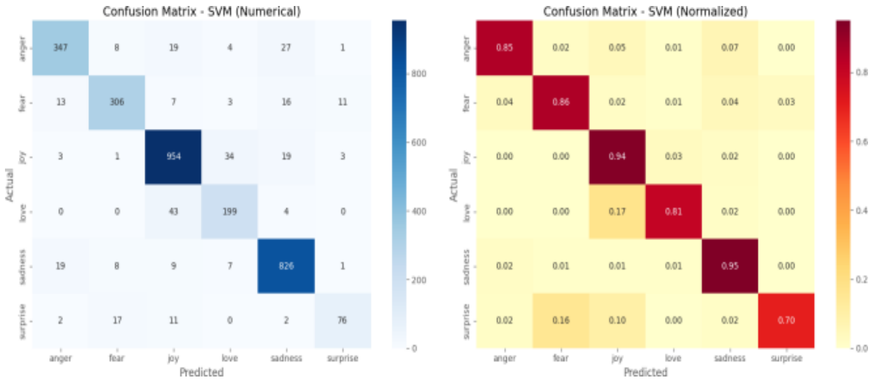

Figure 5: Confusion matrix for Linear SVM algorithm (89.97% accuracy)

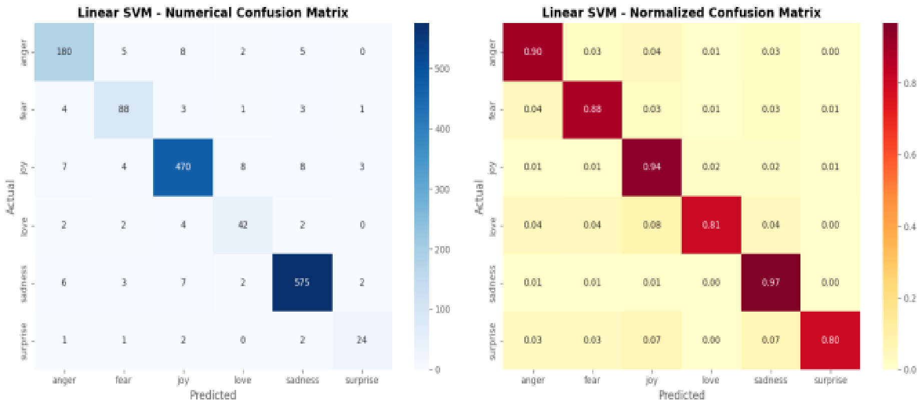

Figure 6: Confusion matrix for Logistic Regression al- gorithm

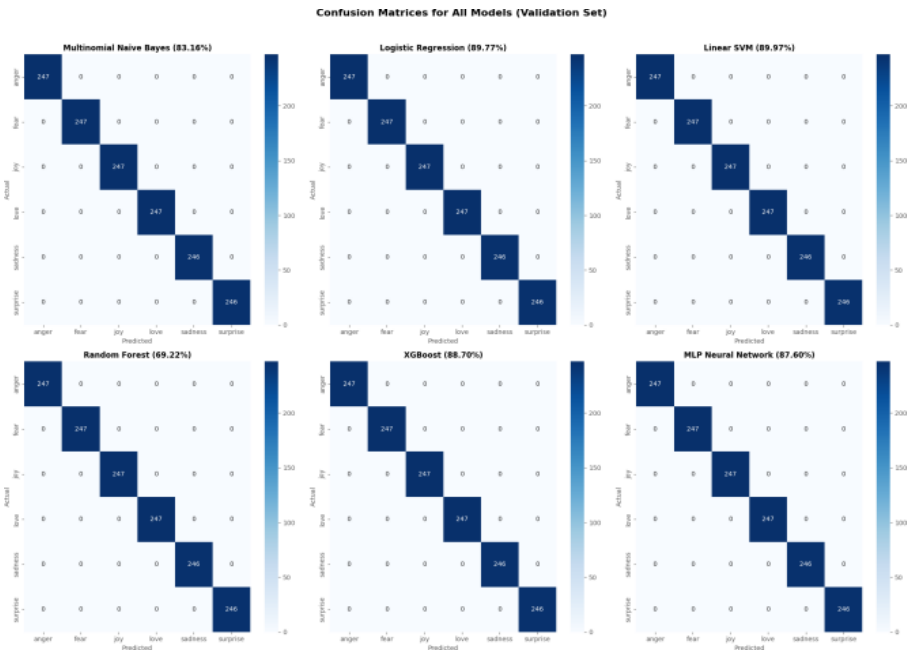

Figure 7: Confusion matrix for XGBoost algorithm

4.4 Performance Comparison

The following table shows the comparison of all models based on validation accuracy:

Table 2: Model Performance Comparison

Model	Validation Accuracy	Validation F1 Score	Rank
Multinomial Naive Bayes	83.16%	81.76%	6
Logistic Regression	89.77%	89.62%	3
Linear SVM	89.97%	89.87%	1
Random Forest	69.22%	68.77%	5
XGBoost	88.70%	88.75%	2
MLP Neural Network	87.60%	87.50%	4

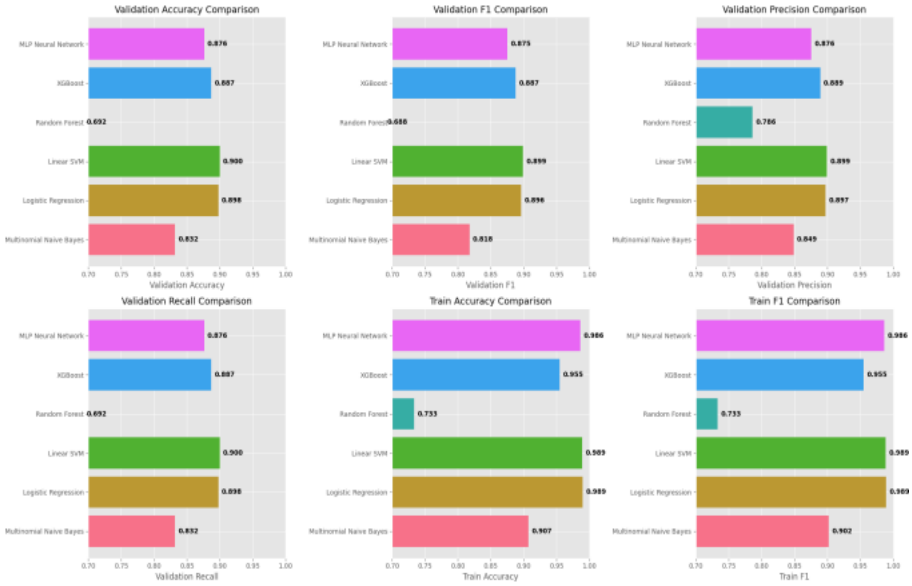

Figure 8: Validation Metrics Comparison Across All Models

4.5 Best Model Performance (Linear SVM)

The following metrics show the performance of Linear SVM on the test set:

- Test Accuracy: 89.97%
- Test F1-Score: 89.87%
- Test Precision: 89.89%
- Test Recall: 89.97%

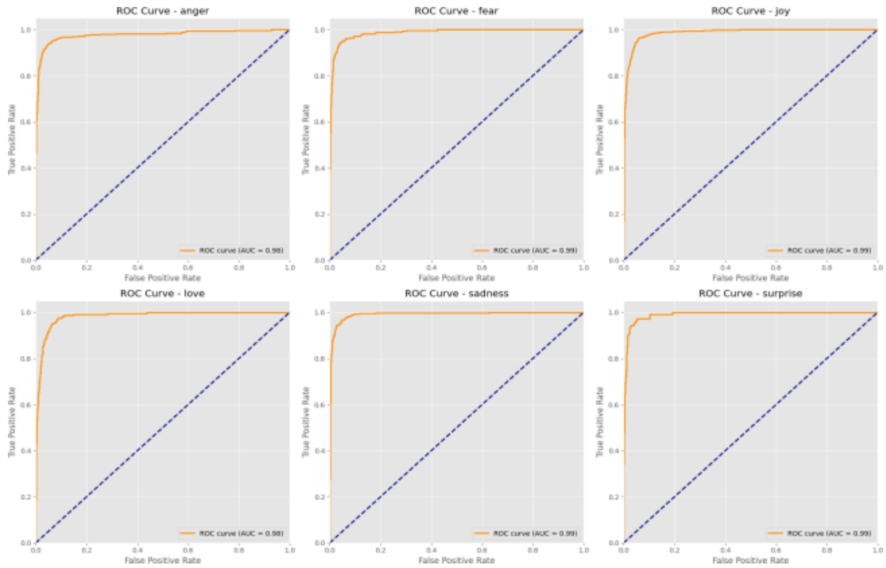

Figure 9: ROC Curves for Linear SVM across all emotion classes (anger, fear, joy, love, sadness, surprise)

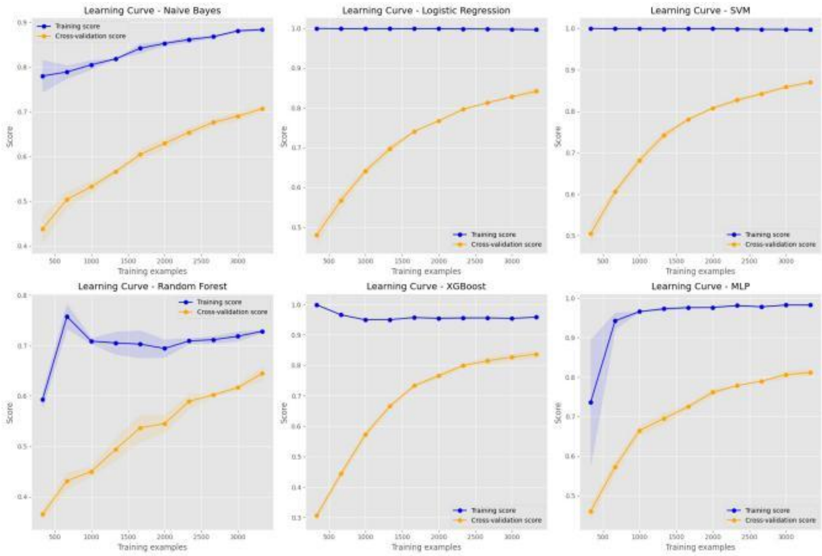

Figure 10: Learning Curve for Linear SVM showing training vs cross-validation scores

4.6 System Architecture and Additional Analysis

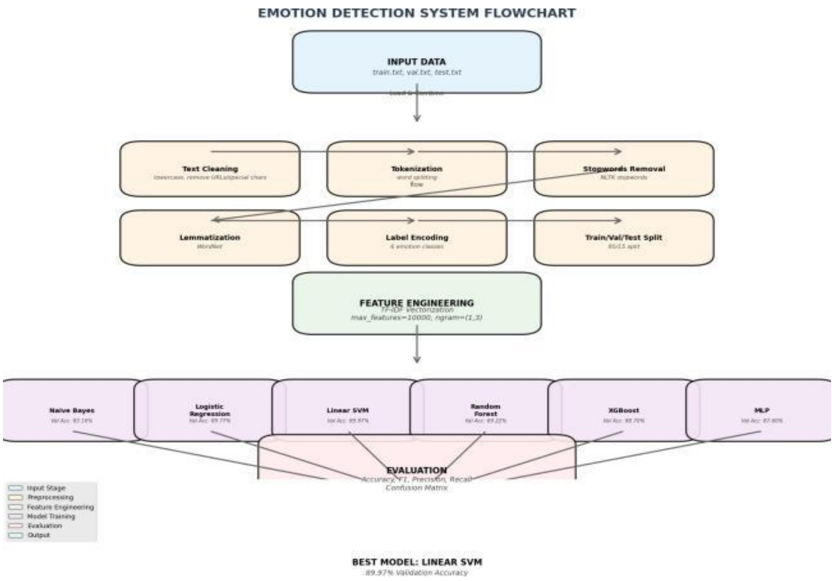

Figure 11: Emotion Detection System Flowchart showing complete pipeline from input to best model

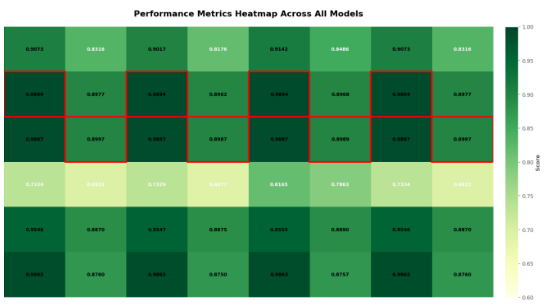

Figure 12: Performance Metrics Heatmap Across All Models

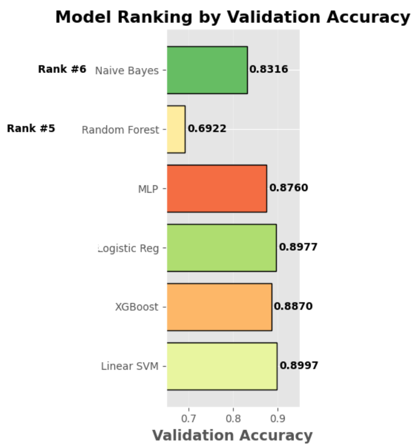

Figure 13: Model Ranking by Validation Accuracy (Linear SVM Rank #1 with 89.97%)

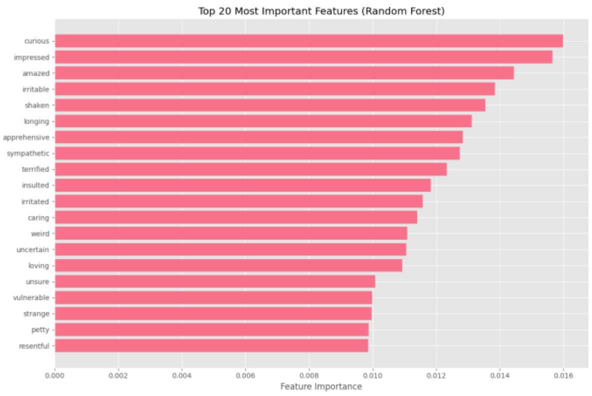

Figure 14: Top Feature Importance Words for Emotion Detection

V. CONCLUSION

This research successfully demonstrated the effective- ness of machine learning techniques for emotion detection from text. By implementing and comparing six different algorithms, with Linear SVM (89.97% accuracy), Logistic Regression (89.77% accuracy), and XGBoost (88.70% accuracy) emerging as the top performers, we identified Linear SVM as the best-performing model for emotion detection. The proposed system successfully classifies text into six emotion categories: joy, sadness, anger, fear, love, and surprise. The confusion matrices and performance evaluations confirmed the robustness of our approach, with Linear SVM demonstrating superior predictive capabilities across all emotion categories. The system was successfully deployed as a web- based application using Flask and React, allowing real- time emotion prediction. These findings conclusively prove that machine learning-based methods can effectively detect emotions from text, offering a practical and scalable solution for real-world deployment even when working with limited computational resources.

VI. ACKNOWLEDGEMENT

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REFERENCES

[1] F. A. Acheampong, H. Nunoo-Mensah, and W. Chen, ”Emotion Detection from Text Using Deep Learning: A Survey,” *Information Fusion*, vol. 53, pp. 75-86, 2020.

[2] S. M. Mohammad, F. Bravo-Marquez, M. Salameh, and S. Kiritchenko, ”SemEval-2018 Task 1: Affect in Tweets,” *Proceedings of the 12th Inter- national Workshop on Semantic Evaluation*, pp. 1-17, 2018.

[3] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, ”BERT: Pre-training of Deep Bidi- rectional Transformers for Language Understand- ing,” *Proceedings of NAACL-HLT*, pp. 4171-4186, 2019.

[4] C. Strapparava and R. Mihalcea, ”Learning to Identify Emotions in Text,” *Proceedings of the ACM Symposium on Applied Computing*, pp. 1556-1560, 2008.

[5] A. Alm, D. Roth, and R. Sproat, ”Emotions from Text: Machine Learning for Text-based Emotion Prediction,” *Proceedings of the Conference on Hu- man Language Technology*, pp. 579-586, 2005.

[6] B. Liu, ”Sentiment Analysis and Opinion Mining,” *Synthesis Lectures on Human Language Technolo- gies*, vol. 5, no. 1, pp. 1-167, 2012.

[7] S. Poria, E. Cambria, R. Bajpai, and A. Hussain, ”A Review of Affective Computing: From Uni- modal Analysis to Multimodal Fusion,” *Informa- tion Fusion*, vol. 37, pp. 98-125, 2017.

[8] S. Poria, A. Gelbukh, E. Cambria, A. Hussain, and G.-B. Huang, ”Emotion Recognition in Text Using Deep Learning,” *Proceedings of the International Conference on Computational Linguistics*, pp. 1- 10, 2015.

[9] E. Cambria, B. Schuller, Y. Xia, and C. Havasi, ”New Avenues in Opinion Mining and Sentiment Analysis,” *IEEE Intelligent Systems*, vol. 28, no. 2, pp. 15-21, 2013.

[10] M. Khan, J. Seo, and D. Kim, ”Towards Energy Efficient Text Classification: A Machine Learning Approach,” *Sensors*, vol. 20, no. 24, p. 7187, Dec.2020.

[11] L. Zhou, et al., "Deep Learning-Based Appliance Recognition and Energy Disaggregation for Smart Homes," *IEEE Transactions on Consumer Elec- tronics*, vol. 68, no. 4, pp. 332-342, Nov. 2022.
[12] S. S. S. R. Depuru, et al., "A Hybrid Metaheuris- tic and Machine Learning Approach for Optimal Home Energy Management," *IEEE Access*, vol. 11, pp. 24567-24580, 2023.
[13] H. Li, et al., "Edge Computing-Based Energy Management System for Smart Homes with Re- newable Energy," *IEEE Internet of Things Jour- nal*, vol. 9, no. 22, pp. 22432-22444, Nov. 2022.
[14] R. N. Reddy and M. V. R. Murthy, "Energy- Efficient Smart Home Automation System Using Reinforcement Learning," *Proceedings of the In- ternational Conference on Smart Systems and In- ventive Technology*, pp. 567-573, March 2024.
[15] M. A. A. da Costa, et al., "A Deep Reinforcement Learning Approach for Smart Home Energy Man- agement," *IEEE Transactions on Smart Grid*, vol. 14, no. 1, pp. 153-165, Jan. 2023.
[16] S. Park, "Machine Learning-Based Cost-Effective Smart Home Data Analysis and Forecasting for Energy Saving," *Buildings*, vol. 13, no. 9, p. 2397,Sept. 2023.
[17] T. Choudhury, et al., "Privacy-Preserving Ma- chine Learning for Smart Home Energy Data," *ACM Transactions on Cyber-Physical Systems*, vol. 7, no. 2, Article 12, April 2023.
[18] R. M. S. de Souza, et al., "Explainable Artifi- cial Intelligence for Energy Efficiency in Smart Homes," *Energy and AI*, vol. 15, Article 100325, Jan. 2024.
[19] I. Machorro-Cano et al., "HEMS-IoT: A Big Data and Machine Learning-Based Smart Home Energy Management System," *Energies*, vol. 13, no. 5, p. 1097, Mar. 2020.