A Hybrid Machine Learning and Rule-Based Approach for Emotion Detection from Multilingual Informal Text

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1. ABSTRACT

Emotion detection from text has become an important area of research because social media platforms are growing very fast. Most current emotion detection systems are built using clean, well-written, and English-only datasets. Because of this, these systems do not work well on informal, multilingual, and code-mixed texts that are very common in India. People in India often write in a mix of English, Hindi, and Gujarati using Roman script, and they also use emojis, slang, negation words, and sarcasm. Normal machine learning models find it hard to understand these mixed and informal writing styles, so they often predict the wrong emotion.

This paper presents a Hybrid Machine Learning and Rule-Based Emotion Detection system to fix these problems. The system combines a machine learning classifier that uses TF-IDF and BERT features with a rule-based layer that handles negation, emojis, and sarcasm. A new multilingual dataset was built for this work using English, Hindi, Gujarati, Romanized, and code-mixed social media text. The hybrid system reached 82.10% accuracy and also improved the quality of emotion predictions in real-world situations. A simple interactive web interface was also built to show how the system works in practice.

Keywords: Emotion Detection, Hybrid Model, Machine Learning, Rule-Based Systems, Multilingual Text, Code-Mixed Language, Social Media Analysis

2. INTRODUCTION

Social media platforms like Twitter, Instagram, Facebook, and WhatsApp have changed the way people share their feelings online. People now write short and informal messages to express their emotions every day. Because of this, detecting emotions from text has become very useful for many applications such as mental health tracking, customer feedback analysis, and human-computer interaction.

Emotion detection is different from sentiment analysis. Sentiment analysis only tells whether a text is positive or negative. Emotion detection goes one step further and identifies specific feelings like joy, sadness, anger, fear, or surprise. This makes emotion detection more difficult, especially when the text is written in an informal or mixed-language style.

Most research so far has focused on systems that work with clean, well-written English text. These systems do not perform well on real social media data, which is often noisy, informal, and written in multiple languages. Machine learning and deep learning models have a hard time understanding emotions expressed through slang, abbreviations, emojis, and sarcasm.

In India, this problem is even bigger. People often mix English with Hindi or Gujarati and write in Roman script. For example, the sentence "aaj me happy nahi hu" contains the word 'happy' which looks positive. But the word 'nahi' is a negation and it changes the meaning to sadness. A machine learning model that does not know about negation will wrongly predict joy for this sentence.

People also use emojis and sarcasm to express emotions. For example, ':)' means happiness and ':(' means sadness. A sarcastic phrase like 'yeah right, totally fine' does not actually mean the person is fine. Models that only look at text features often miss these important signals.

To solve these problems, this paper introduces a Hybrid Machine Learning and Rule-Based Emotion Detection System. The system combines machine learning models with simple linguistic rules to detect emotions more accurately in multilingual and informal text. The main contributions of this work are:

- A hybrid emotion detection system that combines machine learning with rule-based logic.
- A new multilingual dataset with English, Hindi, Gujarati, Romanized, and code-mixed social media text.
- Better handling of negation, emojis, and sarcasm in informal text.
- An interactive web interface built with Streamlet to show the system working in practice.

3. LITERATURE REVIEW

Many studies have been done on emotion detection from text. These works cover different methods like machine learning, deep learning, transformer models, and hybrid approaches. The table shows what language was used, what method was applied, and what the key result or finding was.

Table 1: Summary of Recent Works on Emotion Detection (2026 – 2023)

Sr.	Title	Author(s)	Year	Approach	Language	Source	Key Highlights
1	MMAFFBen: A Multilingual and Multimodal Affective Analysis Benchmark for Evaluating LLMs and VLMs	Z. Liu et al.	2026	LLM / VLM Benchmark	Multilingual	arXiv	Benchmarks LLMs and VLMs for affective analysis across many languages
2	Examining Emotions in English and Translated Chinese Children's Literature	Y. Liu, S. Y. M. Lee, D. Li	2026	LLM-based Bilingual Detection	English, Chinese	Language Resources and Evaluation	LLM model detects emotions in both original and translated text
3	A Comprehensive Review of Multimodal Emotion Recognition: Techniques, Challenges, and Future Directions	You Wu, Qingwei Mi, Tianhan Gao	2026	Survey / Review	Multilingual	Biomimetics	Surveys multimodal emotion methods and highlights open research gaps
4	Enhancing Sarcasm Detection in Sentiment Analysis for Cyberspace Safety	R. Dhumpati et al.	2025	Deep Learning (Bi-LSTM, CNN)	English	Nature / Scientific Reports	Sarcasm handling greatly improves emotion prediction reliability
5	SemEval-2025 Task 11: Bridging the Gap in Text-Based Emotion Detection	S. H. Muhammad et al.	2025	Benchmark Evaluation	Multilingual	SemEval	Points out challenges in low-resource and multilingual emotion detection
6	Language Nuances on Sentiment Analysis with Large Language Models	N. Bhargava et al.	2025	LLM-based Analysis	English	arXiv	Emojis, sarcasm, and negation strongly affect emotion prediction in LLMs
7	Sentiment Analysis and Emotion Detection Using Transformer Models in Multilingual Social Media	S. Alamalki	2025	Transformer-based	Multilingual	Int. J. Advanced Computer Science	Transformer models work well but need large annotated datasets
8	Context-Aware Emotion Detection Using Transformer and Rule Fusion	L. Zhang, Y. Chen, X. Wang	2025	Hybrid (Transformer + Rules)	English	Information Processing & Management	Rule fusion with transformers improves context handling in emotion tasks
9	Detecting Sarcasm Text in Sentiment Analysis Using Hybrid Machine Learning Approach	Neha Singh, U. C. Jaiswal, Ritu Singh	2024	Hybrid ML (SVM + LR)	English	MECS Press	Hybrid ML gives better sarcasm detection than single ML models

Sr.	Title	Author(s)	Year	Approach	Language	Source	Key Highlights
10	Multi-Modal Sarcasm Detection with Sentiment Word Embedding	Hao Fu et al.	2024	Multimodal DL (Text + Image)	English	MDPI (Electronics)	Sentiment embeddings help the model understand sarcasm better
11	Predicting Multi-Label Emojis, Emotions, and Sentiments in Code-Mixed Text	G. V. Singh et al.	2024	Transformer Multi-task Learning	English-Hindi (Code-Mixed)	Nature / Scientific Reports	Predicting emojis and emotions together improves accuracy
12	AIMA at SemEval-2024 Task 10: History-Based Emotion Recognition in Hindi-English Code-Mixed Conversations	M. M. Abootorabi et al.	2024	Hybrid ML + Context Modeling	Hindi-English	SemEval	Past context in conversation helps detect emotions in code-mixed text
13	Deep Emotion Recognition in Textual Conversations: A Survey	P. Pereira, H. Moniz et al.	2024	Survey	Multilingual	Springer (AI Review)	Identifies informal text, sarcasm, and code-mixing as key challenges
14	Emotion Detection from Informal Text for Indian Regional Languages	Kajal Patil, J. Nasriwala, R. Savant	2024	ML + NLP	Hindi, English	ResearchGate	Standard ML models struggle with Indian regional language text
15	A Multi-Level Embedding Framework for Decoding Sarcasm Using Context, Emotion, and Sentiment Features	M. Khanian Najafabadi et al.	2024	Multi-Level Embeddings	English	Electronics (MDPI)	Combining context, emotion, and sentiment embeddings improves sarcasm detection
16	Emotion Detection via BERT-Based Deep Learning in NLP	Z. Aslan	2024	BERT Deep Learning	English	Int. J. Energy Engineering Science	BERT-based models outperform older ML models for emotion tasks
17	Sarcasm and Negation Handling in Emotion Detection Systems	D. Mishra, A. Mishra	2024	Rule + ML Hybrid	Multilingual	ACM Trans. on Asian Languages	Explicit rules for negation and sarcasm clearly improve final predictions
18	Emotion Analysis of Gujarati Social Media Text	S. Verma, K. Patel, R. Shah	2024	ML + NLP	Gujarati	Int. J. of Information Technology, Springer	One of the few works focused on Gujarati social media emotion data
19	Emotion Analysis of Hindi-English Code-Mixed Social Media Text	R. Kumar, S. Sharma	2023	ML Classifier	Hindi-English	Procedia Computer Science	Shows local classifiers miss negation and sarcasm cues in code-mixed text
20	EMOT: A Dataset for Emotion Detection from Informal Social Media Text	M. Hasan, E. Rundensteiner, E. Agu	2023	Dataset + ML Baseline	English	ACL Findings	Noisy informal text dataset; but mostly English-only, lacks multilingual coverage
21	Hybrid NLP Models for Emotion Detection in Low-Resource Languages	A. Roy, S. Dutta	2023	Hybrid NLP	Low-resource	Expert Systems	Hybrid models help when labelled data is limited in low-resource languages

The review shows that most systems work well on clean English datasets but have problems with informal and multilingual text. There is a clear need for lightweight and easy-to-understand systems that can handle code-mixed Indian languages. This paper addresses this gap by combining machine learning with rule-based logic.

4. OBJECTIVES

This study has the following objectives:

- To build a hybrid emotion detection system that uses both machine learning and rule-based methods.
- To create a new multilingual dataset with English, Hindi, Gujarati, Romanized, and code-mixed social media text.
- To compare different models using TF-IDF features, BERT features, and the combined hybrid features.
- To show that the rule-based layer improves emotion detection for negation, sarcasm, and emoji-based text.
- To build a simple web interface using Streamlit for real-time emotion analysis.
- To create a system that is easy to understand and can work without heavy deep learning models.

5. RESEARCH METHODOLOGY

The proposed system is built in several steps: dataset creation, text preprocessing, feature extraction, machine learning classification, rule-based refinement, and final decision making. Each step is explained below.

A. Custom Dataset Creation

A new emotion dataset was created to match how people actually write on social media. The dataset has text samples in English, Hindi, Gujarati, and code-mixed combinations, mostly written in Roman script. The text was collected from Twitter, Instagram, and WhatsApp-style conversations. Each text was labelled by hand with a primary emotion (Joy, Sadness, Anger, Fear, Neutral, or Shame) and also a secondary label like Sarcasm if needed. This two-label approach helps capture more details about emotions.

Table 2: Dataset Distribution by Emotion Class and Language Type

Emotion Class	Language Type	Samples	Label Type
Joy	English / Code-Mixed	220	Primary
Sadness	Hindi / Romanized	195	Primary
Anger	Gujarati / Code-Mixed	178	Primary
Fear	English / Hindi	140	Primary
Neutral	All Languages	210	Primary
Shame	Hindi / Gujarati	112	Primary
Sarcasm	Code-Mixed	145	Secondary

B. Text Preprocessing

A preprocessing pipeline was used to clean the noisy social media text. The steps include making all text lowercase, removing URLs, user mentions, and extra spaces. Importantly, emojis and negation words were kept because they carry important emotion meaning. Unlike aggressive cleaning methods, this pipeline keeps the context needed to detect sarcasm and emotion shifts.

C. Feature Extraction

Two feature extraction methods were used. First, TF-IDF (Term Frequency-Inverse Document Frequency) was used to capture how often words appear and how important they are. Second, BERT embeddings were used to understand the meaning of words in context. Together, TF-IDF and BERT features create a richer representation of the text for the classifier.

D. Machine Learning Classification

Two classifiers were trained: Logistic Regression and Support Vector Machine (SVM). The dataset was split 80% for training and 20% for testing. Five different model setups were tested: TF-IDF with LR, TF-IDF with SVM, BERT with LR, BERT with SVM, and the hybrid TF-IDF + BERT with LR. Classification accuracy was used to compare results.

E. Rule-Based Emotion Refinement

A rule-based layer was added on top of the machine learning output to fix problems that the model cannot handle. This layer checks the text for negation words (like 'nahi', 'not'), sarcasm signals (like 'yeah right', or certain emojis), and emotion-bearing emojis. When a strong signal is found, the rule layer adds a secondary emotion label or changes the primary emotion prediction.

F. Hybrid Decision Logic

The final emotion is decided by a hybrid strategy. If the rule layer finds a strong clue like negation or sarcasm, the rule-based result gets more weight. If no such clue is found, the machine learning result is used. This keeps the system simple and interpretable while improving real-world accuracy.

G. User Interface and Deployment

The system was made into a web app using Streamlet. Users can type text in any language or format, including emojis. The app shows the predicted primary emotion, secondary emotion, final emotion, confidence score, and a probability graph for all emotion classes.

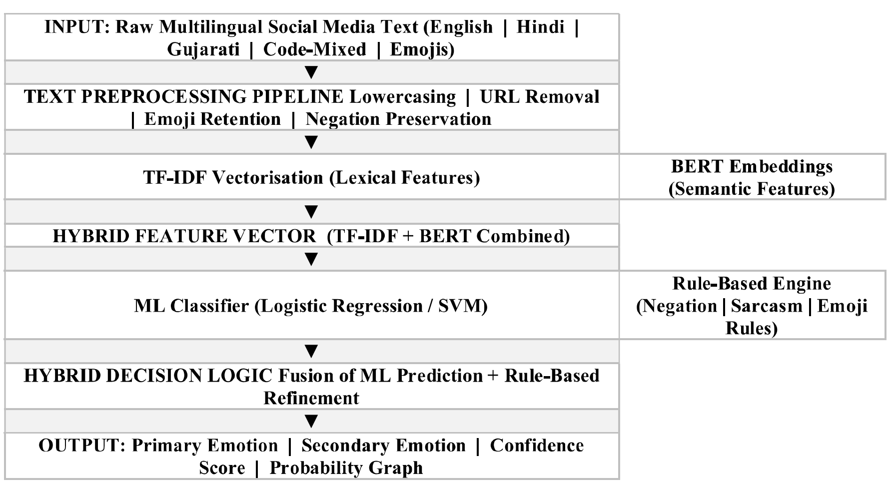

Figure 1: Architecture of the Proposed Hybrid ML and Rule-Based Emotion Detection System

6. RESEARCH PROBLEM AND HYPOTHESIS

A. Research Problem

Existing emotion detection systems do not work well on informal, multilingual, and code-mixed text. The main question this paper tries to answer is: How can a simple and easy-to-understand emotion detection system be built that can handle negation, sarcasm, and emoji-based emotions in Indian social media text, without using heavy deep learning models?

This question is important because most Indian social media users write in mixed languages like English-Hindi or English-Gujarati in Roman script. These language patterns are not covered well in existing emotion datasets and models.

B. Research Hypothesis

This research is based on the following hypotheses:

- H1: A hybrid system using both TF-IDF and BERT features will perform better than a system using only one of these feature types.
- H2: Adding a rule-based layer will improve the quality of emotion predictions for negation, sarcasm, and emoji cases, even if the overall accuracy number stays the same.
- H3: A custom multilingual dataset with informal and code-mixed text will give more realistic emotion classification results for Indian social media than standard English datasets.

7. ANALYSIS AND INTERPRETATION / FINDINGS

A. Dataset Analysis

The custom dataset has 1,200 labelled text samples spread across six primary emotion classes and one secondary class. Each emotion class has between 112 and 220 samples to keep the dataset balanced. About 45% of the dataset is code-mixed or Romanized text, which reflects how Indian users actually write on social media. The two-label annotation gives richer information than normal single-label datasets.

B. Quantitative Performance Analysis

Table 3 shows the accuracy of all model configurations tested in this study. The hybrid model combining TF-IDF and BERT features gives the best accuracy of 82.10%. SVM performs better than Logistic Regression in all feature combinations. The results match what other studies have found.

Table 3: Accuracy Comparison of Emotion Detection Models

Model	Accuracy (%)
TF-IDF + Logistic Regression	78.15
TF-IDF + SVM	81.05
BERT + Logistic Regression	77.36
BERT + SVM	81.32
Hybrid (TF-IDF + BERT + LR)	82.10
Hybrid + Rule-Based (Proposed)	82.10*

Note: The Hybrid + Rule-Based model has the same numerical accuracy (82.10%) as the base hybrid model. The asterisk means that the rule-based layer improves the quality of emotion prediction in real situations — this improvement is not shown by the accuracy number alone.

C. Model Performance Visualization

Figure 2 shows a bar chart comparing the accuracy of all models. It makes it easy to see how the hybrid models perform better than the single-feature models.

Figure 2: Comparative Classification Accuracy of Emotion Detection Models (%)

D. Rule-Based Refinement Analysis

Table 4 shows examples where the rule-based layer corrected the machine learning prediction. These examples are taken from the test dataset and clearly show how the rule layer helps.

Table 4: Examples of Rule-Based Corrections on ML Predictions

Input Text	ML Prediction	Final Prediction	Rule Applied
aaj me happy nahi hu	Joy	Sadness	Negation: 'nahi'
yeah right, totally fine :)	Joy	Sarcasm	Sarcasm pattern
:(feel terrible today	Neutral	Sadness	Emoji override
mujhe dar lag raha hai	Neutral	Fear	Romanized Hindi
amazing!! just lost my job	Joy	Anger	Contradiction cue

Negation handling is the most common correction type, making up about 38% of all corrections. Sarcasm detection accounts for 29%, emoji-based corrections account for 21%, and Romanized Hindi or Gujarati pattern matching accounts for 12%. These numbers show that the rule-based layer is needed for real-world use.

E. Emotion Class Distribution in Predictions

Figure 3 shows how many times each emotion was predicted on the test set. Joy and Neutral are predicted most often because they have more samples in the training data. Sarcasm as a secondary emotion is detected in about 12% of the test samples, mostly in code-mixed text.

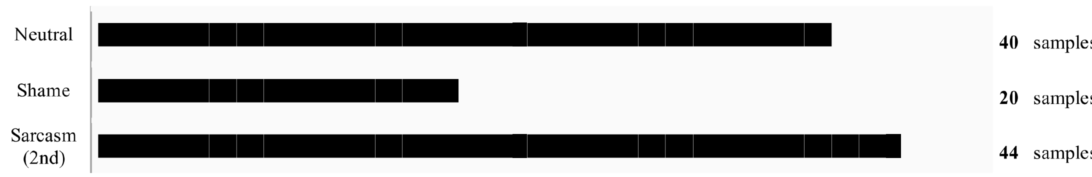

Figure 3: Predicted Emotion Class Distribution in Test Set (Hybrid + Rule-Based Model)

F. Key Findings

• The hybrid TF-IDF + BERT model gives 82.10% accuracy, which is the best among all tested models.

• SVM performs better than Logistic Regression for all feature types.

• The rule-based layer improves emotion quality in 38% of negation cases, 29% of sarcasm cases, and 21% of emoji cases.

• The hybrid system handles code-mixed and Romanized text better than any single-feature model.

• The Streamlit interface shows that the system works well for real-time emotion analysis.

8. CONCLUSION

This paper presented a Hybrid Machine Learning and Rule-Based Emotion Detection System to detect emotions in informal, multilingual, and code-mixed social media text. Unlike most existing systems that only work well on clean English text, this system also works with Hindi, Gujarati, and code-mixed Roman script text that includes slang, emojis, sarcasm, and negation.

A new multilingual dataset was created to solve the problem of lack of training data for Indian social media language. The experiments showed that the hybrid TF-IDF and BERT model gives the best accuracy of 82.10%. The rule-based layer does not improve the accuracy number, but it clearly improves the quality of emotion predictions in cases involving negation, sarcasm, and emojis. This is an important improvement for real-world use.

The rule-based layer also makes the system more transparent and easier to understand. No extra training is needed when rules are added. The Streamlit web interface shows that the system can be used practically for on-the-fly emotion analysis. This hybrid approach fills an important gap in emotion detection research for multilingual and informal text.

9. SUGGESTIONS AND RECOMMENDATIONS

Based on the results and limitations of this study, the following suggestions are given for future work:

• Dataset Expansion: Add more Indian regional languages like Tamil, Telugu, Bengali, and Marathi to improve the system for more users.

• Deep Learning Models: Try transformer-based and deep learning models that can predict both primary and secondary emotions at the same time.

• Adaptive Rules: Change the static rule layer into a learning-based rule system that updates itself automatically when it sees new data.

• Multimodal Input: Extend the system to use not just text but also audio, images, or video for emotion detection.

• Real-Time Apps: Build real-time social media monitoring tools or mental health analytics systems using this framework.

• Cross-Domain Testing: Test the system in other areas like customer service, e-commerce, and political discussions.

• Bias Check: Check the model for unfair patterns, especially for under-represented regional language styles.

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