



Research Paper

Deep Learning-Driven Assessment of Adolescent Emotional Intelligence and Psychological Well-Being Using Optimized Feature Selection

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ABSTRACT

Background: Emotional Intelligence (EI) is an important factor that affects adolescents' academic performance, social behavior, psychological health, and life resilience. Identifying the major emotional intelligence factors that affect adolescent behavior in colleges can help teachers and psychologists design effective intervention strategies. However, the EI datasets contain many emotional and behavioral features that require feature selection and classification methods to improve prediction accuracy. This research recommends a Hybrid Feature Selection-based Emotional Deep Learning (HFS-EDL) Framework for estimating adolescents' emotional intelligence at the undergraduate and postgraduate levels in Tamil Nadu.

Methods: The survey was carried out using a questionnaire with 3510 students across five districts of Tamil Nadu. The dataset includes 25 attributes; age group is the target variable. After data preprocessing, the most significant EI factors were selected using two techniques: Chi-Square and Mutual Information (MI). Three deep learning models, namely Artificial Neural Network (ANN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM), were then used to classify the selected features. Model performance was measured using accuracy, recall, precision, specificity, and error rate.

Results: The experimental results showed that the feature selection method performs better than the full feature set. Mutual Information is most effective with ANN and RNN models, while Chi-Square feature selection is most effective with LSTM.

Conclusion: Overall, the proposed HFS-EDL framework demonstrates the capability to successfully recognize important emotional intelligence factors and improve classification accuracy in predicting an adolescent's emotional intelligence.

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Introduction

Emotional intelligence (EI) is the capacity to sense, comprehend, express, and manage emotions in oneself and others. The RULER model is a well-known approach to conceptualizing EI as five skills: recognizing, understanding, labeling, expressing, and regulating emotions. EI includes interpersonal skills (empathy, listening, managing relationships) and intrapersonal skills (self-awareness, emotional differentiation, self-regulation). Emotional awareness is an important element of emotional intelligence that helps people accurately recognize complex emotions and understand how they affect behavior and decision-making [1]. Studies on emotional intelligence indicate that emotionally intelligent people have higher emotional granularity, meaning they can discriminate between various emotional experiences and use the right coping mechanism. Moreover, emotional intelligence is positively correlated with social interaction, psychological well-being, and adaptive emotional regulation [2]. There is also evidence that emotional intelligence skills can be improved through mindfulness, self-reflection, feedback, journaling, and developing a growth mindset.

Emotional intelligence (EI) is an essential variable that plays a significant role in personal, academic, professional, and social success. Studies indicate that people with high emotional intelligence exhibit better social skills, social interaction, communication, and empathy [3]. EI is also linked with psychological and physical health; for example, it helps people regulate their emotional responses to stress, anxiety, and anger that can have negative impacts on health. Self-regulation is a vital component of EI, facilitating a person's ability to regulate emotional responses, think rationally, and engage positively with others [4]. Self-management also contributes to motivation, leadership effectiveness, conflict resolution, and adaptation to difficult situations. Moreover, emotional intelligence plays a role in resilience by helping individuals manage stress and adversity. Research indicates that individuals with high EI are less vulnerable to the effects of stressors and have more positive emotional and physiological reactions to stressors. In general, emotional intelligence can help people become more resilient, emotionally stable, and adept at problem-solving, which can lead to success in personal and professional life [5].

Xuan Li [6] conducted research on Adolescents' prosocial behavior, which plays a crucial role in promoting mental health, positive social relationships,

and behavioral development. Chaoxin Jiang and Hao Feng [7] conducted A longitudinal study using data from 2,695 adolescents in the Fragile Families and Child Wellbeing Study (FFCWS) to investigate the relationship between bullying victimization, social-emotional competence, and delinquent behavior. Wenle Wang et al. [8] proposed a model for classroom learning behavior recognition (LBR) based on YOLOv5 and an optimized ShuffleNet V2. Marco Andrea Piombo et al. [9] explored how young people use and trust AI and how their emotional intelligence, parenting style, family support, and parental involvement affect these patterns. In a study of 303 Belgian adolescents, Gaëlle Vanhoffelen et al. [10] examined how socio-demographic factors influenced chatbot adoption and emotional experiences when using the AI chatbot My AI on Snapchat. Shuyue Zhang et al. [11] conducted a three-wave longitudinal study to explore the self-motivated associations between solitude, perceived control, and emotional intelligence among adolescents. This research contributes the following:

- This research proposed a Hybrid Feature Selection-based Emotional Deep Learning Framework (HFS-EDL) for predicting the emotional intelligence of adolescents studying as undergraduates and postgraduates in Tamil Nadu.
- This research used two feature selection methods, namely Chi-Square and Mutual Information, to select the top k Emotional Intelligence factors that play a vital role in the classroom behavior of adolescents.
- This research used three deep learning algorithms, namely ANN, RNN, and LSTM, to identify the emotional intelligence factors responsible for the classroom behavior of Adolescents based on Age.

Materials and Methods

This research aims to propose a Hybrid Feature Selection-based Emotional Deep Learning Framework (HFS-EDL) for predicting the emotional intelligence of adolescents studying as undergraduates and postgraduates in Tamil Nadu. The research begins by framing a questionnaire that identifies the emotional problems faced by adolescents and early-adulthood college students through personal interviews. The questionnaire was developed through discussions with a professional psychologist, doctors, teachers, and famous sports personalities and used a five-point Likert scale. Data for this research were collected from Thiruvallur, Kanchipuram, Chengalpattu, Cuddalore, and Villupuram Districts of Tamil Nadu. A total of 3510 students participated in this research. Of these,

1344 were male, and 2166 were female. Among the 3510 students, 1551 belong to the age group 18_to_20, 671 belong to the age group 21_to_23, 648 belong to the age group 23_to_25, and 640 belong to the age group 25_to_30. In total, the dataset has 25 dependent variables, and Age has been designated as the target variable for the emotional intelligence dataset.

The dataset has been pre-processed, and further, the most influential attributes have been selected using feature selection methods like the Chi-Square method [12] & Mutual Information method [13]. The Chi-Square method created the following contingency table for all the input variables against age. Chi-square statistics were calculated, and the significance threshold was set. The top attributes with values less than the significance value were chosen as the best attributes and framed as a new dataset. Mutual Information was computed for all input variables in the emotional intelligence dataset with respect to the target variable y . The mutual information score was used to

rank the attributes, and the top k attributes were selected and framed as a new dataset. The Feature Assortment segment present in the HFS-EDL framework is given in Figure 1.

The input variables and target variables were fed into the ANN algorithm in the HFS-EDL framework. The number of inputs, hidden, and output layers was chosen to design the ANN architecture. Then, the number of neurons in the hidden layer was defined, along with the activation functions. Small random values were used to start the weights and biases. The ANN training parameters, such as the loss function, optimizer, learning rate, and batch size, were also defined. The Input training data was used to Propagate Forward for each epoch, evaluating layer by layer and applying the activation functions.

The dissimilarity between the predicted values and the goal values was computed; then the gradients of the loss with respect to all weights and biases were

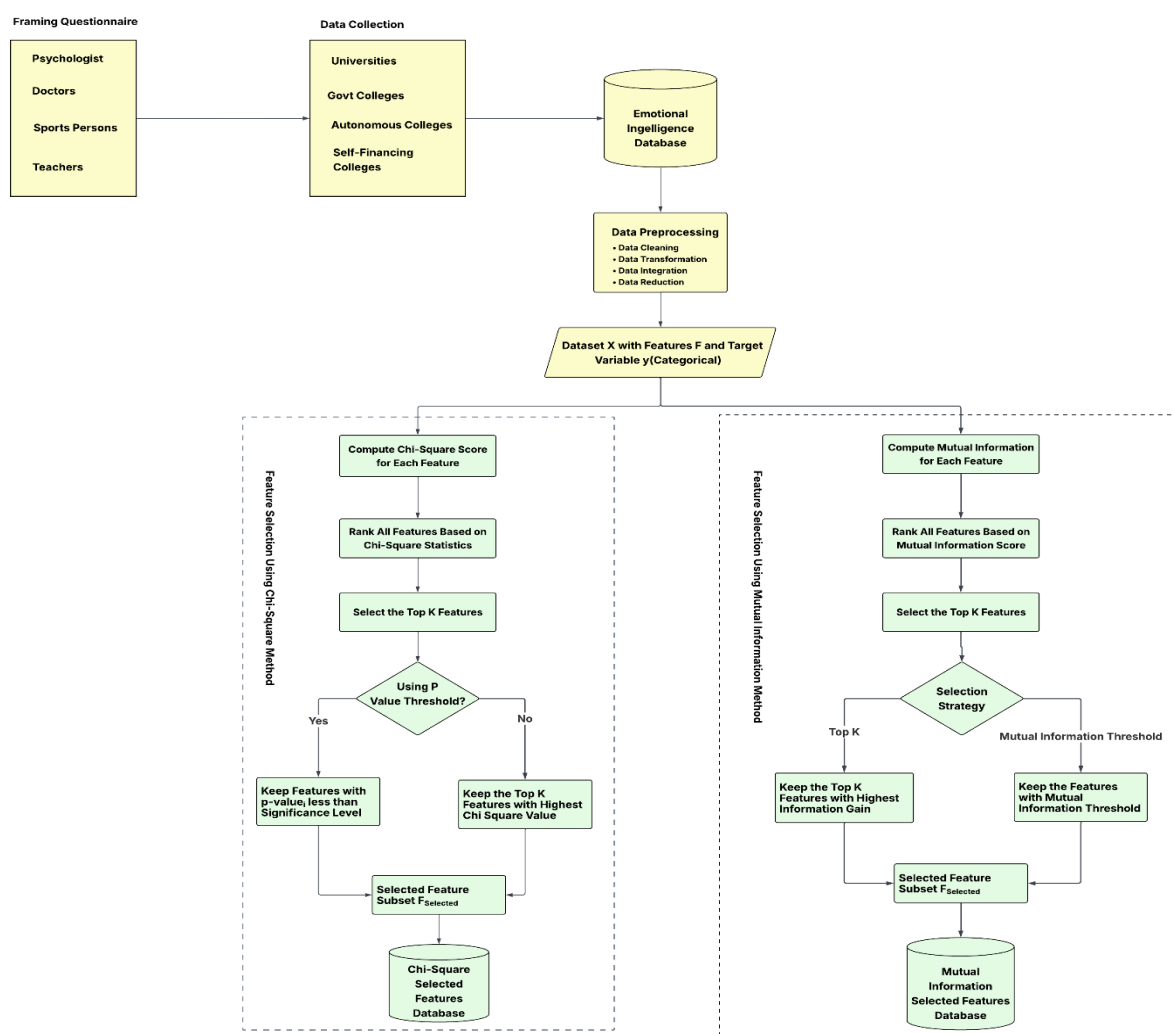


Figure 1. Feature selection module present in hybrid feature selection based emotional deep learning framework (HFS-EDL).

computed using the chain rule, and the weights were updated. The procedure continued until each input variable was mapped to the target class Age. The HFS-EDL Framework architecture was designed similarly to an ANN, with an RNN module [14]. For each input variable, the RNN first initializes the hidden state and computes the Forward Pass Through Time using the current input x_t and hidden state h_{t-1} . It also calculates the loss value using the prediction and the original target class. The weights are updated, and the value is backpropagated; backpropagation through time is calculated. The process repeats until all input variables are fed into the target class. The LSTM module in the HFS-EDL Framework takes input variables one step at a time and has a memory cell to save relevant information from previous inputs. It has three gating elements: the forget gate, the input gate, and the output gate. The forget gate determines what information from the previous cell state to forget, and the input gate determines what information to store in the memory cell. The cell state is then updated by combining the retained information with the newly selected information. Lastly, the output gate regulates which

information is fed to the hidden state and used as the network output. This process is repeated until all input variables are classified into one of the target classes. Figure 2 shows the DL model existing in the proposed model.

Results

The proposed model is simulated using Python 3.8.5 on a PC with an i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, 250GB SSD, and 1TB HDD. The parameter settings are given as follows: learning rate: 0.01, dropout: 0.5, batch size: 5, and activation: ReLU. For experimental validation, 70% of the data is used for training and 30% for testing.

The Chi-Square feature selection method was used in the HFS-EDL Framework and implemented in Python using several scientific computing and machine learning libraries. The NumPy library was used for efficient numerical operations and array manipulation, and Pandas was used to load, preprocess, and manipulate the Emotional Intelligence dataset.

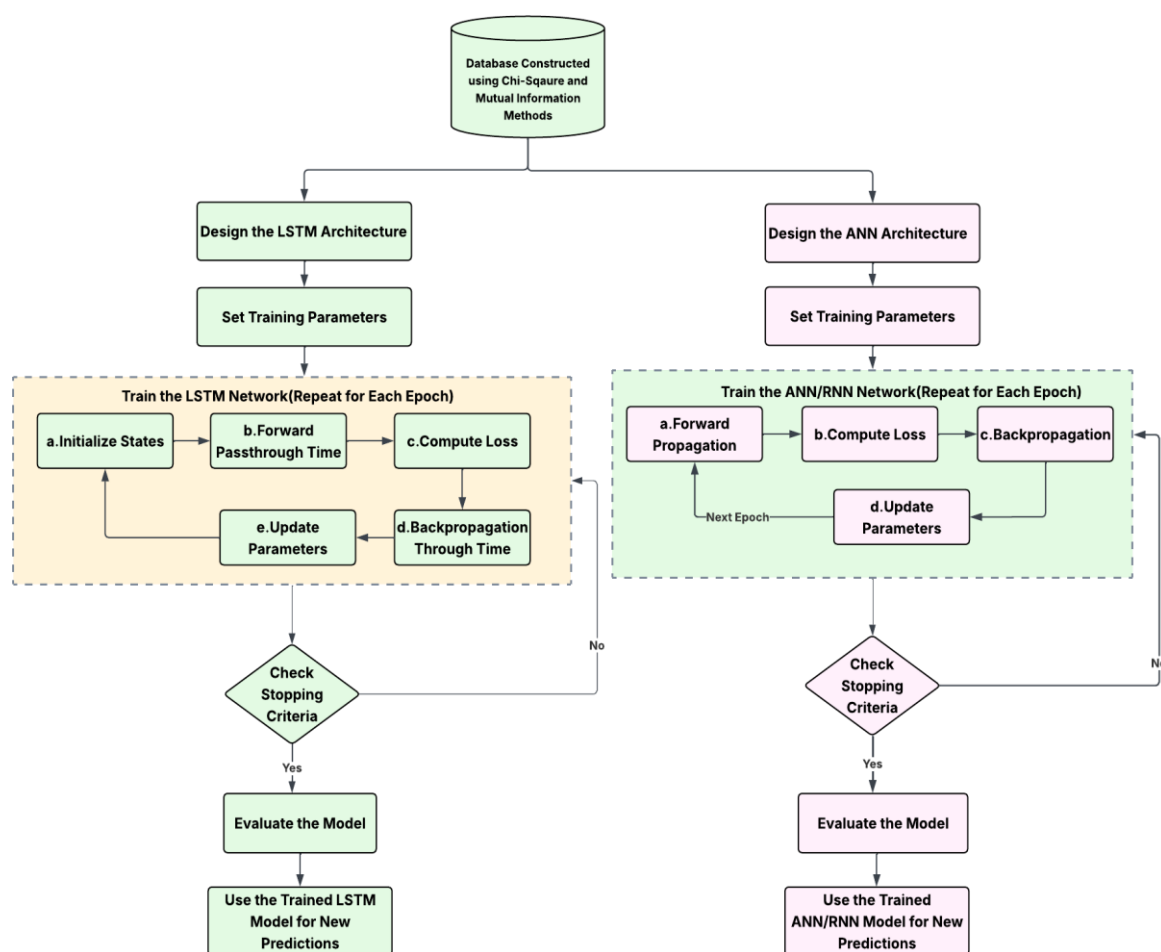


Figure 2. The deep learning modules present in the hfs-edl framework.

Figure 3 shows the features chosen by the Chi-Square method. Three types of ANN, RNN, and LSTM models were tested on the Emotional Intelligence dataset, with Chi-Square and Mutual Information (MI) feature selection applied, as well as the full set of features. The results in Table 1 and Figure 4 show that feature selection significantly impacts classification results across all three models. Among all RNN configurations, this model also achieved the lowest false positive (5.6%), false negative (12.0%), false discovery (13.6%), and error rates (8.0%). In comparison, the lowest accuracy (87.8%) and highest error rate (12.2%) were obtained using an RNN with Chi-Square feature selection, indicating that the RNN architecture benefits more from feature selection using Mutual Information. Likewise, the ANN model performed best with Mutual Information feature

selection, achieving an accuracy of 92.0%, recall of 87.5%, precision of 86.8%, and specificity of 94.1%. The ANN-MI model also had the lowest false discovery rate (13.1%) when compared to all ANN configurations. The ANN model was trained with features selected by Chi-Square, achieving an accuracy of 90.8%, and with full features, an accuracy of 89.9%.

Discussion

In conclusion, the experimental results demonstrate the importance of feature selection in improving classification performance over using the full Emotional Intelligence dataset. For the ANN model, mutual information feature selection gave the best results, while Chi-Square feature selection was more effective for the LSTM model. While RNN-MI and

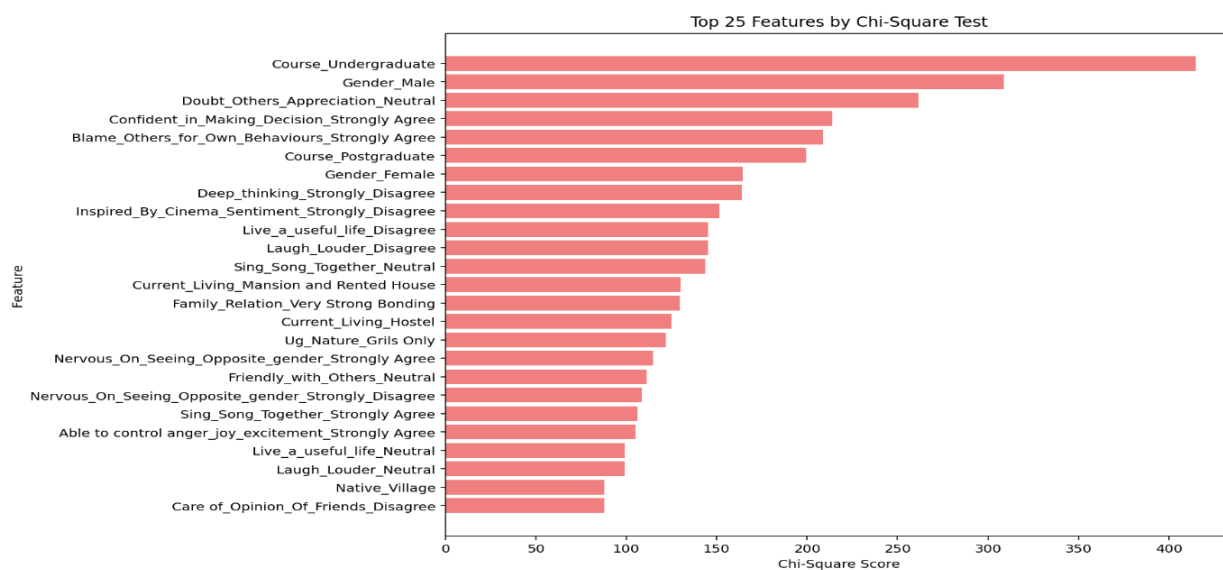


Figure 3. Top 25 features selected by chi-square method.

Table 1. Performance metrics of the emotional intelligence dataset.

	LSTM+Chi-Square	LSTM+MI	LSTM Full Emotional	RNN+Chi-Square	RNN+MI	RNN Full Emotional	ANN+Chi-Square	ANN+MI	ANN Full Emotional
Recall	0.876	0.846	0.855	0.790	0.879	0.829	0.855	0.875	0.843
Specificity	0.941	0.928	0.932	0.917	0.943	0.921	0.934	0.941	0.925
Precision	0.856	0.827	0.840	0.764	0.863	0.814	0.830	0.868	0.841
Negative Predictive Value	0.940	0.927	0.930	0.914	0.941	0.920	0.933	0.940	0.925
False Positive Rate	0.058	0.071	0.067	0.082	0.056	0.078	0.065	0.058	0.074
False Negative Rate	0.123	0.153	0.144	0.209	0.120	0.170	0.144	0.124	0.156
False Discovery Rate	0.143	0.172	0.159	0.235	0.136	0.185	0.169	0.131	0.158
Accuracy	0.918	0.901	0.904	0.878	0.920	0.891	0.908	0.920	0.899
Error Rate	0.082	0.099	0.096	0.122	0.08	0.109	0.092	0.08	0.101

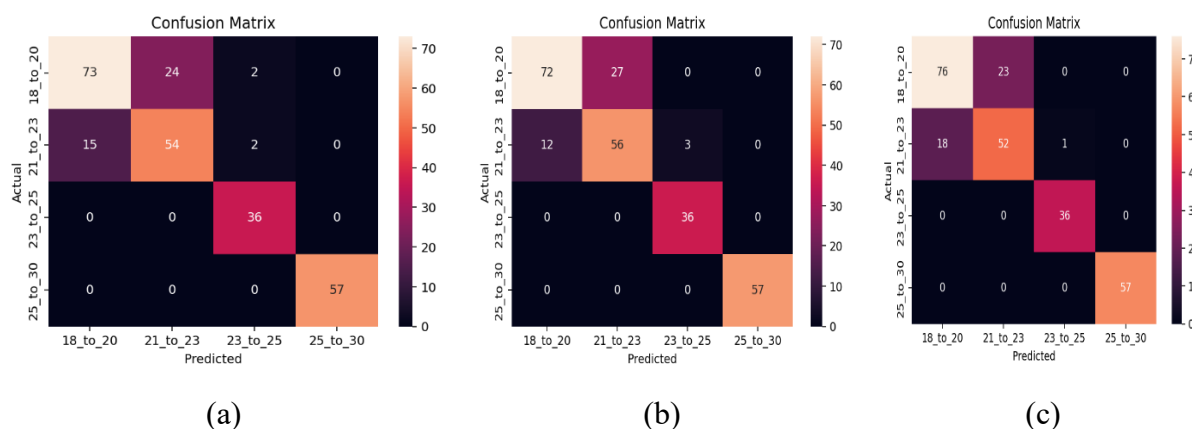


Figure 4. Confusion matrices of (a) Chi-Square with LSTM, (b) Mutual Information with RNN, and (c) Mutual Information with ANN.

ANN-MI achieved the best classification accuracy of 92.0%, the LSTM-Chi-Square model showed strong recall, precision, and specificity, making it a suitable candidate for identifying key patterns in the Emotional Intelligence dataset.

Conclusion

This study proposed a Hybrid Feature Selection-based Emotional Deep Learning (HFS-EDL) Framework for predicting the emotional intelligence of undergraduate and postgraduate students in Tamil Nadu. The framework combined two feature selection methods, Chi-Square and Mutual Information, with three deep learning algorithms, ANN, RNN, and LSTM. The study identified the major emotional factors by collecting and analyzing an exhaustive dataset of emotional intelligence for 3510 adolescents from different age groups across various districts of Tamil Nadu. The results showed that classification performance improved significantly when using feature selection rather than the full feature set. The RNN-MI and ANN-MI models achieved the highest grouping accuracy (92.0%) among the evaluated models, demonstrating the effectiveness of Mutual Information in selecting the most relevant emotional intelligence features. The LSTM-Chi-Square model achieved the highest recall, precision, and specificity, demonstrating its ability to identify important emotional intelligence patterns with high reliability. These findings confirm the importance of selecting relevant emotional intelligence factors before classification to improve the predictive performance and reduce the computational complexity.

Ethical Approval

Not applicable.

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Conflicts of Interest

The authors report no competing interests to declare.

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