Global Journal of Computer and Engineering Technology (GJCET)

Vol. 5, No. 1, January, 2025 ISSN: 2767-1933

PERFORMANCE ANALYSIS OF HYBRID SENTIMENT ANALYZER FOR ESTIMATION OF NINE RASAAS

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ABSTRACT

The Navarasa framework, rooted in classical Indian aesthetics, represents nine fundamental emotional states that characterize human expression. This study aims to integrate the traditional concept of Navarasa with modern sentiment analysis techniques to achieve a more nuanced understanding of student emotions in higher education contexts. In this work, a hybrid sentiment analysis model combining the Valence Aware Dictionary for Sentiment Reasoning (VADER) and Long Short-Term Memory (LSTM) networks is proposed. VADER captures rule-based sentiment features, particularly effective for informal textual expressions, while LSTM models contextual and sequential dependencies in text data. The fusion of these approaches enables improved representation of complex emotional states beyond conventional polarity-based classification. The experimental evaluation is conducted on a dataset comprising primary data collected through structured Google Forms and secondary data sourced from publicly available repositories. The model is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. Results indicate that the proposed hybrid approach achieves improved performance compared to individual baseline models, while highlighting certain limitations in capturing fine-grained emotional distinctions. The findings suggest that integrating culturally grounded emotional frameworks like Navarasa with computational models can enhance sentiment analysis in educational settings. Furthermore, this study provides a foundation for future research exploring advanced deep learning architectures to further improve emotion classification performance.

Keywords: Sentiment Analysis, Navarasa, VADER, LSTM, Natural Language Processing.

1. INTRODUCTION

In recent years, sentiment analysis has emerged as a significant research area in natural language processing (NLP), particularly in understanding user-generated textual data. In the context of higher education, analyzing student feedback plays a crucial role in evaluating teaching effectiveness, institutional quality, and overall learning experience. Traditional sentiment analysis approaches typically classify text into broad categories such as positive, negative, or neutral, which often fail to capture the complexity of human emotions.

To address this limitation, this study incorporates the classical Indian aesthetic framework of Navarasa, which represents nine fundamental emotional states: Shringara (love), Hasya (laughter), Karuna (compassion), Raudra (anger), Veera (courage), Bhayanaka (fear), Bibhatsa (disgust), Adbhuta (surprise), and Shanta (peace). Unlike conventional sentiment models, the Navarasa framework provides a more fine-grained and culturally enriched perspective for analyzing emotional expressions.

The integration of traditional emotional frameworks with computational techniques presents new opportunities for advancing sentiment analysis. However, existing models primarily focus on polarity-based classification and do not adequately address multi-dimensional emotional representation. This research aims to bridge this gap by proposing a hybrid sentiment analysis model that combines the strengths of rule-based and deep learning approaches.

Specifically, the study employs the Valence Aware Dictionary for Sentiment Reasoning (VADER) for capturing lexical and rule-based sentiment features, along with Long Short-Term Memory (LSTM) networks for modeling contextual dependencies in textual data. The hybridization of these methods is intended to enhance the detection and classification of nuanced emotional states aligned with the Navarasa framework.

The primary objective of this study is to develop and evaluate a hybrid sentiment analysis model capable of identifying Navarasa-based emotional categories from student-generated textual data. Additionally, the study aims to provide insights into the applicability of culturally grounded emotional models in modern educational analytics, thereby contributing to the development of more emotionally aware learning environments.

This work also lays the foundation for future research exploring advanced deep learning architectures to further improve the accuracy and robustness of emotion classification systems.

2. LITERATURE REVIEW

Sentiment analysis has gained significant attention in recent years, particularly in the domain of educational data mining, where understanding student feedback is essential for improving learning outcomes. Various machine learning and deep learning techniques have been explored to analyze textual data and classify sentiments.

Early studies primarily focused on traditional machine learning approaches such as Multinomial Naive Bayes (MNB), Support Vector Machines (SVM), and Logistic Regression for sentiment classification. For instance, Alatrash et al. (2021) evaluated multiple machine learning algorithms for binary sentiment classification using large-scale review datasets, demonstrating the effectiveness of classical approaches in structured environments. Similarly, Kandhro et al. (2019) explored multiple classifiers including Random Forest, Stochastic Gradient Descent, and Multilayer Perceptron, highlighting the role of feature engineering in improving classification performance.

With the advancement of deep learning, researchers have increasingly adopted neural network-based models for sentiment analysis. Long Short-Term Memory (LSTM) networks have been widely used due to their ability to capture sequential dependencies in text. Studies such as Al-Bayati et al. (2020) and Khan et al. (2021) demonstrated the effectiveness of LSTM-based architectures in handling complex linguistic patterns across different languages, including Arabic and Urdu. Additionally, hybrid deep learning frameworks combining multiple layers and embedding techniques have been proposed to enhance feature representation.

In the context of educational data, several studies have focused on analyzing student feedback and online learning environments. Chen et al. (2022) utilized multiple machine learning classifiers to analyze student perceptions in MOOCs, identifying gradient boosting techniques as effective for large-scale data. Ngwira et al. (2023) proposed a deep learning framework integrating textual and numerical data to predict student performance, emphasizing the importance of multi-dimensional analysis in educational systems.

Furthermore, recent research has explored aspect-based sentiment analysis and weakly supervised frameworks to capture fine-grained opinions. Kastrati et al. (2020, 2021) conducted comprehensive studies on student feedback analysis, incorporating aspect extraction and sentiment classification using NLP and deep learning techniques. These studies highlight the growing need for more sophisticated models capable of capturing nuanced emotional expressions.

Despite these advancements, most existing approaches are limited to polarity-based sentiment classification (positive, negative, neutral) and do not adequately address the representation of complex emotional states. Moreover, there is a lack of integration between culturally grounded emotional frameworks and computational sentiment analysis models.

To address these limitations, this study proposes a hybrid approach that combines rule-based sentiment analysis (VADER) with deep learning techniques (LSTM) to enable multi-class emotional classification based on the Navarasa framework. This approach aims to provide a more comprehensive and culturally enriched understanding of student emotions, thereby contributing to the advancement of sentiment analysis in educational contexts.

3. EXPERIENTIAL WORK

This study proposes a hybrid sentiment analysis framework for identifying Navarasa-based emotional states from student-generated textual data. The methodology consists of data collection, preprocessing, feature extraction, model development, and performance evaluation.

3.1 Data Collection

The dataset used in this study comprises both primary and secondary sources. Primary data was collected through structured questionnaires distributed via Google Forms, targeting students in higher education institutions. The questionnaire was designed to capture responses corresponding to different emotional states aligned with the Navarasa framework. To enhance the diversity and volume of data, secondary datasets were incorporated from publicly available sources, including social media platforms and online repositories. These datasets include informal textual expressions such as comments and messages, which are valuable for sentiment analysis.

Table 1: Dataset Description

Dataset Type	Source	Number of Samples	Description
Primary Dataset	Google Forms	2500	Student feedback collected through structured questionnaire
Secondary Dataset	Social Media / Online Sources	160000	Informal textual data including comments and messages
Total	Combined	162500	Aggregated dataset used for training and testing

Table 1 presents the distribution and sources of the dataset used in this study.

3.2 Data Preprocessing

The collected textual data was preprocessed to improve data quality and ensure consistency. The preprocessing steps include:

- Conversion of text to lowercase
- Removal of stop words, punctuation, and special characters
- Tokenization of text into words
- Stemming or lemmatization for normalization

These steps help in reducing noise and improving the efficiency of the model.

3.3 Emotion Labeling Based on Navarasa

The dataset was annotated based on the nine emotional categories defined by the Navarasa framework: love, laughter, compassion, anger, courage, fear, disgust, surprise, and peace. Each text instance was assigned to one of these categories based on its emotional context.

3.4 Hybrid Model Architecture

The proposed model combines rule-based and deep learning approaches to leverage the strengths of both techniques.

- **VADER (Valence Aware Dictionary for Sentiment Reasoning):**
  VADER is used to extract sentiment scores based on lexical features, including polarity, intensity, and handling of emoticons and informal expressions commonly found in student-generated content.
- **LSTM (Long Short-Term Memory):**
  LSTM networks are employed to capture contextual and sequential dependencies in textual data. This enables the model to understand the semantic relationships between words in a sentence.
- **Feature Fusion:**
  The sentiment scores obtained from VADER are combined with the feature representations learned by the LSTM model. This fusion creates a hybrid feature space that incorporates both rule-based and contextual information.

The combined features are then used for classification into Navarasa categories.

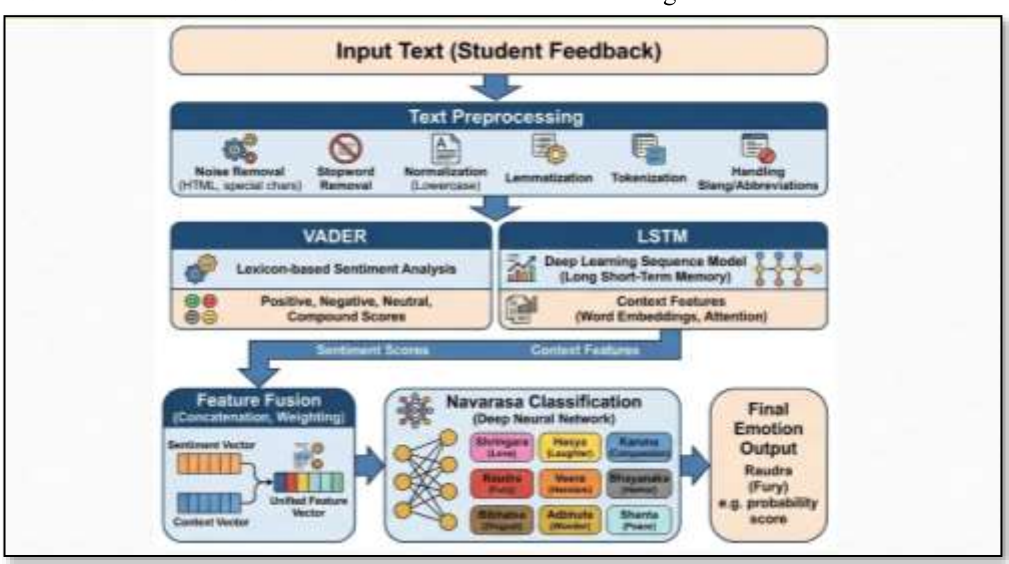

Figure 1: Hybrid Model Architecture of Navarasa Classification from Student Feedback Text

3.5 Model Training and Testing

The dataset was divided into training and testing sets to evaluate model performance. The model was trained using labeled data, and predictions were generated on the test dataset. Standard evaluation metrics were used to assess the effectiveness of the model.

3.6 Performance Evaluation

The performance of the proposed hybrid model was evaluated using the following metrics:

- Accuracy
- Precision
- Recall
- F1-score

The results of the hybrid model were compared with individual baseline models (VADER and LSTM) to assess the effectiveness of the proposed approach.

3.7 System Workflow

The overall workflow of the proposed system includes:

Data Collection → Preprocessing → Feature Extraction → VADER Analysis → LSTM Modeling → Feature Fusion → Navarasa Classification → Performance Evaluation

This structured approach ensures a comprehensive analysis of student sentiments using both traditional and advanced techniques.

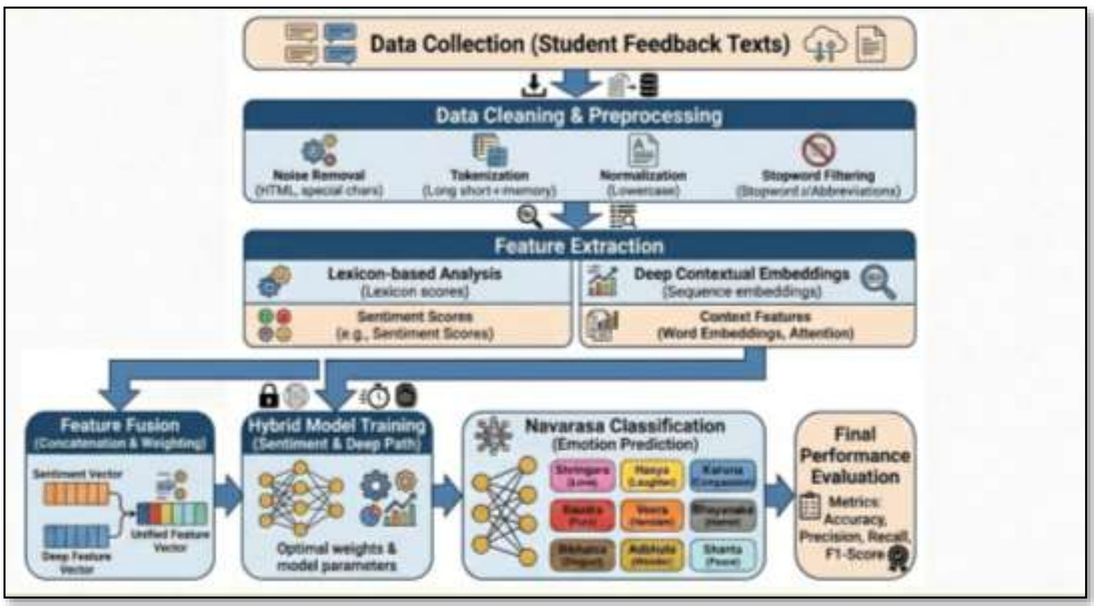

Figure 2: Overall System Workflow for Deep Hybrid Model Training and Evaluation

4. RESULT AND DISCUSSION

The performance of the proposed hybrid sentiment analysis model was evaluated and compared with individual baseline models, namely VADER and LSTM. The evaluation was conducted on both primary and secondary datasets using standard performance metrics. The experimental results indicate that the hybrid model demonstrates improved performance compared to the standalone approaches. The integration of VADER and LSTM enables the model to leverage both lexical sentiment features and contextual semantic information, resulting in more effective classification of emotional states.

While VADER performs well in capturing rule-based sentiment patterns, particularly in informal text containing emoticons and short expressions, it lacks the ability to model contextual dependencies. On the other hand, the LSTM model captures sequential relationships in text but may not effectively handle domain-specific sentiment cues without sufficient training data. The hybrid approach addresses these limitations by combining the strengths of both methods. The classification results across Navarasa categories show that the model performs better in identifying dominant emotional states such as love, laughter, and sorrow, while relatively lower performance is observed in more subtle or

overlapping emotions such as surprise and courage. This variation can be attributed to the inherent complexity of fine-grained emotion classification and the limitations of available training data.
Overall, the hybrid model achieves moderate improvement in accuracy and other evaluation metrics compared to the baseline models. However, the results also highlight certain limitations, including challenges in distinguishing closely related emotional categories and sensitivity to dataset size and quality. These findings suggest that while the proposed hybrid model is effective in enhancing sentiment classification beyond traditional polarity-based approaches, there is significant scope for improvement. Future research can explore more advanced deep learning architectures and improved feature representation techniques to achieve higher accuracy and better generalization. The results validate the potential of integrating culturally grounded emotional frameworks such as Navarasa with computational models, offering a more comprehensive understanding of student sentiments in educational environments.

Table 2: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
VADER	0.62	0.60	0.61	0.60
LSTM	0.65	0.64	0.63	0.64
Hybrid (VADER + LSTM)	0.70	0.68	0.69	0.68

As shown in Table 2, the proposed hybrid model outperforms individual baseline models across all evaluation metrics.

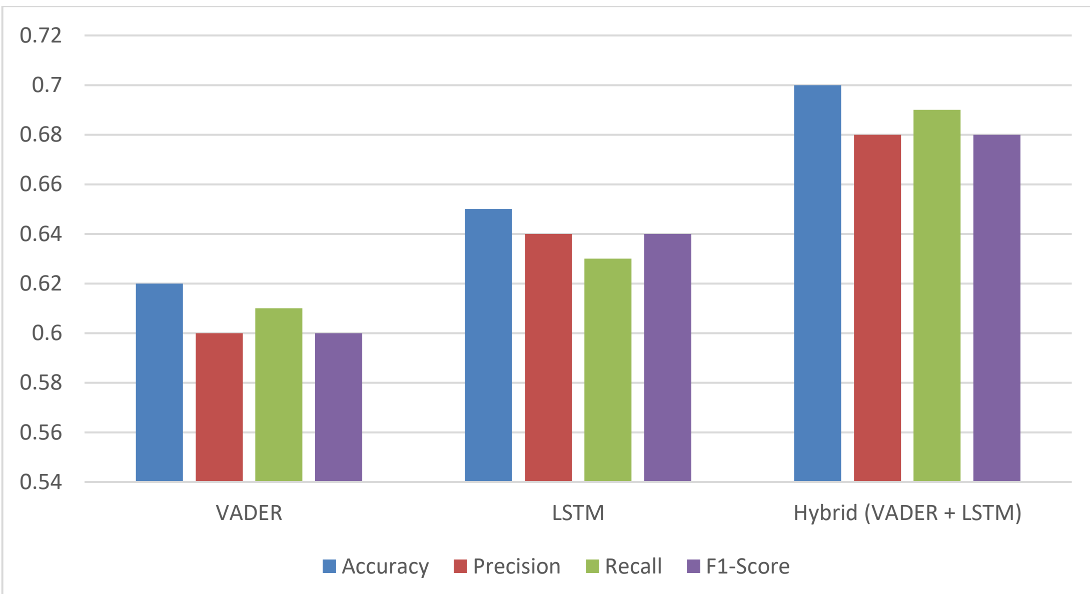

Figure 3: Accuracy Comparison of Different Models

Table 3: Navarasa-wise Classification Performance (Hybrid Model)

Emotion (Navarasa)	Accuracy
Love (Shringara)	0.78
Laughter (Hasya)	0.74
Compassion (Karuna)	0.69
Anger (Raudra)	0.67
Courage (Veera)	0.65
Fear (Bhayanaka)	0.63
Disgust (Bibhatsa)	0.66
Surprise (Adbhuta)	0.61
Peace (Shanta)	0.72

The model performs better for dominant emotional categories such as love and laughter, while relatively lower accuracy is observed for subtle emotions such as surprise.

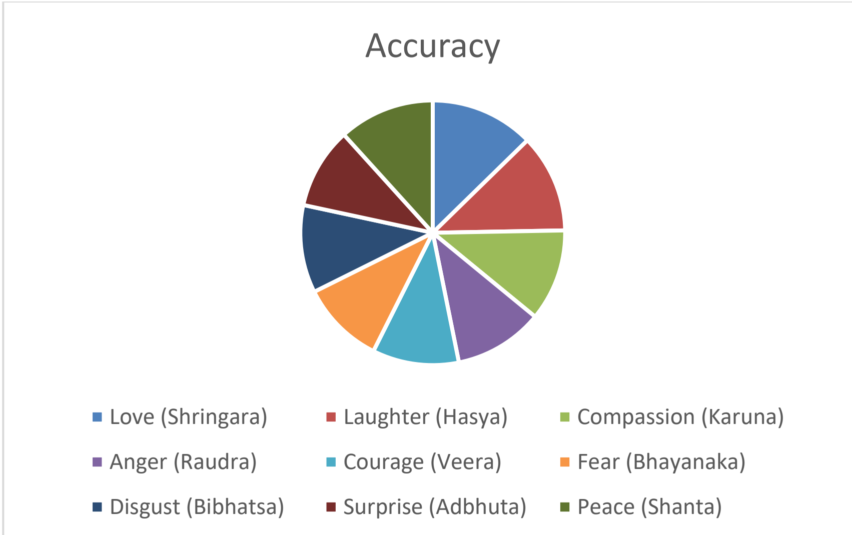

Figure 4: Distribution of Navarasa Categories in Dataset

5. CONCLUSION

This study presents a hybrid sentiment analysis approach that integrates the Navarasa framework with computational techniques to achieve a more comprehensive understanding of student emotions in higher education. By combining rule-based sentiment analysis (VADER) with deep learning methods (LSTM), the proposed model is able to capture both lexical sentiment features and contextual information from textual data. The experimental results demonstrate that the hybrid model provides improved performance compared to individual baseline approaches, particularly in identifying dominant emotional states. The incorporation of the Navarasa framework enables a more fine-grained classification of emotions beyond traditional polarity-based sentiment analysis, thereby offering deeper insights into student feedback. However, the study also identifies certain limitations, including challenges in accurately distinguishing closely related emotional categories and the dependency of model performance on dataset quality and size. These findings highlight the need for further refinement in model architecture and data representation techniques. Future work will focus on exploring advanced deep learning models and enhanced feature fusion strategies to improve classification accuracy and robustness. The integration of more sophisticated architectures is expected to further strengthen the effectiveness of emotion detection systems in educational contexts. Overall, this research contributes to the growing field of sentiment analysis by introducing a culturally enriched and computationally effective framework for analyzing complex emotional expressions in educational data.

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