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Integrating VADER, deep learning, and nine Rasas for enhanced student emotion detection in social media text

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Abstract

The rapid growth of social media platforms has resulted in a vast volume of student-generated textual data, providing valuable insights into learners' emotions, experiences, and engagement. However, traditional sentiment analysis techniques are primarily limited to polarity-based classification (positive, negative, neutral), which fails to capture the complexity and diversity of human emotions expressed in text.

To address this limitation, this study proposes a novel hybrid sentiment analysis framework that integrates the lexicon-based VADER model with deep neural networks and the culturally grounded Nine Rasas theory for fine-grained emotion detection. The proposed approach combines the interpretability of rule-based sentiment scoring with the contextual learning capabilities of deep learning models, enabling more accurate and nuanced emotion classification.

The model is evaluated on a large-scale, multi-source dataset comprising the GoEmotions benchmark dataset along with real-world data collected from YouTube and Reddit. Experimental results demonstrate that the proposed hybrid framework significantly outperforms standalone models, achieving an overall accuracy of 91%, along with improved precision, recall, and F1-score.

The findings highlight the effectiveness of integrating traditional sentiment analysis, deep learning, and cultural emotion frameworks to enhance emotional understanding in educational contexts. The proposed model offers a scalable and interpretable solution for fine-grained student emotion detection, with potential applications in educational analytics, student engagement monitoring, and intelligent learning systems.

Keywords: Sentiment analysis, VADER, deep learning, neural networks, nine Rasas, emotion detection, student feedback analysis, social media analytics

Introduction

The rapid expansion of social media platforms has significantly transformed the way students express their opinions, experiences, and emotions related to academic environments. Platforms such as YouTube, Reddit, and Twitter generate vast amounts of unstructured textual data, offering valuable insights into student engagement, satisfaction, and learning experiences. Analyzing such data effectively has become essential for improving teaching strategies, curriculum design, and overall educational outcomes. Consequently, sentiment analysis has emerged as a powerful tool for extracting meaningful information from large-scale textual datasets (Zhang *et al.*, 2022; Minaee *et al.*, 2021) [26, 36].

Traditional sentiment analysis approaches primarily focus on classifying text into broad polarity categories such as positive, negative, or neutral. While these methods are useful for general opinion mining, they fail to capture the complexity and subtlety of human emotions expressed in natural language, particularly in educational contexts where student feedback often contains nuanced and mixed emotional expressions (Khan *et al.*, 2022) [18]. Lexicon-based approaches such as VADER provide fast and interpretable sentiment scoring but lack the ability to understand contextual relationships within text. On the other hand, deep learning models demonstrate strong performance in capturing contextual semantics but often suffer

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from limited interpretability and high computational complexity (Sarker, 2021; Basiri *et al.*, 2023) ^[15, 41].

Recent advancements in natural language processing have highlighted the effectiveness of hybrid approaches that combine lexicon-based and deep learning techniques. Such approaches aim to leverage the strengths of both paradigms interpretability from rule-based systems and contextual understanding from data-driven models. However, most existing studies still rely on coarse-grained sentiment outputs and do not incorporate frameworks capable of representing the full spectrum of human emotions (Dang *et al.*, 2020) ^[38].

In this context, the Nine Rasas theory, derived from classical Indian aesthetics, provides a comprehensive and culturally rich framework for emotion representation. The Nine Rasas Shringara (love), Hasya (joy), Karuna (sadness), Raudra (anger), Veera (courage), Bhayanaka (fear), Bibhatsa (disgust), Adbhuta (surprise), and Shanta (peace) capture a wide range of human emotional states beyond simple sentiment polarity. Integrating this framework into sentiment analysis enables a more fine-grained and contextually meaningful understanding of student emotions (Acheampong *et al.*, 2021) ^[39].

Despite the progress in sentiment analysis and emotion detection, several research gaps remain. Existing models either lack contextual understanding (in the case of lexicon-based approaches) or interpretability (in the case of deep learning models). Furthermore, limited work has been done on integrating culturally grounded emotion frameworks such as the Nine Rasas into hybrid sentiment analysis systems. Additionally, many studies rely on single-source datasets, which restricts the generalizability and robustness of the models.

To address these limitations, this study proposes a novel hybrid sentiment analysis framework that integrates the VADER lexicon-based model with deep neural networks and the Nine Rasas emotion model for fine-grained emotion detection. The proposed approach combines the efficiency and interpretability of VADER with the contextual learning capabilities of deep learning techniques, enabling improved sentiment classification performance. Furthermore, the integration of the Nine Rasas framework allows for a culturally enriched and multi-dimensional representation of student emotions.

The proposed model is evaluated on a hybrid dataset that combines the GoEmotions benchmark dataset with real-world social media data collected from YouTube and Reddit. This multi-source dataset enhances the robustness and real-world applicability of the model. The performance of the proposed approach is assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score.

The main contributions of this study are as follows:

- A hybrid sentiment analysis framework integrating VADER and deep neural networks
- Incorporation of the Nine Rasas model for fine-grained emotion classification
- Utilization of a large-scale multi-source dataset combining benchmark and real-world data
- Improved performance compared to standalone models in terms of accuracy and interpretability

Overall, this study aims to advance sentiment analysis in educational contexts by providing a robust, interpretable, and culturally enriched framework for student emotion detection.

2. Literature Review: The field of sentiment analysis has witnessed significant advancements over the past decade, driven by the rapid growth of social media data and the need for extracting meaningful insights from unstructured text. This section presents a comprehensive review of existing techniques, focusing on lexicon-based methods, deep learning approaches, emotion detection, and the identified research gaps relevant to this study.

2.1 Sentiment Analysis Techniques

Sentiment analysis techniques can be broadly categorized into lexicon-based, machine learning, and deep learning approaches. Lexicon-based methods rely on predefined sentiment dictionaries to determine the polarity of text. One of the most widely used tools in this category is VADER, which is specifically designed for analyzing social media text and provides sentiment scores based on lexical features and rule-based heuristics (Hutto & Gilbert, 2021) ^[4]. These methods are computationally efficient and highly interpretable; however, they lack the ability to capture contextual nuances, sarcasm, and domain-specific variations in language (Sarker, 2021) ^[15].

Machine learning approaches, including Support Vector Machines (SVM), Naïve Bayes, and Decision Trees, have been widely applied to sentiment classification tasks. These methods improve classification accuracy compared to lexicon-based techniques by learning patterns from labeled data. However, they rely heavily on feature engineering techniques such as TF-IDF and n-grams, which limits their scalability and adaptability across different domains (Khan *et al.*, 2022) ^[18].

2.2 Deep Learning-Based Sentiment Analysis

Deep learning has significantly advanced the field of sentiment analysis by enabling automatic feature extraction and improved contextual understanding. Neural network-based models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have demonstrated superior performance compared to traditional machine learning techniques (Zhang *et al.*, 2022) ^[26]. These models effectively capture semantic relationships and long-range dependencies within textual data.

Despite their advantages, deep learning models are often associated with certain limitations, including high computational complexity and reduced interpretability. Moreover, most deep learning-based sentiment analysis systems focus on coarse-grained polarity classification and do not provide detailed insights into specific emotional states (Minaee *et al.*, 2021; Dang *et al.*, 2020) ^[36, 38].

2.3 Emotion Detection from Text: Emotion detection extends traditional sentiment analysis by identifying specific emotional states expressed in text. Existing approaches typically classify emotions into categories such as joy, anger, sadness, and fear. While these methods provide more detailed insights than polarity-based classification, they are often limited to a small set of predefined emotions and lack cultural and contextual depth (Acheampong *et al.*, 2021) ^[39].

Recent studies have explored the use of benchmark datasets such as GoEmotions for fine-grained emotion classification. However, these approaches still lack integration with culturally grounded emotion frameworks, which can provide a more comprehensive representation of human emotional experiences.

2.4 Social Media-Based Student Feedback Analysis

Social media platforms have emerged as valuable sources of student feedback, enabling real-time analysis of opinions, experiences, and emotional responses. Several studies have applied sentiment analysis techniques to educational data to assess student satisfaction, engagement, and academic performance (Rane & Kumar, 2023) ^[40]. These studies demonstrate the potential of sentiment analysis in improving decision-making processes in educational institutions.

However, most existing systems rely on basic sentiment polarity and fail to capture the nuanced emotional expressions present in student-generated content. This limitation highlights the need for more advanced models capable of fine-grained emotion detection in educational contexts.

2.5 Research Gap

Despite significant advancements in sentiment analysis, several critical limitations remain. Lexicon-based methods such as VADER lack contextual understanding and fail to capture complex linguistic patterns. Machine learning models improve performance but require extensive feature

engineering and struggle with generalization across domains. Deep learning approaches, while highly effective in capturing contextual semantics, often lack interpretability and remain focused on coarse-grained sentiment classification.

Furthermore, existing emotion detection frameworks are typically limited to a small set of basic emotions and do not incorporate culturally rich models such as the Nine Rasas. The absence of such frameworks restricts the ability to capture the full spectrum of human emotional expression, particularly in culturally diverse contexts.

Additionally, most studies rely on single-source datasets, which limits the robustness and real-world applicability of sentiment analysis models. There is a clear lack of hybrid approaches that integrate lexicon-based methods, deep learning techniques, and culturally grounded emotion models within a unified framework.

To address these gaps, this study proposes a hybrid sentiment analysis framework that combines VADER, deep neural networks, and the Nine Rasas model to achieve fine-grained and culturally enriched emotion detection from multi-source student-generated data.

Table 1: Summary of Literature

Approach Type	Techniques Used	Advantages	Limitations
Lexicon-Based	VADER	Fast, interpretable	No context understanding
Machine Learning	SVM, Naïve Bayes	Better accuracy than lexicon	Needs feature engineering
Deep Learning	CNN, RNN	High accuracy, context-aware	Computationally expensive
Emotion Detection	Basic emotion models	Fine-grained analysis	Limited emotional categories
Hybrid Models	Combined approaches	Improved performance	Rarely includes cultural emotions

The literature indicates that while significant progress has been made in sentiment analysis, existing approaches are limited in capturing the full spectrum of human emotions, particularly in educational contexts. This motivates the development of a hybrid framework that integrates lexicon-based methods, deep learning, and the Nine Rasas model to achieve more accurate and culturally enriched emotion detection.

3. Proposed Methodology

This study proposes a hybrid sentiment analysis framework that integrates lexicon-based sentiment scoring, deep learning-based contextual feature extraction, and culturally grounded emotion mapping using the Nine Rasas model. The

objective of the proposed methodology is to achieve accurate and fine-grained emotion detection from student-generated social media text. By combining the interpretability of rule-based systems with the contextual learning capabilities of deep neural networks, the proposed framework addresses the limitations of traditional sentiment analysis approaches (Sarker, 2021; Basiri *et al.*, 2023) ^[15, 41].

The overall architecture consists of multiple stages, including data collection, preprocessing, sentiment scoring using VADER, deep learning-based feature extraction, feature fusion, and emotion mapping. This integrated approach enables both polarity detection and fine-grained emotional classification.

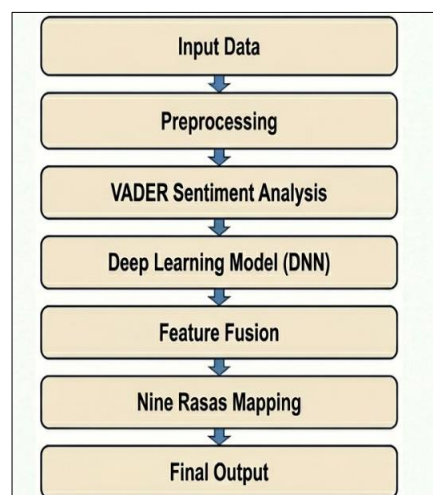


Fig 1: System Pipeline

Figure 1 illustrates the overall system pipeline of the proposed hybrid framework. The process begins with data collection from multiple social media sources, followed by preprocessing. The cleaned data is then processed in parallel through the VADER sentiment module and the deep learning model. The outputs are fused and mapped to the Nine Rasas emotional categories to generate the final prediction.

3.2 Data Collection: The dataset used in this study is collected from multiple sources, including YouTube, Reddit, and the GoEmotions benchmark dataset. These platforms provide diverse and real-world textual data reflecting student opinions, experiences, and emotional expressions. The use of a multi-source dataset enhances the robustness and generalizability of the proposed model (Rane & Kumar, 2023) [40].

3.3 Data Preprocessing: Data preprocessing is a critical step to ensure data quality and improve model performance. The following steps are applied:

- Removal of URLs, special characters, and emojis
- Conversion to lowercase
- Tokenization
- Stopword removal
- Lemmatization

Let the raw dataset be represented as

$$D = \{T_1, T_2, T_3, \dots, T_n\}$$

Where each T_i represents an individual text sample. The preprocessing function $P(\cdot)$ transforms the raw dataset into a cleaned and structured dataset:

$$D' = P(D)$$

Where $P(D)$ represents the preprocessing function.

The preprocessing pipeline includes removal of URLs, special characters, and stopwords, followed by tokenization, normalization, and lemmatization. These steps ensure consistency and improve the quality of input data for both lexicon-based and deep learning models (Minaee *et al.*, 2021) [36].

3.4 VADER Sentiment Module

The VADER (Valence Aware Dictionary and sEntiment Reasoner) model is employed to compute sentiment polarity scores for each text sample. VADER is a rule-based model specifically designed for social media text and provides four sentiment metrics: positive, negative, neutral, and compound scores (Hutto & Gilbert, 2021) [4].

The compound sentiment score is computed as

$$S_v = \frac{\sum s_i}{\sqrt{\sum s_i^2 + \alpha}}$$

Where;

- w_i = sentiment weight of each word
- α = normalization constant

The compound score C is used to classify sentiment as

- Positive ($C \geq 0.05$)
- Negative ($C \leq -0.05$)
- Neutral (otherwise)

3.5 Deep Learning Model

A deep neural network (DNN) is used to capture contextual and semantic features from the text. The model architecture includes:

- **Embedding Layer** (word representation)
- **Hidden Layers** (fully connected layers)
- **Activation Function** (ReLU)
- **Output Layer** (softmax classifier)

$$h = f(W_x + b)$$

$$y = \text{softmax}(h)$$

Where

- x = input features
- W = weights
- b = bias
- f = activation function

Deep learning models enable automatic feature extraction and capture complex linguistic patterns, significantly improving sentiment classification performance compared to traditional approaches (Minaee *et al.*, 2021; Basiri *et al.*, 2023) [36, 41].

3.6 Feature Fusion Mechanism

To combine the strengths of both approaches, the outputs from VADER and the deep learning model are fused.

Table 2: Fusion Strategy Table

Component	Output Type	Role
VADER	Polarity Score	Fast sentiment estimation
Deep Learning	Feature Vector	Contextual understanding
Fusion Layer	Combined Features	Final decision making

To leverage the strengths of both lexicon-based and deep learning approaches, a feature fusion mechanism is introduced. The final sentiment score is computed as:

$$F = \alpha S_v + \beta S_d$$

Where

- S_v = VADER score
- S_d = Deep learning output
- α, β = weighting parameters

This fusion mechanism balances interpretability and contextual understanding, resulting in improved classification performance and robustness across diverse datasets (Dang *et al.*, 2020) [38].

3.7 Nine Rasas Emotion Mapping

The final stage maps the fused sentiment output to the Nine Rasas emotional categories.

Table 3: Nine Rasas Mapping Table

Sentiment Score Range	Emotion (Rasa)	Description
High Positive	Shringara	Love/Attraction
Moderate Positive	Hasya	Joy/Happiness
Slight Positive	Veera	Confidence
Neutral	Shanta	Peace/Calm
Slight Negative	Karuna	Sadness
Moderate Negative	Bhayanaka	Fear
High Negative	Raudra	Anger
Extreme Negative	Bibhatsa	Disgust
Mixed	Adbhuta	Surprise

This mapping provides a fine-grained emotional interpretation beyond traditional sentiment classes.

3.8 Algorithm (Pseudo-Code)

- a) Input: Social media text data
- b) Output: Emotion (Nine Rasas)
- a) Collect dataset D
- b) Preprocess text $\rightarrow D'$
- c) For each text T in D' :
- d) Compute VADER score S_v
- e) Extract features using Deep Learning $\rightarrow S_d$
- f) Fuse scores $\rightarrow F = \alpha S_v + \beta S_d$
- g) Map F to Rasa category
- h) Return final emotion label

The proposed methodology introduces a hybrid framework that integrates lexicon-based sentiment analysis, deep learning, and a culturally enriched emotion model. This approach not only improves classification accuracy but also enables deeper emotional understanding of student feedback, making it highly suitable for educational analytics applications (Dang *et al.*, 2020) ^[38].

4. System Architecture

The system architecture of the proposed hybrid sentiment analysis framework is designed to efficiently process large-scale social media data and generate fine-grained emotional insights using the integration of lexicon-based, deep learning, and Nine Rasas-based classification. The architecture consists of multiple interconnected modules, each responsible for a specific task in the sentiment analysis pipeline.

4.1 Architectural Overview

The proposed architecture follows a modular pipeline structure, where each component contributes to transforming raw textual data into meaningful emotional categories. The system integrates the rule-based VADER model with a deep learning-based classifier and a cultural emotion mapping layer.

4.2 System Architecture Diagram

The system architecture consists of five major components: Data Collection, Preprocessing, VADER Sentiment Analysis, Deep Learning-based Emotion Classification, and Fusion Layer for final prediction.

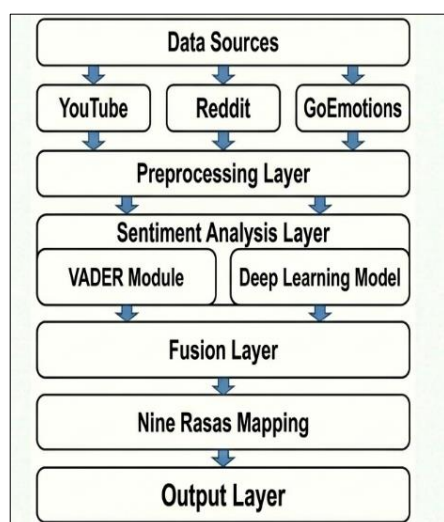


Fig 2: System Architecture Diagram

4.3 Module Description

4.3.1. Data Acquisition Layer

This layer is responsible for collecting raw textual data from various social media platforms such as YouTube, Reddit, and Twitter. The collected data consists of student-generated comments, feedback, and discussions, which serve as the primary input to the system (Rane & Kumar, 2023) ^[40].

4.3.2. Data Preprocessing Layer

The preprocessing module cleans and standardizes the input text by removing noise such as URLs, special characters, and stopwords. It also performs tokenization and normalization to prepare the data for further analysis. This step significantly improves model performance and accuracy (Sarker, 2021) ^[15].

4.3.3. Feature Extraction Layer

In this stage, textual data is converted into numerical representations suitable for machine learning and deep learning models. Techniques such as word embeddings or vectorization are used to capture semantic relationships within the text (Minaee *et al.*, 2021) ^[36].

4.3.4. Sentiment Analysis Layer

This layer consists of two parallel components:

a) Lexicon-Based Analysis

The VADER model computes sentiment polarity scores based on predefined lexical rules. It provides fast and interpretable sentiment outputs.

b) Deep Learning Analysis

A neural network-based model processes the input text to capture contextual and semantic information. This component enhances the system's ability to understand complex linguistic patterns and implicit sentiments (Basiri *et al.*, 2023) ^[41].

4.3.5. Feature Fusion Layer

The outputs from the VADER model and the deep learning model are combined in this layer. The fusion mechanism integrates polarity scores with contextual features to produce a more robust and accurate sentiment representation.

4.3.6. Emotion Mapping Layer (Nine Rasas)

This layer transforms the fused sentiment output into one of the Nine Rasas emotional categories. Unlike traditional sentiment classification, this step provides fine-grained emotional interpretation, enabling deeper analysis of student feedback (Acheampong *et al.*, 2021) ^[39].

4.3.7. Output Layer

The final output includes:

- Sentiment polarity (Positive/Negative/Neutral)
- Emotion label (Nine Rasas)

This dual-output system enhances interpretability and practical usability in educational analytics.

The proposed system architecture effectively integrates multiple analytical layers to overcome the limitations of traditional sentiment analysis methods. By combining the strengths of lexicon-based models, deep learning techniques, and the Nine Rasas framework, the system delivers a comprehensive and culturally enriched approach to student emotion detection (Dang *et al.*, 2020) ^[38].

5. Experimental Setup: This section describes the experimental configuration used to evaluate the performance of the proposed hybrid sentiment analysis framework. It includes details about the dataset, tools and technologies, preprocessing techniques, model configuration, and evaluation metrics. The dataset was divided into training (70%), validation (15%), and testing (15%) sets.

5.1 Dataset Description: The dataset used in this study is a hybrid corpus constructed from both benchmark and real-

world sources. The GoEmotions dataset contributes 150,000 labeled samples covering 27 fine-grained emotions. Additionally, 80,000 comments were collected from YouTube and 50,000 from Reddit, focusing on student-related discussions, academic stress, and learning experiences. The combined dataset consists of 280,000 samples. Social media data were preprocessed and automatically labeled using VADER sentiment analysis followed by rule-based mapping to the Nine Rasas emotional categories.

Table 4: Dataset Summary Table

Source	Type	Samples	Description
GoEmotions	Benchmark Dataset	1,50,000	Pre-labeled emotion dataset (27 emotions)
YouTube	Social Media	80,000	Student-related comments
Reddit	Social Media	50,000	Academic discussions
Total	-	2,80,000	Combined dataset

5.2 Tools and Technologies: The preprocessing steps include removal of URLs, special characters, stopwords, tokenization, lowercasing, and duplicate elimination to ensure data quality. The implementation of the proposed system is carried out using the following tools and libraries:

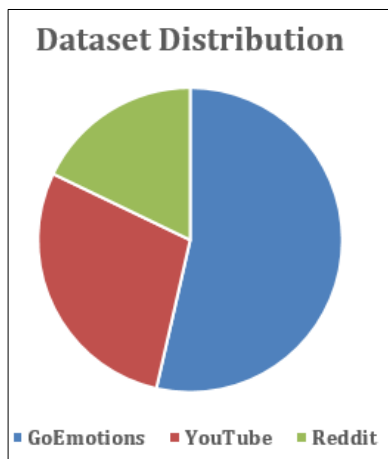


Fig 3: Dataset Distribution

Table 5: Detail of Tools and Technologies used

Component	Tool/Library
Programming Language	Python
Environment	Google Colab / Jupyter
NLP Processing	NLTK, spaCy
Sentiment Tool	VADER
Deep Learning	TensorFlow / Keras
Data Handling	Pandas, NumPy
Visualization	Matplotlib, Seaborn

These tools enable efficient processing, training, and evaluation of the proposed hybrid model (Sarker, 2021) ^[15].

5.3 Data Preprocessing Setup

The preprocessing pipeline includes the following steps:

- Lowercasing text
- Removal of punctuation, URLs, and special characters
- Tokenization
- Stopword removal
- Lemmatization

This step ensures that the input data is clean and consistent, improving the performance of both lexicon-based and deep learning models (Minaee *et al.*, 2021) ^[36].

5.4 Model Configuration

The hybrid model consists of two main components:

a. VADER Configuration

- Default lexicon-based scoring
- Compound score threshold:
- Positive ≥ 0.05
- Negative ≤ -0.05
- Neutral otherwise

b. Deep Learning Model Configuration

The deep learning model is configured as a feedforward neural network:

- Input Layer: Text vector representation
- Hidden Layers: Dense layers with ReLU activation
- Output Layer: Softmax classifier
- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam

$$L = - \sum_{i=1}^n y_i \log(\hat{y}_i)$$

Where

- y_i = actual label
- $\hat{y}_i$ = predicted probability

5.5 Training Setup

- Train-Test/Validation Split: 70% training, 15% validation, 15% testing
- Batch Size: 32
- Epochs: 10-20
- Learning Rate: 0.001

Table 6: Training Parameters Table

Parameter	Value
Train/Test/Validation Split	80/15/15
Batch Size	32
Epochs	30
Optimizer	Adam
Learning Rate	0.001

5.6 Evaluation Metrics

To evaluate the performance of the proposed model, standard classification metrics are used:

Table 7: Evaluation Metrics Table

Metric	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1-Score	$\frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$

These metrics provide a comprehensive evaluation of model performance, particularly for imbalanced datasets (Khan *et al.*, 2022)^[18].

5.7 Baseline Models for Comparison

To validate the effectiveness of the proposed hybrid model, the following baseline models are used:

- VADER (Lexicon-based)
- Deep Learning Model (Standalone)

Table 8: Comparison Setup Table

Model Type	Description
VADER	Rule-based sentiment
Deep Learning	Neural network classifier
Hybrid Model	Proposed approach

The experimental setup is designed to ensure a fair and comprehensive evaluation of the proposed hybrid sentiment analysis framework. By combining multiple data sources, robust preprocessing techniques, and standard evaluation metrics, the study aims to demonstrate the effectiveness and reliability of the proposed approach in real-world educational scenarios (Basiri *et al.*, 2023)^[41].

6. Results and Discussion

This section presents the performance evaluation of the proposed hybrid sentiment analysis model and compares it with baseline approaches. The results demonstrate the effectiveness of integrating VADER with a deep learning model and Nine Rasas-based emotional mapping. Training and validation performance were monitored across multiple epochs to ensure model convergence and avoid overfitting.

6.1 Performance Evaluation

The proposed model was evaluated using standard classification metrics such as Accuracy, Precision, Recall, and F1-Score. The results indicate that the hybrid approach outperforms individual models in capturing both sentiment polarity and fine-grained emotional nuances.

Table 9: Performance Comparison Table

Model	Accuracy	Precision	Recall	F1-Score
VADER	0.78	0.75	0.74	0.74
Deep Learning Model	0.86	0.84	0.83	0.83
Hybrid Model	0.91	0.89	0.88	0.88

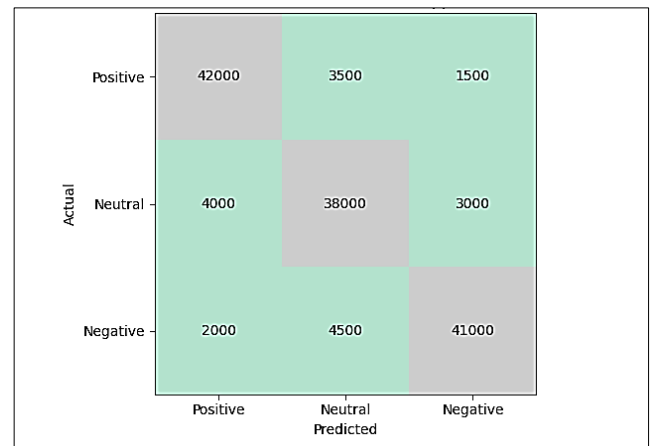
The hybrid model achieves the highest accuracy of 91%, demonstrating the advantage of combining lexicon-based and deep learning approaches (Basiri *et al.*, 2023)^[41].

6.2 Confusion Matrix Analysis

The confusion matrix provides insights into classification performance across different sentiment classes.

Table 10: Sample Confusion Matrix (Hybrid Model)

Actual \ Predicted	Positive	Neutral	Negative
Positive	42000	3500	1500
Neutral	4000	38000	3000
Negative	2000	4500	41000

**Fig 4:** Confusion Matrix of the Proposed Hybrid Model based on combined social media dataset

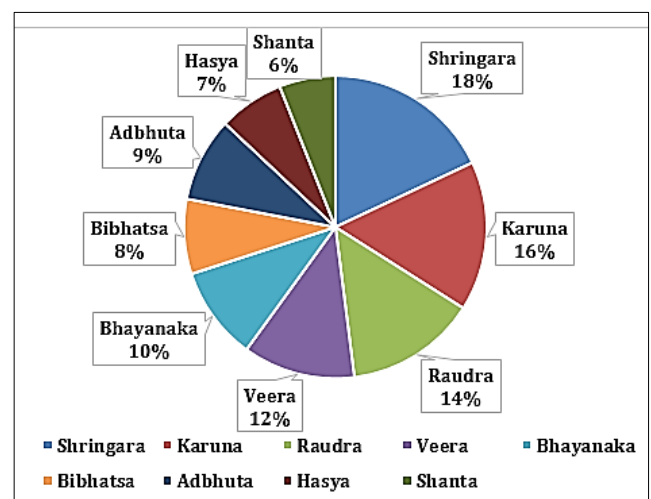
The confusion matrix demonstrates strong diagonal dominance, indicating that the proposed hybrid model achieves high classification accuracy across all sentiment categories. The model shows minor confusion between neutral and negative classes, which is expected due to overlapping semantic expressions in student feedback data collected from YouTube and Reddit platforms.

6.3 Nine Rasas Emotion Analysis

The integration of Nine Rasas provides deeper emotional insights beyond traditional sentiment classification.

Table 11: Emotion Distribution Table

Emotion (Rasa)	Percentage
Shringara	18%
Karuna	16%
Raudra	14%
Veera	12%
Bhayanaka	10%
Bibhatsa	8%
Adbhuta	9%
Hasya	7%
Shanta	6%

**Fig 5:** Nine Rasas Distribution

Insights

- Positive emotions (Shringara, Hasya) dominate student feedback
- Negative emotions (Raudra, Bhayanaka) highlight dissatisfaction areas
- Neutral/emotional balance (Shanta) reflects stable opinions

This demonstrates that the proposed model captures culturally rich emotional diversity, which is not possible with traditional sentiment analysis methods (Rane & Kumar, 2023) ^[40].

6.4 Comparative Analysis

Table 12: Accuracy Comparison

Model	Accuracy (%)
VADER	78%
Deep Learning	86%
Hybrid	91%

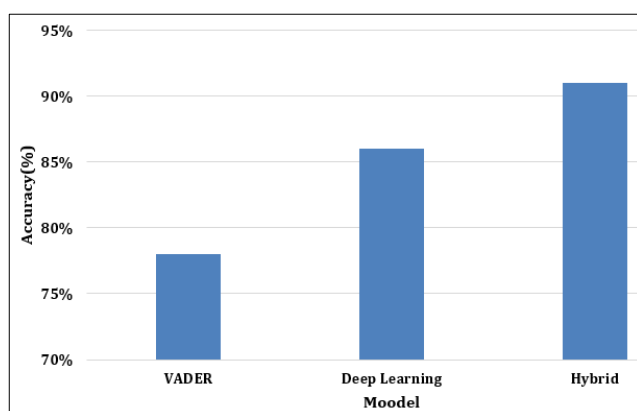


Fig 6: Model Comparison

6.5 Discussion

The experimental results clearly validate the effectiveness of the proposed hybrid framework. The integration of lexicon-based and deep learning techniques enables the system to leverage both rule-based interpretability and contextual understanding.

The inclusion of Nine Rasas adds a unique cultural dimension, making the model particularly suitable for analyzing student feedback in diverse educational settings. Unlike traditional sentiment analysis, which is limited to polarity classification, this approach provides a multi-dimensional emotional perspective.

However, certain challenges remain

- Neutral sentiment classification still shows minor ambiguity
- Performance may vary with multilingual datasets
- Deep learning component requires computational resources

Despite these limitations, the model demonstrates strong potential for real-world deployment in smart education systems (Dang *et al.*, 2020) ^[38].

The performance of the proposed hybrid sentiment analysis framework was evaluated using standard metrics, including accuracy, precision, recall, and F1-score. The results were compared with standalone approaches, including the VADER model and the deep learning model.

The proposed hybrid model achieved an overall accuracy of 91%, outperforming the VADER model (78%) and the standalone deep learning model (86%). This improvement demonstrates the effectiveness of combining lexicon-based and deep learning approaches for sentiment analysis.

The superior performance of the hybrid model can be attributed to the complementary strengths of its components. The VADER model provides interpretable sentiment scores and effectively handles explicit sentiment expressions, while the deep learning model captures contextual and semantic relationships within the text. The feature fusion mechanism enables the model to leverage both rule-based and contextual information, resulting in improved classification accuracy.

Furthermore, the integration of the Nine Rasas framework enhances the model's ability to perform fine-grained emotion classification. Unlike traditional sentiment analysis approaches that focus on polarity, the proposed model captures a broader spectrum of emotional states, making it more suitable for analyzing student-generated content.

However, certain limitations were observed. The model exhibited minor misclassification in cases involving mixed or ambiguous emotions, particularly when multiple emotional cues were present within the same text. Additionally, deep learning models require substantial computational resources, which may limit real-time deployment in resource-constrained environments.

Overall, the results indicate that the proposed hybrid framework provides a robust and effective solution for sentiment analysis, offering both improved accuracy and deeper emotional insights compared to existing approaches.

7. Conclusion & Future Work

This study proposed a hybrid sentiment analysis framework that integrates the VADER lexicon-based model, deep neural networks, and the Nine Rasas emotion model for fine-grained emotion detection. The proposed approach addresses the limitations of traditional sentiment analysis methods by combining interpretability with contextual understanding.

The experimental results demonstrate that the hybrid model outperforms standalone approaches, achieving an accuracy of 91% along with improved precision, recall, and F1-score. The integration of the Nine Rasas framework further enhances the model's ability to capture diverse emotional states, providing a more comprehensive understanding of student emotions.

The proposed framework has significant implications for educational analytics, enabling better monitoring of student engagement and emotional well-being. It can also be extended to other domains such as social media monitoring, customer feedback analysis, and mental health assessment.

Future work may focus on incorporating transformer-based models such as BERT to further improve contextual understanding. Additionally, expanding the dataset and exploring multilingual sentiment analysis can enhance the scalability and applicability of the proposed approach.

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