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Research paper

Student Sentiment Analysis with Academic Performance and job Placement Using Attention Based Deep Recurrent Learning

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Abstract

Technological evolution has significantly innovated education, with student feedback sentiment analysis functions to assess the educational quality achieved. Amid numerous teaching and learning processes, educational institutions utilize technology to collect information regarding student experiences and assess their teaching methods. Educational institutions should provide a healthy learning environment and facilitate a successful teaching and learning process. The level of satisfaction through placement performance reflects a clear understanding of the university environment and the services provided to students. For most current sentiment analysis of students' feedback methods, capturing the complex semantic features is laborious and cumbersome, and these features are not entirely relevant to the analysis of student sentiments. This work proposes a novel sentiment analysis of students' feedback on academic and placement performance using Deep Learning (DL), specifically the Ridge-Regularized Bidirectional Gated Recurrent Attention-Based Classifier (RR-BGRAC). First, with the raw samples obtained from the student placement dataset serving as a base for student feedback, Ridge Class-balanced Bidirectional Gated Recurrent Attention-based Round-robin Feature engineering is applied. The feature engineering in our work involves reducing dimensionality by selecting the most relevant features for performing semantic analysis in order to ascertain the placement. With class-balanced samples and the most relevant features as the basis, the Softmax Classifier is applied to generate a suggested job role based on academic strengths. Based on the student placement data and focusing on the student feedback sentiments, the proposed DL-based RR-BGRAC method is experimentally demonstrated. The results show that the accuracy rate and recall rate of student sentiment analysis are improved by 15% and 18%, respectively, and training time and space are minimized by 19% and 16%, compared to traditional methods.

Keywords: *Deep Learning; Ridge Regularization; Bidirectional Gated Recurrent Neural Network; Round Robin, Attention.*

1. Introduction

The evolution of Artificial Intelligence technology has been motivating over the past few years, and activities such as academic conferences and scientific research in AI have proliferated globally. The field of Educational Artificial Intelligence (EAI) encompasses several disciplines and aids teachers in enhancing students' learning.

In [1], measures were taken using an Enhanced Ensemble Model Architecture to assess the misconceptions of teacher candidates regarding the concept of the greenhouse effect, employing Artificial Intelligence (AI) for comparison with human experts. It was inferred that the AI algorithm, utilizing a Multilayer Perceptron (MLP) with the highest accuracy rate, was employed in predicting teacher candidates' misconceptions. In addition, the research findings revealed a significant difference between the AI algorithm and human expert evaluation, as indicated by the kappa value. However, it failed to extract the sentiments with the aid of MLP.

Bidirectional Encoder Representations from Transformers Bidirectional Long Short-Term Memory ATTENTION (BERT-BiLSTM-Attention (BBA) was proposed in [2] by extracting sentiments, providing a deeper understanding of students' experiences by ascertaining areas of enhancement to meet students' requirements better. Deep learning techniques, specifically Bidirectional Encoder Representations from Transformers (BERT), were employed to extract sentiment from course evaluations. Additionally, an attention mechanism was incorporated to allocate weights to distinct input sequences, focusing on relevant information efficiently and enhancing overall precision and accuracy. However, the data imbalance was not considered by using BERT.

In the digital era, where textual data is ubiquitous, understanding the nuanced sentiments embedded within texts has become crucial for various applications that aim to enhance customer experiences with brands. Among them, data imbalance is a common issue where instances in one or more classes far outnumber those in the others, as is the case in the educational domain. The data imbalance issue for sentiment analysis of users' opinions task was addressed in [3] employing a generative adversarial network (GAN) model. Artificial Intelligence (AI) based sentiment analysis has received greater awareness for analyzing emotional states. In [4], measures were taken using AI-based sentiment analysis to enhance the quality of vocational education.

A heterogeneous DL method for document-based sentiment analysis was proposed in [5] to classify the available statements into positive, negative, or neutral with improved accuracy. However, another method, focusing on accuracy through concurrent conversion mixed methods, was applied in [6] to analyze student sentiment towards programming. A plethora of machine learning (ML) techniques were presented in [7] for comprehending student perceptions. They provided actionable insights to boost their feedback practices, promoting a more positive and advantageous learning environment. A novel sentence-level sentiment analysis method for mining online product reviews employing natural language processing and DL techniques was designed in [8]. A hybrid DL method was proposed in [9] to focus on low-resource languages. Additionally, with the pre-trained multilingual embeddings, the softmax function was activated, and classification was performed accordingly.

University teaching practices play a significant role, as far as educational researchers are concerned. This is because the teaching practices are pivotal in emphasizing students' interest, engagement, learning, and overall academic performance. Several AI techniques were employed in [10] to assess human emotions and identify conceptual misconceptions. Conventional sentiment analysis methods often struggle with the inherent ambiguity and complexity of human language. To address these aspects, a novel method called the Fuzzy Hierarchical Convolutional Neural Network (Fuzzy HCN-Net) was proposed in [11], offering improved precision and accuracy. A detailed study on ML and DL techniques for analyzing sentiments for extracting aspect terms was presented in [12] with minimal cost and time.

A study that utilizes AI to explore the students' preferences for university teaching practices was detailed in [13]. In addition to analyzing the responses, a generative pre-trained transformer was employed. This, in turn, facilitated the analysis of a large amount of information, ensuring accuracy and precision. A systematic literature review on sentiment analysis for evaluation in higher education was conducted in [14]. Advanced ML techniques were applied in [15] to provide insights into education.

Although the work has achieved definite objectives, specific research gaps require attention. Firstly, insufficient research on sample balancing can cause bias, resulting in poor performance. Several research works focus primarily on prediction based on students' feedback, with less emphasis on relevant features. They also utilized the entire preprocessed sample data, rather than focusing on the most relevant features, in order to obtain placement results based on academic performance. Moreover, the current work first balances the sample, and then, based on the academically oriented relevant feature subset, classification is made using student feedback, thereby emphasizing placement. To address the above-mentioned gaps, this work proposes a novel DL method called Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC) for accuracy and precise analysis of students' feedback for academic-oriented placement.

1.1. Contributions of the work

The Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC) include the following:

- To propose a method called Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC) to ensure accurate and precise student sentiment analysis according to feedback with academic-oriented placement in a computationally efficient manner. To apply Ridge Class-balanced Regularization to minimize training time, Ridge Regularization is used for the target Suggested Job Role feature by measuring the highest posterior probability results corresponding to the ground truth class. To propose a Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection model to select the optimal or pertinent features for sentiment analysis of student feedback by splicing the output feature vector results via forward and reverse direction, improving overall precision.
- To design a Softmax-activated Student Feedback Sentiment Analysis Classifier to classify the students' sentiments according to their feedback and academic-oriented performance in an accurate manner.
- To perform a simulation and evaluate the results to demonstrate the superiority of the proposed method.

1.2. Organization of the work

The organization of the work is as follows: Section 2 presents the related work about student sentiment analysis using their feedback employing ML and DL techniques. Section 3 introduces the Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC) and explains it via diagrammatic representations. Section 4 describes the experimental setup in both qualitative and quantitative terms, accompanied by tables and illustrative representations. The discussion is presented in Section 5. Finally, the conclusion is presented in Section 6.

2. Related works

The lack of discernment of course predictions and student anxieties in a Data Analytics course generates a significant gap in the practice of teaching and also in course learning. Effective feedback practice provides the organization with information that helps improve both teaching and learning processes. Additionally, according to the responses given by the students, classification can be made into either textual or grading categories. A survey of sentimental analysis on educational data was provided in [16]. A sentiment classification using ML techniques focusing on the classification accuracy was proposed in [17]. Despite improving classification accuracy, the training time factor was not focused on. To address this aspect, text mining methods were analyzed in [18], resulting in a significant improvement in training time.

The importance and utilization of student evaluation of teaching (SET) data within academic institutions has long been controversial. Numerous scholars have questioned whether SET can accurately estimate teaching efficiency, leading several institutions to use student experience measures as an alternative. A multi-criteria decision-making recommendation method was designed in [19] using recommender systems with improved precision and accuracy. An in-depth analysis focusing on the association between scores and student comments was presented in [20], which improved precision and accuracy. A hybrid stacking approach with gradient boosting was applied in [21] for sentiment analysis to generate insights into the emotional status of students. The drawback of this method is that the students' experience is not revealed, resulting in bias. To address this aspect, an indirect method was proposed in [22] by collecting feedback from students and using it to gather their opinions as posts, improving accuracy.

Selecting the right career path poses a notable challenge for students, particularly when time is limited. In [23], challenges involved in career prediction are addressed by instituting a method that integrates feature prioritization, streamlining feature selection to enhance prediction precision. This objective was achieved through student sentiment analysis, which accurately forecasted career trajectories. Sentiment analysis and natural language processing were applied in [24] to analyze student feedback on faculties and generate students' higher learning experiences. However, another method to validate the strengthening of students' opinions using sentiment intensity was designed in [25] to improve education. The ML technique was applied in [26] to concentrate on the online learning aspects of students' feedback.

In [27], a method integrating fuzzy logic with bidirectional long short-term memory (BiLSTM) for sentiment analysis of students' e-learning experiences was proposed. Also, employing fuzzy logic, uncertainties were handled accurately. However, selecting a comprehensive and cost-efficient method for articulating text sentiment is not trivial, especially when dealing with short texts. In [28], a versatile mechanism was proposed to address this aspect, based on multiple interpretations with the intention of encoding information regarding a text's polarity, subjectivity, and ambiguity, thereby improving classification accuracy. Weighted word vector features were introduced in [29] to estimate view polarity.

Sentiment analysis is a vital part of artificial intelligence. A comprehensive evaluation of the Transformer methods was conducted in [30] for sentiment analysis in education. AI and ML methods were employed in [31] to recognize and interpret opinions, emotions, and sentiment polarity in text data. A hybrid deep learning model named SentiNet was developed in [32] for sentiment analysis, aiming to enhance accuracy and service quality. However, the time was higher.

The proposed DL-based Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC) method in this study aims to address the drawbacks of previous methods by introducing a combination of Ridge Regularized Bidirectional Gated Recurrent Attention and Softmax classifier for analyzing students' feedback when dealing with academic-oriented placement. The objective is to enhance performance and achieve higher accuracy rates compared to previous methods. Moreover, the method is designed to be efficient in terms of computational complexity while providing accurate and precise results.

3. Methodology

Student Feedback can be analyzed employing sentiment analysis and deep learning by training models on textual data. This can be achieved by classifying job roles based on identifying emotional trends in the job market, personal career aspirations, and company culture, thereby matching students with suitable job roles. It can be included in job placement by measuring the tone of the job descriptions beyond technical skills. By mastering a job seeker's sentiments through sentiment analysis, employers (i.e., organizations) and recruiters (i.e., employees) can make more informed decisions regarding job placement. By employing deep learning models, we can control the natural language intricacy by converting words into vectors (i.e., word embeddings), encapsulating context and dependencies, and allowing fine-grained analysis to enhance teaching and learning experiences. In this section, a Deep Learning (DL) based method called Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC) is designed.

As shown in the figure 1, student placement data is first used to measure student feedback sentiment analysis regarding academic-based placement performance. Initially, to ensure class balance, suggested job role patterns are identified using Ridge Class-balanced Regularization with academic performance data. Following this, Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection selects the most relevant feature subset that associates student sentiment analysis with job role and academic performance. Finally, a softmax classifier is applied to the class-balanced and relevant feature subset to classify the suggested job role for academic-based placement performance. The elaborate details of the RR-BGRAC method are provided in the following sub-sections.

3.1. Data collection

The Student Feedback Sentiment Analysis, which includes Academic and Placement Performance, is referred to as student placement data. The dataset is taken from Kaggle. It is extracted from https://www.kaggle.com/datasets/koshikasaiprasad/student-placement-data/data. The dataset includes 20,000 sample records and thirty-nine features. The dataset size is 4.87MB. By employing this set of sample records and features, placements were made according to the suggested job role provided as final class labels. Table 1, presented below, describes the dataset.

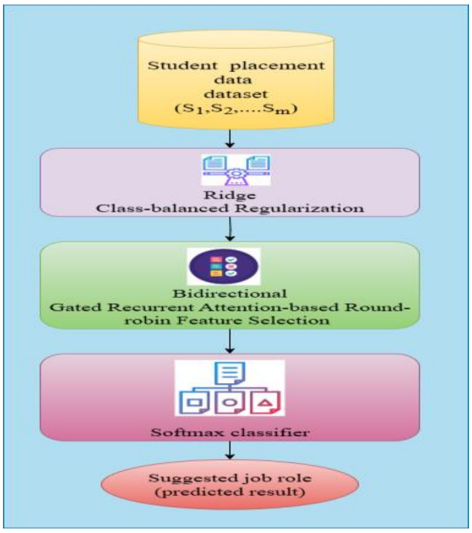


Fig. 1: Block Diagram of Ridge Regularized Bidirectional Gated Recurrent Attention-Based Classifier (RR-BGRAC).

Table 1: List of Features using Student Feedback Sentiment Analysis dataset

S. No	Features	S. No	Features	S. No	Features	S. No	Features
1	Academic percentage in Operating Systems	11	Logical quotient rating	21	olympiads	31	Salary Range Expected
2	percentage in Algorithms	12	hackathons	22	reading and writing skills	32	In a relationship?
3	Percentage in Programming Concepts	13	coding skills rating	23	memory capability score	33	Gentle or Tough behaviour?
4	Percentage in Software Engineering	14	public speaking points	24	Interested subjects	34	Management or Technical
5	Percentage in Computer Networks	15	Can work long time before system?	25	interested career area	35	Salary/work
6	Percentage in Electronics Subjects	16	Self-learning capability?	26	Job/Higher Studies?	36	hard/smart worker
7	Percentage in Computer Architecture	17	Extra-courses did	27	Type of company want to settle in?	37	Worked in teams ever?
8	Percentage in Mathematics	18	certifications	28	Taken inputs from seniors or elders	38	Introvert
9	Percentage in Communication Skills	19	workshops	29	interested in games	39	Suggested Job Role
10	Hours working per day	20	Talent tests taken?	30	Interested Types of Books		

The University Employability Dataset is employed for conducting the experiments. It is obtained from https://www.opendatabay.com/data/science-research/d0b808c0-b16f-4bf8-8447-a60a8b5bd877. This dataset offers detailed placement data for students. The dataset includes 15 features or columns, as described in Table 2. The dataset is presented in CSV format (Placement_Data_Full_Class.csv) and has a size of 19.71 kB. It consists of 215 unique records. 148 valid records indicated in the salary column, and 67 instances denoted as salary information are missing.

Table 2: Feature Description Using University Employability Dataset

S. No	Features	Description	S. No	Features	Description
1	sl_no	A serial number for every student record	9	degree_t	The type or field of their undergraduate degree (Comm&Mgmt, Sci&Tech, or Other)
2	gender	Student's gender, either Male ('M') or Female ('F')	10	workex	A Boolean indicator for whether the student has prior work experience
3	ssc_p	Ratio obtained in Secondary School Certificate (10th Grade)	11	etest_p	The percentage obtained in the employability test conducted by the college
4	ssc_b	The Board of Education for Secondary School (Central or Others)	12	specialization	The specialization chosen during their Post Graduation (MBA), either Marketing & Finance (Mkt&Fin) or Marketing & Human Resources (Mkt&HR)
5	hsc_p	The proportion obtained in Higher Secondary Certificate (12th Grade)	13	mba_p	The percentage obtained in their MBA programme
6	hsc_b	The Board of Education for Higher Secondary (Central or Others)	14	status	The placement status of the student, denoting if they were 'Placed' or 'Not Placed'
7	hsc_s	The specialization chosen in Higher Secondary Education (Commerce, Science, or Other)	15	salary	The salary presented by the corporate to the placed candidates
8	degree_p	The fraction obtained in their Undergraduate Degree			

The Student Feedback Sentiment Analysis with Academic and Placement Performance dataset details include academic and extra-curricular activities. In this work, sentiment analysis boosts the quality of recommendations that conventionally depend heavily on quantitative scores by analyzing data from student feedback.

$$X = \begin{bmatrix} S_1F_1 & S_1F_2 & \dots & S_1F_n \\ S_2F_1 & S_2F_2 & \dots & S_2F_n \\ \dots & \dots & \dots & \dots \\ S_mF_1 & S_mF_2 & \dots & S_mF_n \end{bmatrix} \tag{1}$$

With the above m samples and n features provided as input from the raw dataset DS, the input matrix X is formulated below to generate placement performance job role as result Y using the proposed method.

3.2. Ridge class-balanced bidirectional gated recurrent attention-based round-robin feature engineering

Feature engineering in deep learning encompasses preparing and transforming raw samples that a deep learning model can efficiently utilize to learn and make predictions. The feature engineering involves data preprocessing and minimizing the dimensionality of raw data by selecting the most relevant features for performing semantic analysis in identifying student placement. This work uses a Ridge Class-balanced Bidirectional Recurrent Attention-based Round-robin Feature engineering model. Figure 2 shows the flow diagram of the Ridge Class-balanced Bidirectional Gated Recurrent Attention-based Round-robin Feature engineering model.

As shown in the above figure 2, the feature engineering model involves preprocessing and feature selection. First, preprocessing is performed using Ridge class-balanced regularization, which initially shrinks the coefficients to minimize overfitting. Following this, the sample training data is fine-tuned to address the class imbalance (i.e., for the target Suggested Job Role feature). Next, the class-balanced samples as input are subjected to a Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection model for selecting relevant features for sentiment analysis of student feedback for placement based on academic features. Finally, with the selected relevant features, the Softmax-activated Student Feedback Sentiment Analysis Classifier is applied to analyze the features for placement in several job roles.

3.2.1. Ridge class-balanced regularization

Regularization is, in fact, a paramount element in deep learning. Ridge Class-balanced Regularization is employed to address two common issues, namely class imbalance and overfitting. It combines the L2 regularization of ridge regression with class-balancing methods to create a more robust and accurate model. Ridge regularization, also known as L2 regularization, is a statistical technique used in machine learning to prevent overfitting and enhance generalization ability. Class-balanced weighting is used to assign a higher weight to the minority class and a lower weight to the majority class. This work applies a Class-Balanced Regularization function to alleviate classifier imbalance in weight norms, based on Ridge Regularization, for the target Suggested Job Role feature. Let us assume a training data set '$DS = \{(X_i, Y_i)\}$', where each sample 'X_i' is labeled as '$Y_i \in [1,2,\ldots,C]$'. Let 'm_k' represent the training samples for class 'k', and let '$N = \sum_{k=1}^{C} m_k$' be the total number of training samples. Then, the imbalance factor, '$IF = \frac{m_{max}}{m_{min}}$', measures the degree of imbalance in the given dataset. Then, the most frequently employed classifier is linear classification, which measures the output probabilities as given below for the target Suggested Job Role feature.

$$Prob_k = \varphi\left(w_k f_b(x_i)\right) \tag{2}$$

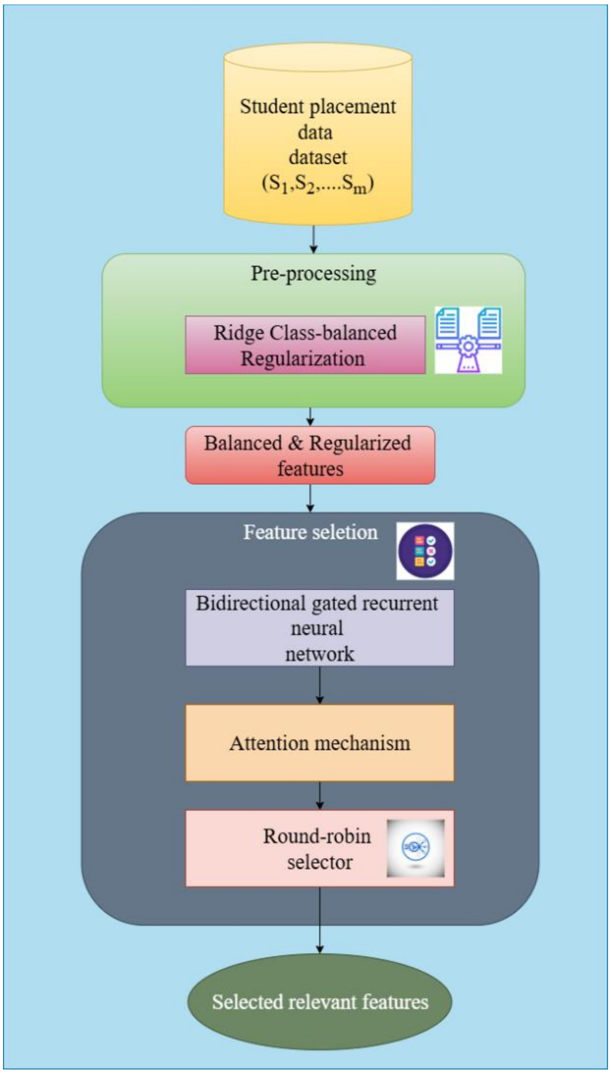


Fig. 2: Ridge Class-BALANCED Bidirectional Gated Recurrent Attention-BASED Round-ROBIN Feature ENGINEERING.

From the above equation (2), 'φ' denotes a sigmoid activation function, and the results are stored as the predicted probability of a sample belonging to the '$k-th$' class. Following this, the predicted probability results '$f_b(x_i)$' are based on the feature representation of sample 'x_i' and weight 'w_k' respectively. Moreover, the highest posterior probability results corresponding to the ground truth class should be generated to make correct classification decisions. To fine-tune the imbalanced classifier for the target Suggested Job Role feature, 'τ' is given below.

$$w'_k = \frac{w_k}{|w_k|^T} \tag{3}$$

From the above equation (3), the fine-tuned class balanced results 'w'_k' are arrived at based on the Ridge Regularization factor '$|.|$', classified weight 'w_k' for corresponding 'k' class, and new classifier weight 'vw'_k' after applying the results. Finally, after applying Ridge Regularization to the classifier weights to generate class-balanced results, the Cross-Entropy Loss function is derived as follows.

$$\mathcal{L} = \sum l\left(Prob_k, Prob'_k\right) + \alpha \sum_k ||w_k||^2 \tag{4}$$

From the above equation (4), the class-balanced regularized results for the target Suggested Job Role feature are arrived at based on the minimal cross-entropy loss function '$\mathcal{L}$' regularized via the regularization factor 'α', respectively.

3.2.2. Bidirectional gated recurrent attention-based round-robin feature selection model

In feature selection, exploration involves comprehensively examining different and novel combinations of features to identify potentially better solutions within the global search space. On the other hand, exploitation focuses on refining and enhancing previously identified feature subsets to find optimal solutions. In our work to efficiently balance these two processes, a Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection model is designed to prioritize the most important feature combinations for carrying forward, thereby optimizing the Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection model structure.

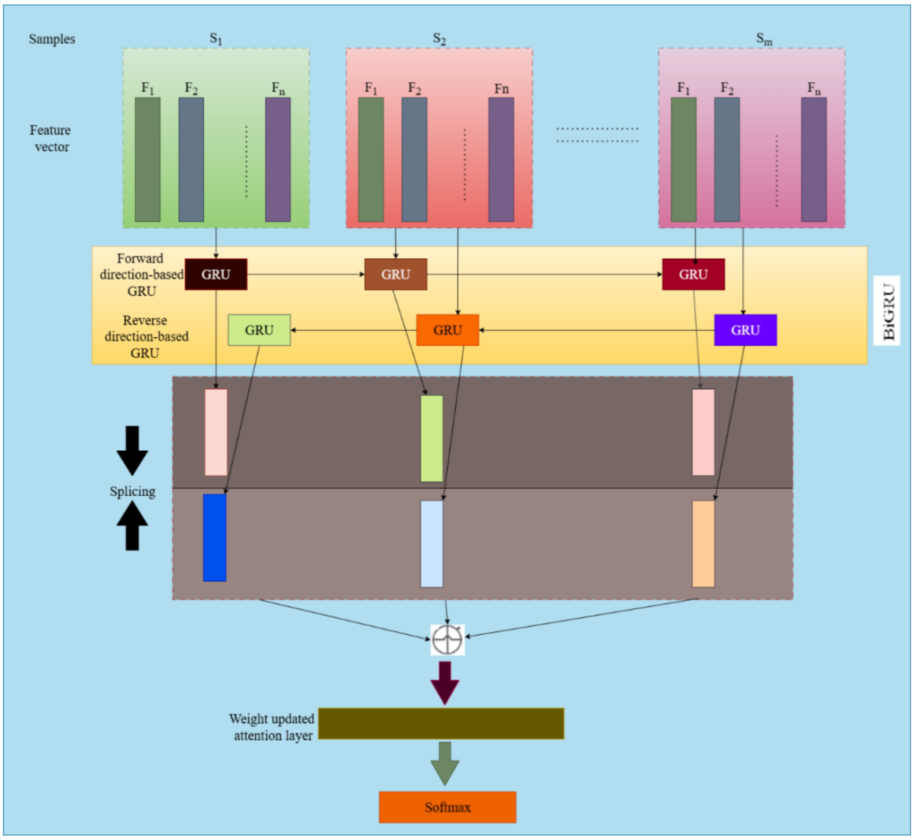


Fig. 3: Structure Of Bidirectional Gated Recurrent Attention-Based Round-Robin Feature Selection Model.

As shown in the above figure 3, the Round Robin function is initially applied to maintain a balance between exploitation and exploration. Followed by which at each time instance, Bidirectional Gated Recurrent Neural Network accepts a feature input vector 'F' and combines the output vector 'H_{t-1}' at the previous time instance to fine-tune the hidden layer state 'H_t'. In this work, the Bidirectional Gated Recurrent Neural Network (BGRNN) extracts contextual semantic information features, focusing on both positive and reverse sequences. Specifically, we form a single representation by integrating the outputs from one forward direction and the other in the backward direction, also referred to as splicing. Taking concatenating or splicing the output feature vector results based on both directions further enhances sentiment classification accuracy. Finally, an attention mechanism is included that enhances BGRNN by allowing it to selectively concentrate on and allocate higher significance to specific features, thereby boosting the model's potential to capture relevant features and provide more accurate student feedback analysis, including academic and placement performance. Although BGRNN captures past and future dependencies, including attention, it emphasizes dynamic weighting, allowing the feature engineering process to prioritize features that demand student feedback sentiment analysis, particularly in academic-oriented placement performance.

A round-robin feature selection process employs an iterative method to select a subset of features repeatedly. The round-robin feature is used to group features and generate multiple views or subsets of data. Features are added to these subsets in a round-robin fashion, ensuring that each subset receives a turn to comprise the next feature. Each feature is ranked to ensure that the top-ranked features are distributed evenly across the dataset. This feature selection aims to create feature subsets that are both balanced and diverse, thereby enhancing the model's performance. As stated above in the proposed method, all individual features are ranked according to their fitness measures to perform Round Robin, and a distinct rank is obtained despite the presence of equivalent fitness values. This is formulated as given below.

$$\mathrm{Prob}_i = \frac{\mathrm{fit}_i}{\sum_{j=1}^{K} \mathrm{fit}_j} \tag{5}$$

From the above equation (5), 'fit_i' represents the fitness of the '$i-th$' feature. Also, the features are split into two equal and disjoint groups. Moreover, all individual features are ranked based on the fitness values and allocated probability below to ensure a trade-off between exploitation and exploration.

$$\mathrm{fit}_i = \begin{cases} \beta^{-}\left(\frac{8i}{K(K+2)}\right); i \leq \frac{K}{2} \\ \beta^{+}\left(\frac{8i}{K(K+2)}\right); i \leq \frac{K}{2} \end{cases} \tag{6}$$

Based on the above formula (6), the probability of selecting a parent feature is determined by striking a balance between exploration and exploitation. Hence, an individual feature is selected based on its fitness. Now, at each time instance, the Gated Recurrent Neural Network accepts a feature input vector 'F_i'from a group and combines the output vector 'H_{t-1}' at the previous time instance to update its hidden layer node at 'H_t'. Then, the probability of selecting an individual feature as the subsequent rule that determines a parent is given below.

$$R_t = \sigma(W_R F_t + \lambda_R H_{t-1} + B_R) \tag{7}$$

$$U_t = \sigma(W_U F_t + U + B_U) \tag{8}$$

$$H_t = (1 - R_t) * H_{t-1} + U_t \tag{9}$$

From the above equations (7), (8), and (9), the reset threshold 'R_t' and the update threshold 'U_t' control the feature information update of each hidden layer activated via sigmoid 'σ' based on the coefficient matrices 'W_R, W_U' and bias matrices 'B_R, B_U' respectively. The contextual semantic information features of BGRNN processes are stored in a vector; however, the vector length is fixed. The contextual semantic information features are constrained, preventing the model's interpretation from reaching its optimal. The method can ascertain more features, reinforce the generalization potential, and minimize over-fitting by including adaptive weights. In BGRNN, attention weights are calculated using a tanh function to determine the relevance of each feature. This score is then converted into an attention weight for allowing the network to select the most important parts of the features. The attention weight for each feature vector is arrived at as given below.

$$w_i = \chi_a^T \tanh(w_a H_i + b) \tag{10}$$

From the above equation (10), the attention weight 'w_i' for each feature vector 'F_i' is arrived at based on the random weight matrix 'w_a', random vector 'χ_a', offset vector 'b', activated via the 'tanh' function. Followed by which the adaptive weight score is then represented as given below.

$$ws_i = \frac{\exp(w_i)}{\sum_{k=1}^{L} \exp(w_i k)} \tag{11}$$

Finally, the output vector (i.e., the most representative form of features selected for further processing) is obtained based on the random weight below.

$$FS_i = Out_i = \sum_{j=1}^{L} ws_i H_j \tag{12}$$

According to the above, the attention model associates the target matrix with the weight matrix via a perception function. Finally, the output vector 'Out_i' represents the most representative features selected.

3.3. Softmax-activated student feedback sentiment analysis classifier

Finally, the classification method selects the output of the max classifier function to achieve a final student feedback-based sentiment analysis with respect to academic-oriented placement performance. After the attention layer allocates weights to the features output by the BGRNN layer, the results are input into the softmax classifier. The classifier outputs the final result in the form of an array. To fulfill the research aims, sentiment analysis is correlated with suggested job roles by analyzing student feedback. Additionally, by associating and correlating students' academic features with their strengths and relevant job roles, institutions can map students' matched academic features to strengths and relevant job roles, thereby providing personalized suggestions and guidance for future career development. This is achieved using a softmax classifier, which measures the probability that a sample belongs to a particular class, as shown below.

$$\text{softmax}(Prob_C) = \frac{\exp(w_C(X))}{\sum_u \exp(w_u(X))} \tag{13}$$

From the above equation (13), 'X' denotes the sample to be classified for placement performance by analyzing student feedback, 'u' denotes one of the 'C' classes, with the result being stored in '$Prob_C$', denoting the probability that the sample 'X' belongs to the '$C - th$' class. The pseudo-code representation of the Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier is given below.

Algorithm 1: Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \dots, S_m\}$', Features '$F = \{F_1, F_2, \dots, F_n\}$', Classes '$C = \{C_1, C_2, \dots, C_u\}$'

Output:
1: Initialize '$m = 20000$', '$n = 39$', '$u = 34$'
2: Begin
3: Foreach Dataset 'DS' with Samples 'S' and Features 'F'
4: Generate input vector matrix according to (1)
//feature engineering
//Class-balanced Preprocessing
5: Measure output probabilities via linear classification according to (2)
6: Fine-tune imbalanced classifier results according to (3)
7: Generate class-balanced results by introducing the Cross Entropy Loss function according to (4)
8: Return class-balanced results
//Robust exploitation and exploration-based feature selection
9: Rate features based on the fitness according to (5)
10: Rank all individual features by ensuring a trade-off between exploitation and exploration according to (6)
11: Formulate selection probability to select an individual feature as a parent according to (7), (8), and (9)
12: Evaluate attention weight for each feature vector according to (10)
13: Evaluate adaptive weight score according to (11)

14: Generate output vector according to (12)
15: Return the most representative form of features selected 'FS'
//classification based on Student Feedback Sentiment
16: Generate softmax classifier results to measure the probability that a sample belongs to a particular class according to (13)
17: Return classified output
18: End for
19: End

As outlined in the algorithm, analyzing student sentiment based on feedback and performance for job placement in different roles is divided into two sections. They are feature engineering and classification. First, the Student Feedback Sentiment Analysis with Academic and Placement Performance dataset obtained as input is subjected to a Ridge Class-balanced Bidirectional Gated Recurrent Attention-based Round-robin Feature engineering model. Here, preprocessing and feature selection are performed separately. The Ridge Class-balanced Regularization model is initially applied to the raw data samples. To avoid an imbalance degree, the Ridge Regularization function is applied for the target Suggested Job Role feature. The class-balanced regularized results for the target Suggested Job Role feature are obtained based on a minimal cross-entropy loss function. This, in turn, helps minimize the time required for sentiment analysis of students. Next, the Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection model is applied to the class-balanced data samples. The first Round Robin function is applied to balance exploitation and exploration. Then, BGRNN is applied to extract contextual semantic information features, integrating the outputs from one forward direction and the other in the backward direction via splicing. Splicing output feature vector results based on both directions improves the precision and accuracy of sentiment classification. Finally, an attention mechanism is included that selectively concentrates on and assigns higher significance to specific features, thereby enhancing the model's potential to acquire relevant information and facilitating a more precise analysis of student feedback, including academic and placement performance.

4. Experimental Setup

This section presents the current analysis of the proposed Deep Learning (DL)-based method, called Ridge, Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC), for sentiment analysis of student feedback to measure placement based on academic performance. Simulations are performed in Python, a general-purpose high-level programming language for modeling, simulating, and analyzing multi-domain dynamical systems on a computer with an Intel(R) Core (TM) i7-6700HQ CPU at 2.60 GHz and 32 GB of RAM, running Windows. The parametric metrics for evaluating student feedback consist of train, precision, recall, and accuracy. Fair comparison analysis is made using the five methods, RR-BGRAC, Enhanced Ensemble Model Architecture [1], and BERT-BiLSTM-Attention (BBA) [2], hybrid DL method [9], and Fuzzy HCN-Net [11], where the same synthetic sample data, Student Feedback Sentiment Analysis with Academic and Placement Performance dataset, was extracted from https://www.kaggle.com/datasets/koshikasaiprasad/student-placement-data/data. University Employability Dataset is obtained from https://www.opendatabay.com/data/science-research/d0b808c0-b16f-4bf8-8447-a60a8b5bd877.

4.1. Qualitative analysis

In this section, a case analysis of student feedback on sentiment analysis for placement, focusing on academic performance, is presented using the Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC) method. With the samples obtained from the information provided in Tables 1 and 2, Ridge Class-balanced Bidirectional Gated Recurrent Attention-based Round-robin Feature engineering is applied. Here, two processes, namely, preprocessing and feature selection, are performed. With the suggested job role, student feedback on sentiment analysis is validated, and class balancing is performed. The class-balanced Regularization function is shown in Figure 4.

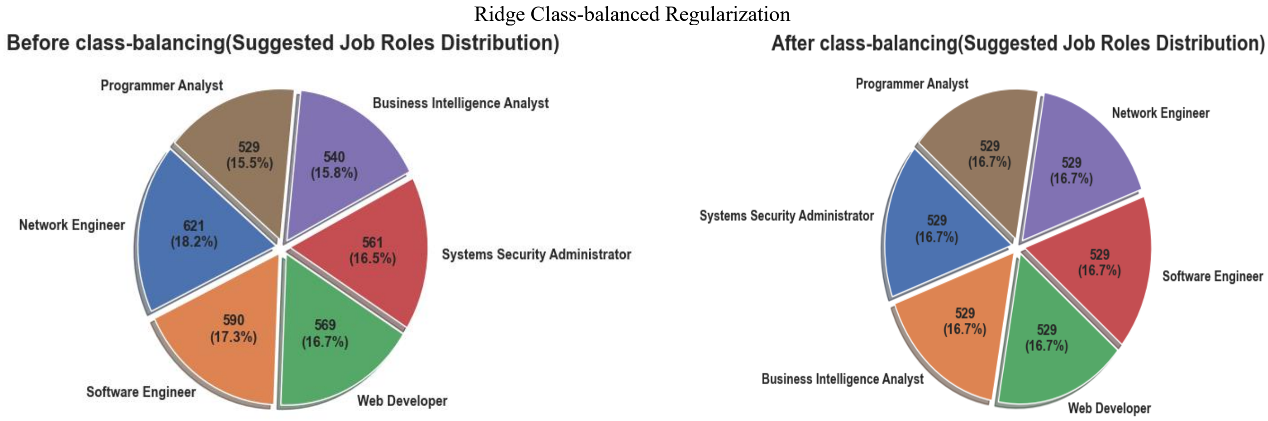


Fig. 4: Ridge Class-Balanced Regularization Applied to the Suggested Job Role.

As shown in the above figure, with the suggested job role considered a feature for class balance, the ridge regularization function was applied to generate class-balanced results for further processing. Following this, the class-balanced samples are used as input to the feature selection process, which outputs features for mapping student academic records to suggested job roles. Therefore, minimal training is required. Figure 5 shows the results of features selected using the Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection model.

Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection Results

```
Feature Ranking (High → Low):
                                   Feature  Importance
0         Percentage in Communication skills    0.067715
1            Percentage in Computer Networks    0.067072
2                  Percentage in Mathematics    0.066639
3                  percentage in Algorithms    0.066560
4    Acedamic percentage in Operating Systems    0.066387
5        Percentage in Software Engineering    0.066171
6      Percentage in Computer Architecture    0.066051
7       Percentage in Programming Concepts    0.065883
8      Percentage in Electronics Subjects    0.065556
9                       Interested subjects    0.051533
10         Type of company want to settle in?    0.050623
11                           certifications    0.048972
12                      coding skills rating    0.048923
13                                workshops    0.047511
14                      interested career area     0.041718
15                       Job/Higher Studies?    0.016752
16                    Management or Technical    0.016697
17                     Salary Range Expected    0.016468
18       Taken inputs from seniors or elders    0.016057
19                              Salary/work    0.016031
20                         talenttests taken?    0.015712
21                         hard/smart worker    0.014970

🎯 Round-Robin Groups :
View_1: ['Percentage in Communication skills', 'percentage in Algorithms', 'Percentage in Computer Architecture', 'Interested subjects', 'coding skills r
ating', 'Job/Higher Studies?', 'Taken inputs from seniors or elders', 'hard/smart worker']
View_2: ['Percentage in Computer Networks', 'Acedamic percentage in Operating Systems', 'Percentage in Programming Concepts', 'Type of company want to se
ttle in?', 'workshops', 'Management or Technical', 'Salary/work']
View_3: ['Percentage in Mathematics', 'Percentage in Software Engineering', 'Percentage in Electronics Subjects', 'certifications', 'interested career ar
ea ', 'Salary Range Expected', 'talenttests taken?']

✅ Selected Features:
View_1: ['Percentage in Communication skills', 'percentage in Algorithms', 'Percentage in Computer Architecture', 'coding skills rating']
View_2: ['Percentage in Computer Networks', 'Acedamic percentage in Operating Systems', 'Percentage in Programming Concepts']
View_3: ['Percentage in Mathematics', 'Percentage in Software Engineering', 'Percentage in Electronics Subjects', 'interested career area ', 'Salary Rang
e Expected', 'talenttests taken?']
```

	Acedamic percentage in Operating Systems	percentage in Algorithms	Percentage in Programming Concepts	Percentage in Software Engineering
0	64	72	68	60
1	62	88	63	63
2	68	93	91	92
3	79	75	79	78
4	72	76	88	60
...	...	...	...	...
3169	68	82	60	61
3170	74	92	87	63
3171	64	65	74	69
3172	81	85	71	72
3173	71	75	63	94

Percentage in Computer Networks	Percentage in Electronics Subjects	Percentage in Computer Architecture	Percentage in Mathematics
89	72	62	70
62	62	70	62
81	83	61	67
81	87	88	60
78	72	78	85
...	...	...	...
92	77	78	81
71	71	63	71
72	87	87	60
82	92	67	78
67	81	89	69

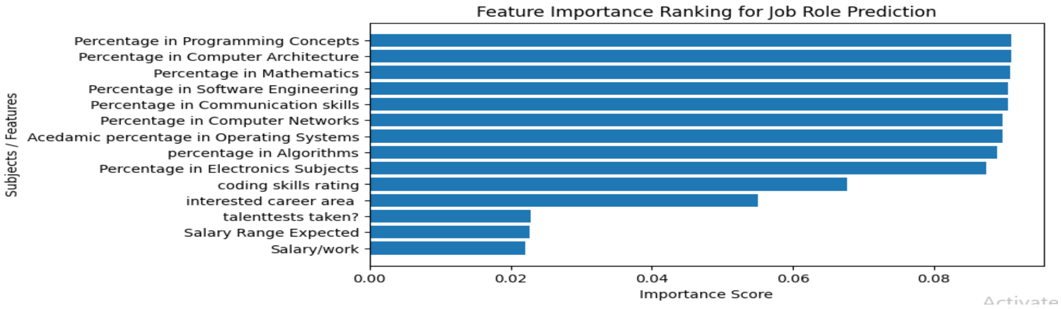
coding skills rating	talenttests taken?	Salary Range Expected	interested career area	Salary/work
2	no	salary	security	work
3	no	salary	Business process analyst	salary
6	yes	salary	testing	salary
5	yes	Work	security	work
7	yes	Work	Business process analyst	salary
...	...	...	...	...
5	yes	salary	security	work
5	no	salary	testing	work
6	no	Work	Business process analyst	work
1	yes	salary	Business process analyst	salary
3	no	Work	security	salary

[3174 rows x 13 columns]

Fig. 5: Feature Selection Results.

From the above feature, the selected results, which utilize Bidirectional Gated Recurrent Attention-based Round-robin in turn, help improve overall precision and recall. Finally, the class-balanced samples and feature-selected results are sent to the classification process to provide information based on the features, as determined by the. Figure 6 shows the classified results.

Softmax-activated Student Feedback Sentiment Analysis Classified results



	Feature	Importance
2	Percentage in Programming Concepts	0.091038
6	Percentage in Computer Architecture	0.090980
7	Percentage in Mathematics	0.090752
3	Percentage in Software Engineering	0.090527
8	Percentage in Communication skills	0.090463
4	Percentage in Computer Networks	0.089733
0	Acedamic percentage in Operating Systems	0.089686
1	percentage in Algorithms	0.089042
5	Percentage in Electronics Subjects	0.087382
9	coding skills rating	0.067759
12	interested career area	0.055015

```
Conditions of Suggested Job Role prediction
|--- Percentage in Software Engineering <= 62.50
|   |--- Percentage in Mathematics <= 72.50
|   |   |--- Percentage in Programming Concepts <= 90.50
|   |   |   |--- Percentage in Communication skills <= 74.50
|   |   |   |   |--- class: Network Engineer
|   |   |   |--- Percentage in Communication skills >  74.50
|   |   |   |   |--- class: Software Engineer
|   |   |--- Percentage in Programming Concepts >  90.50
|   |   |   |--- percentage in Algorithms <= 93.50
|   |   |   |   |--- class: Software Engineer
|   |   |   |--- percentage in Algorithms >  93.50
|   |   |   |   |--- class: Programmer Analyst
|   |--- Percentage in Mathematics >  72.50
|   |   |--- Percentage in Communication skills <= 86.00
|   |   |   |--- Percentage in Computer Architecture <= 90.50
|   |   |   |   |--- class: Business Intelligence Analyst
|   |   |   |--- Percentage in Computer Architecture >  90.50
|   |   |   |   |--- class: Software Engineer
|   |   |--- Percentage in Communication skills >  86.00
|   |   |   |--- Percentage in Mathematics <= 76.50
|   |   |   |   |--- class: Programmer Analyst
|   |   |   |--- Percentage in Mathematics >  76.50
|   |   |   |   |--- class: Web Developer
|--- Percentage in Software Engineering >  62.50
|   |--- Percentage in Electronics Subjects <= 89.50
|   |   |--- Percentage in Computer Architecture <= 62.50
|   |   |   |--- Acedamic percentage in Operating Systems <= 91.50
|   |   |   |   |--- class: Business Intelligence Analyst
|   |   |   |--- Acedamic percentage in Operating Systems >  91.50
|   |   |   |   |--- class: Programmer Analyst
|   |   |--- Percentage in Computer Architecture >  62.50
|   |   |   |--- Percentage in Communication skills <= 86.50
|   |   |   |   |--- class: Network Engineer
|   |   |   |--- Percentage in Communication skills >  86.50
|   |   |   |   |--- class: Systems Security Administrator
|   |--- Percentage in Electronics Subjects >  89.50
|   |   |--- coding skills rating <= 7.50
|   |   |   |--- Acedamic percentage in Operating Systems <= 89.50
|   |   |   |   |--- class: Web Developer
|   |   |   |--- Acedamic percentage in Operating Systems >  89.50
|   |   |   |   |--- class: Software Engineer
|   |   |--- coding skills rating >  7.50
|   |   |   |--- Percentage in Computer Architecture <= 71.50
|   |   |   |   |--- class: Programmer Analyst
|   |   |   |--- Percentage in Computer Architecture >  71.50
|   |   |   |   |--- class: Systems Security Administrator
```

✅ Classified results:

	Percentage in Programming Concepts	Percentage in Computer Architecture	Percentage in Mathematics	Percentage in Software Engineering
0	68	62	70	60
1	63	70	62	63
2	91	61	67	92
3	79	88	60	78
4	88	78	85	60
...	...	...	...	...
3169	60	78	81	61
3170	87	63	71	63
3171	74	87	60	69
3172	71	67	78	72
3173	63	89	69	94

Percentage in Communication skills	Percentage in Computer Networks	Acedamic percentage in Operating Systems	percentage in Algorithms
61	89	64	72
80	62	62	88
62	81	68	93
84	81	79	75
72	78	72	76
...	...	...	...
69	92	68	82
67	71	74	92
73	72	64	65
93	82	81	85
86	67	71	75

Percentage in Electronics Subjects	coding skills rating	interested career area	Suggested Job Role
72	2	security	Systems Security Administrator
62	3	Business process analyst	Business Intelligence Analyst
83	6	testing	Web Developer
87	5	security	Software Engineer
72	7	Business process analyst	Network Engineer
...	...	...	...
77	5	security	Web Developer
71	5	testing	Programmer Analyst
87	6	Business process analyst	Programmer Analyst
92	1	Business process analyst	Programmer Analyst
81	3	security	Network Engineer

[3174 rows x 12 columns]

Fig. 6: Classifies Results Using Softmax-Activated Student Feedback Sentiment Analysis.

Finally, as shown in Figure 6 above, the classified results of mapping student feedback sentiment analysis with the suggested job role are generated according to the conditions stated above. With the placement results obtained for each student based on their feedback, an accurate sentiment analysis formulation is said to be modeled. The quantitative analysis results for sentiment analysis on student feedback are provided in the following sub-sections.

4.2. Quantitative analysis

Using student feedback, parametric metrics for evaluating sentiment analysis, including academic and Placement Performance, and University Employability, consist of training time, precision, recall, and accuracy. A fair comparison analysis is made using the five methods: RR-BGRAC, Enhanced Ensemble Model Architecture [1], BERT-BiLSTM-Attention (BBA) [2], a hybrid DL method [9], and Fuzzy HCN-Net [11]. The same sample data were used to validate the performance metrics for all methods.

4.2.1. Performance analysis of Computational complexity

Computational complexity is measured in terms of time and space. While selecting composite features involved in sentiment analysis with Academic, which involves academic performance using student feedback, a significant amount of time is consumed. It is referred to as the time complexity. The training time or time complexity is mathematically formulated as given below.

$$\mathrm{TC} = \sum_{i=1}^{m} S_i * \mathrm{Time}\left(\mathrm{softmax}(\mathrm{Prob}_C)\right) \tag{14}$$

From the above equation (14), the time complexity is measured 'TC' using the samples involved in simulation 'S_i' and the time consumed in obtaining classified results while performing student sentiment analysis for job placement concerning different job roles' $\mathrm{Time}\left(\mathrm{softmax}(\mathrm{Prob}_C)\right)$'. It is measured in terms of seconds (sec).

Space complexity refers to the maximum amount of memory space required by an algorithm for identifying student sentiment analysis. It is mathematically computed as follows,

$$SC = \sum^{m} S_i \cdot Mem(softmax(Prob_c)) \tag{15}$$

Here, 'SC represents the space complexity, and s' $\mathrm{Mem}\left(\mathrm{softmax}(\mathrm{Prob}_C)\right)$ denotes the time needed to obtain results while performing student sentiment analysis for job placement concerning different job roles. It is measured in terms of kilobytes (kB).

Tables 3 and 4 present the overall analysis of the time complexity and space complexity of the proposed RR-BGRAC and existing methods, including the Enhanced Ensemble Model Architecture [1], BBA [2], a hybrid DL method [9], and Fuzzy HCN-Net [11], in comparison to different input samples. Among the four existing methods, the proposed RR-BGRAC method minimizes time complexity by selecting highly relevant features for student sentiment analysis related to placement performance.

Table 3: Time Complexity Analyses

Samples	Time complexity (sec)				
	RR-BGRAC	Enhanced Ensemble Model Architecture [1]	BBA [2]	Hybrid DL method [9]	Fuzzy HCN-Net [11]
1500	42	49.5	55.5	59.45	63.25
3000	48.35	57.25	62.55	64.75	67.85
4500	55	63.15	69.15	73.25	77.45
6000	59.15	65.55	71.35	75.45	79.25
7500	64.35	69.15	75.25	77.85	81.25
9000	69.25	74.35	79.35	83.25	86.85
10500	78.15	85.25	91.55	94.25	97.25
12000	85.35	91.45	98.65	104.15	109.35
13500	93.15	99.35	105.25	110.45	116.25
15000	98.15	105.25	111.15	118.55	123.45

Table 4: Space Complexity Analyses

Samples	Space complexity (kB)				
	RR-BGRAC	Enhanced Ensemble Model Architecture [1]	BBA [2]	Hybrid DL method [9]	Fuzzy HCN-Net [11]
1500	112	126	140	148	159
3000	120.3	134.8	146	158.4	167.1
4500	133.5	143.6	152.4	164	176
6000	138.5	148.5	161	175.3	184.8
7500	146	160	168	178	192
9000	152.5	165	175.2	186	201.5
10500	158.2	168	179.5	191.5	205.8
12000	163.4	175.6	188.6	199.4	208.6
13500	168.5	183	193.6	203.2	212.3
15000	177.3	187.6	201	210	220.1

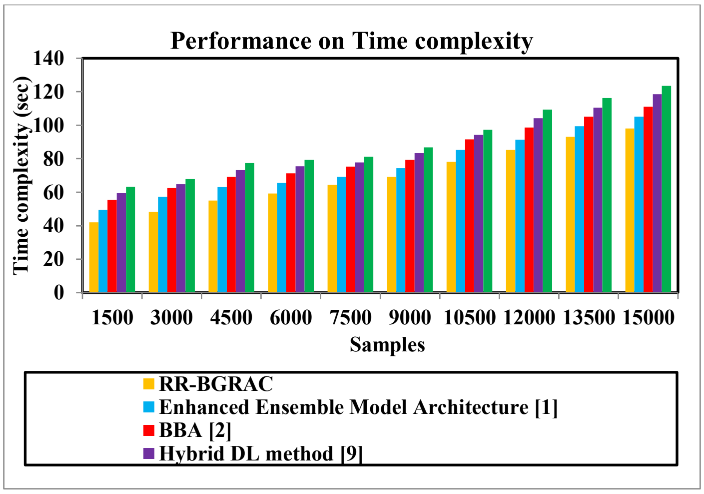


Fig. 7: Samples Versus Time Complexity.

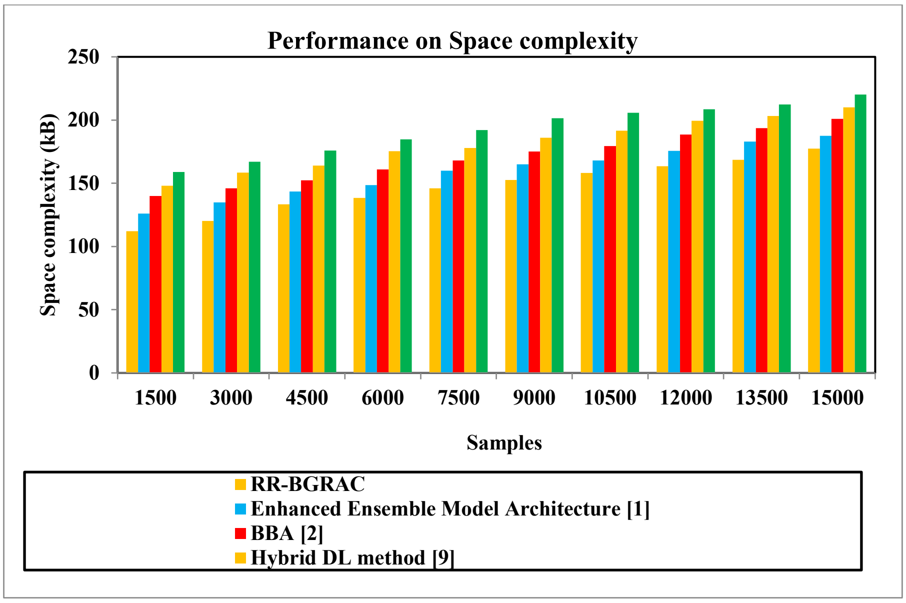


Fig. 8: Samples Versus Space Complexity.

Figures 7 and 8 show the timespace complexity analysis involved in the overall sentiment analysis of student feedback regarding placement in different job roles. The time and space complexities are analyzed using samples ranging from 1500 to 15000. To ensure a fair comparison, sample data from the student placement feedback dataset were used for all five methods, and time and space complexity were analyzed by substituting the values in equations (14) and (15). From the figure, it is inferred that an increase in time and complexity was observed using all five methods. However, simulation performed on 1500 sample data improved by minimizing time and space complexity using the proposed RR-BGRAC method compared to the Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11]. The reason was that applying the Ridge Class-balanced Regularization function alleviated the classifier imbalance. Next, for the target Suggested Job Role feature to make correct classification decisions, the highest posterior probability results corresponding to the ground truth class were generated using the Ridge Regularization function. This, in turn, minimized the time required for the proper RR-BGRAC method by 11% compared to [1], 20% compared to [2], 20% compared to [9], and 24% compared to [11]. Additionally, the space complexity is minimized by 8%, 14%, 19%, and 24% using the proposed RR-BGRAC method compared to [1], [2], [9], and [11].

4.2.1. Performance analysis of precision, recall, and accuracy

Second, this section discusses the analysis of precision, recall, and accuracy involved in student feedback regarding sentiment analysis towards placement, considering the academic aspects. The precision, recall, and accuracy are measured as given below.

$$\text{Pre} = \frac{\text{TP}}{\text{TP+FP}} \tag{16}$$

$$\text{Rec} = \frac{\text{TP}}{\text{TP+FN}} \tag{17}$$

$$\text{Acc} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{18}$$

From the above equations (16), (17) and (18) precision ‘Pre’, recall ‘Rec’ and accuracy ‘Acc’ is measured based on the true positive rate ‘TP’ (i.e. students with network engineer capability placed as network engineer) true negative rate ‘TN’ (i.e. students with software engineer capability placed as software engineer), false positive rate ‘FP’ (i.e. students with network engineer capability placed as software engineer) and false negative rate ‘FN’ (i.e. students with software engineer capability placed as network engineer)respectively. Tables 5, 6, and 7 present the overall precision, recall, and accuracy analysis using the proposed RR-BGRAC and existing methods, including the Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11], for different input samples. Among the four existing methods, the proposed RR-BGRAC method improved three performance metrics — precision, recall, and accuracy — for student sentiment analysis regarding placement performance.

Table 5: Precision Analyses

Samples	Precision				
	RR-BGRAC	Enhanced Ensemble Model Architecture [1]	BBA [2]	Hybrid DL method [9]	Fuzzy HCN-Net [11]
1500	0.96	0.94	0.92	0.91	0.88
3000	0.92	0.84	0.74	0.7	0.66
4500	0.91	0.83	0.73	0.68	0.64
6000	0.88	0.8	0.7	0.65	0.63
7500	0.85	0.77	0.67	0.64	0.61
9000	0.83	0.75	0.65	0.62	0.6
10500	0.85	0.77	0.67	0.64	0.62
12000	0.87	0.79	0.69	0.66	0.64
13500	0.9	0.82	0.72	0.68	0.66
15000	0.92	0.84	0.74	0.71	0.67

Table 6: Recall Analyses

Samples	Recall RR-BGRAC	Enhanced Ensemble Model Architecture [1]	BBA [2]	Hybrid DL method [9]	Fuzzy HCN-Net [11]
1500	0.98	0.98	0.98	0.97	0.97
3000	0.96	0.88	0.83	0.8	0.77
4500	0.94	0.84	0.79	0.76	0.73
6000	0.91	0.83	0.78	0.75	0.72
7500	0.9	0.82	0.77	0.74	0.7
9000	0.88	0.8	0.75	0.72	0.68
10500	0.84	0.76	0.71	0.68	0.66
12000	0.87	0.79	0.74	0.7	0.67
13500	0.9	0.82	0.77	0.73	0.71
15000	0.92	0.79	0.74	0.71	0.68

Table 7: Accuracy Analyses

Samples	Accuracy RR-BGRAC	Enhanced Ensemble Model Architecture [1]	BBA [2]	Hybrid DL method [9]	Fuzzy HCN-Net [11]
1500	0.95	0.93	0.91	0.9	0.88
3000	0.92	0.85	0.81	0.78	0.75
4500	0.9	0.83	0.79	0.76	0.73
6000	0.87	0.8	0.76	0.74	0.71
7500	0.83	0.77	0.73	0.7	0.67
9000	0.81	0.74	0.7	0.68	0.65
10500	0.78	0.7	0.66	0.64	0.61
12000	0.83	0.76	0.72	0.7	0.67
13500	0.85	0.78	0.74	0.71	0.68
15000	0.87	0.8	0.76	0.73	0.7

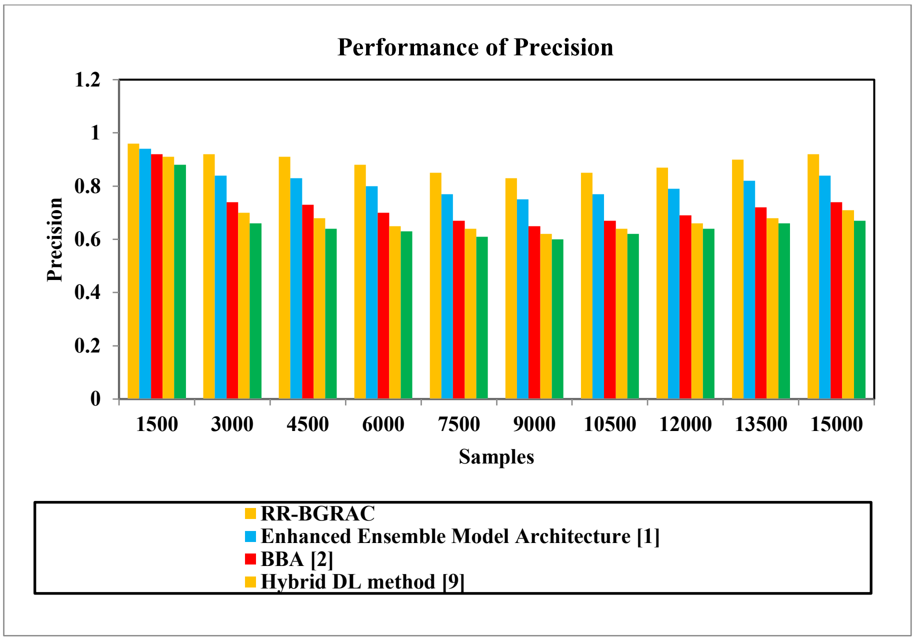


Fig. 9: Samples Versus Precision.

Figure 9 above shows the precision results obtained using the five methods: RR-BGRAC, Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11]. The input is considered as samples and is varied within the ranges of 1500, 3000, and up to 15000 for ten iterations. From the above figure, neither an increase nor a decrease in precision value was observed when the sample size was increased. Additionally, a comparative analysis reveals higher precision improvements using RR-BGRAC compared to [1], [2], [9], and [11]. With the input of 1,500 samples, the precision is obtained as 0.96, 0.94, 0.92, 0.91, and 0.88 for RR-BGRAC, the Enhanced Ensemble Model Architecture [1], BBA [2], the Hybrid DL method [9], and Fuzzy HCN-Net [11], respectively. Ten different accuracy results are observed for the databases. The proposed RR-BGRAC method's precision improvement was achieved by applying the Bidirectional Gated Recurrent Neural Network model. Applying this model aided in extracting contextual semantic information features, concentrating on both positive and reverse sequence direction. Therefore, by combining the outputs from the forward and backward directions, known as splicing, a single representation is finally formed. This improves the RR-BGRAC method's precision by 8% compared to [1], 19% compared to [2], and 30% compared to [2], and 35% compared to [2].

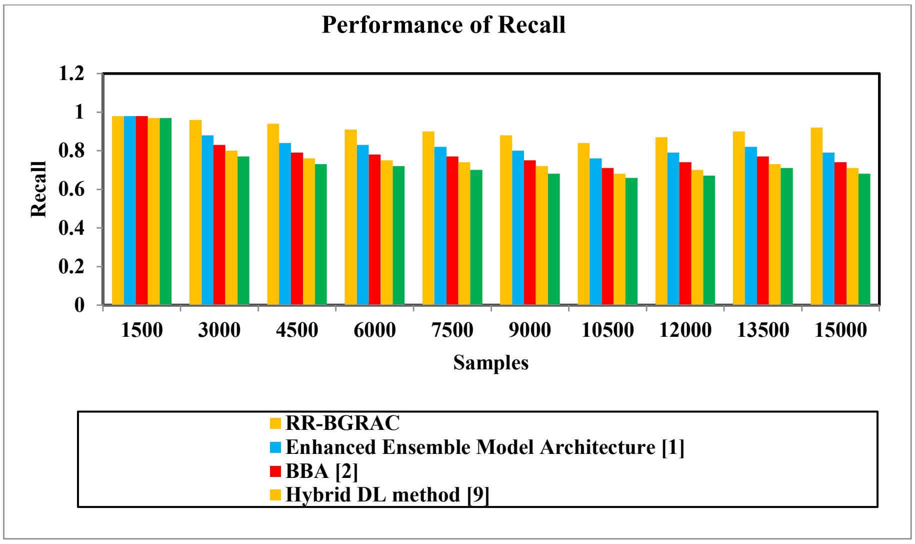


Fig. 10: Samples Versus Recall.

Figure 10 above illustrates the recall results obtained using the proposed method, RR-BGRAC, and four existing methods: Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11]. From the student placement data, 1,500 to 15,000 samples are collected for experiments. Similar sample data from the same dataset were used for all five methods and substituted in equation (17) to ensure fair comparison. From the above figure, the recall rate of the proposed RR-BGRAC method was comparatively better than [1], [2], [9], and [11]. With the input of 1500 samples, the recall is obtained as 0.98, 0.98, 0.98, 0.97, and 0.97 for RR-BGRAC, Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11]. The recall improvement using the RR-BGRAC method was owing to the application of the Round Robin function, wherein all individual features are ranked based on the fitness measures. Also, a distinct rank is generated despite equivalent fitness values. In addition to making an inevitable trade-off between exploitation and exploration, all individual features were ranked according to the fitness value. This, in turn, improved the overall recall rate of the RR-BGRAC method by 9% compared to [1], 14% compared to [2], 21% compared to [2], and 26% compared to [2].

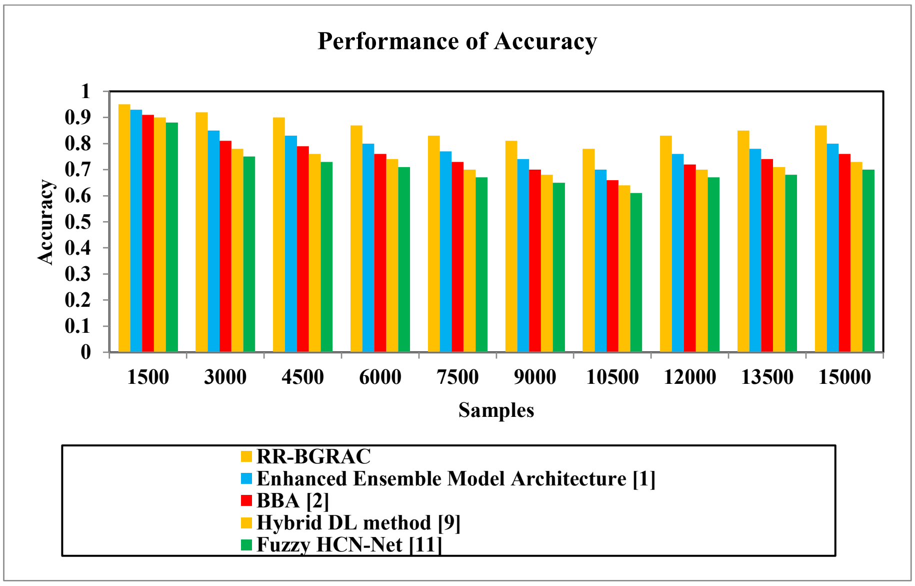


Fig. 11: Samples Versus Accuracy.

Finally, Figure 11 presents the accuracy results of student feedback sentiment analysis during placement validation for several job roles. In the experiment conducted, samples are taken as input in the ranges of 1500 to 15000 from student placement data. The horizontal axis represents the samples, and the vertical axis denotes the accuracy observed using the five methods: RR-BGRAC and four existing methods, namely Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11]. From the above figurative representation, the accuracy of the RR-BGRAC method was observed to be better than that of [1], [2], [9], and [11]. Consider the mathematical calculation with the 1500 samples in the first iteration. By applying the proposed RR-BGRAC, 1435 samples are accurately validating job placement, and the accuracy is obtained as 0.95. Similarly, 1400, 1375, 1350, and 1315 are correctly validating job placement, with accuracies of 0.93, 0.91, 0.9, and 0.88 for the existing Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11], respectively. The accuracy improvement is due to the application of contextual semantic information features processed by BGRNN. However, contextual semantic information features are constrained by the fixed vector length. By using adaptive weights, the RR-BGRAC method identifies more features, thereby reinforcing its generalization potential and minimizing overfitting. This improves the RR-BGRAC method's accuracy by 8% compared to [1] and 12% compared to [2], 18% compared to [2], and 23% compared to [2].

4.2.3. Comparison analysis of time and space complexity, precision, recall, and accuracy for proposed and existing methods using student placement data and university employability dataset

The analysis of the proposed RR-BGRAC and the existing Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11] is compared and executed in Python using student placement data. Tables 8 and 9 provide a detailed comparison of the proposed RR-BGRAC with existing methods.

Table 8: Overall Performance Analysis Results Using Student Placement Data

Methods	Time complexity (ms)	Space complexity (kB)	Precision	Recall	Accuracy
RR-BGRAC	69.29	147	0.88	0.91	0.86
Enhanced Ensemble Model Architecture [1]	76.02	159.2	0.81	0.83	0.8
BBA [2]	81.97	170.5	0.72	0.79	0.76
Hybrid DL method [9]	86.14	181.3	0.68	0.76	0.73
Fuzzy HCN-Net [11]	90.22	192.7	0.66	0.73	0.70

Table 9: Overall Performance Analysis Results, University Employability Dataset

Methods	Time complexity (ms)	Space complexity (kB)	Precision	Recall	Accuracy
RR-BGRAC	55.43	132	0.92	0.95	0.9
Enhanced Ensemble Model Architecture [1]	64.25	145.8	0.88	0.92	0.87
BBA [2]	68.78	168.5	0.85	0.9	0.86
Hybrid DL method [9]	72.95	170.2	0.78	0.88	0.84
Fuzzy HCN-Net [11]	80.45	184.3	0.75	0.84	0.8

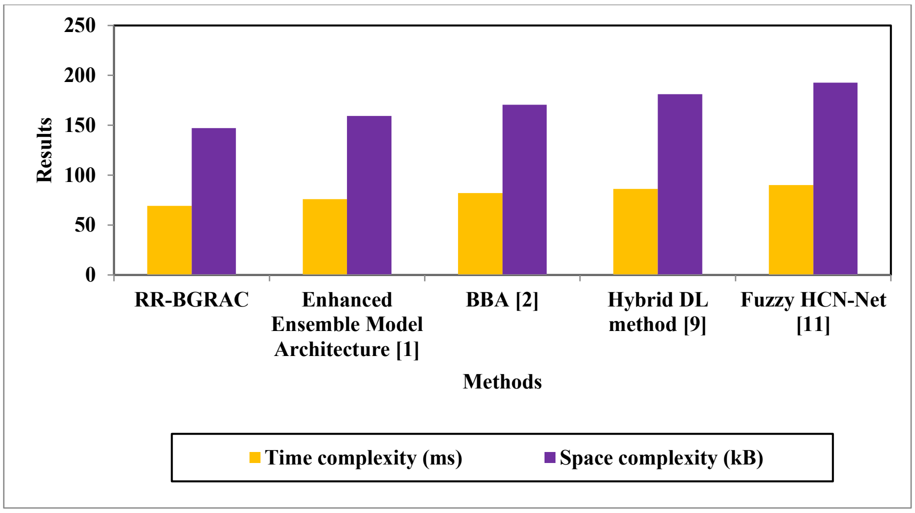


Fig. 12: Overall Performance Results of Time Complexity and Space Complexity Using Student Placement Data.

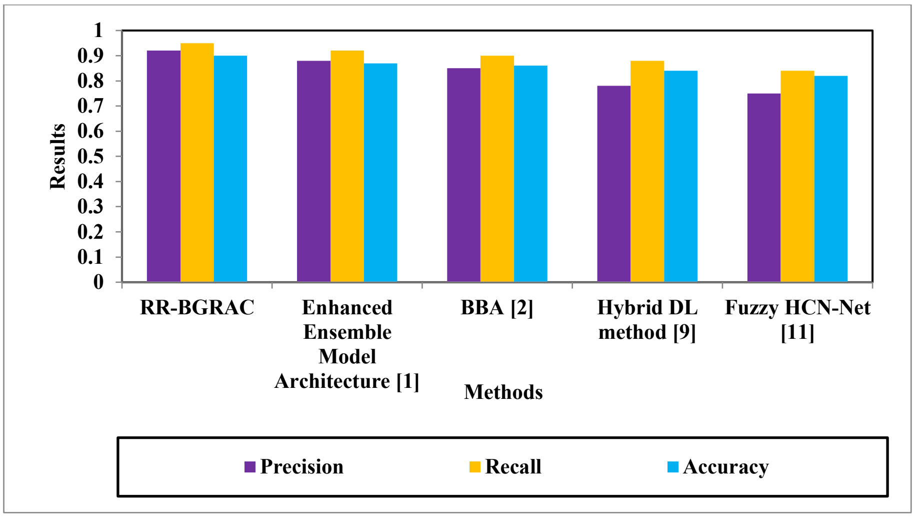


Fig. 13: Overall Performance Results of Precision, Recall, and Accuracy Using Student Placement Data.

Figures 12 and 13 demonstrate the overall performance results of different parameters for five methods: RR-BGRAC, the existing Enhanced Ensemble Model Architecture [1], BBA [2], Hybrid DL method [9], and Fuzzy HCN-Net [11]. These results clearly indicate that the performance of all parameters using the proposed RR-BGRAC, in terms of precision, recall, and accuracy, is significantly improved by 0.88, 0.91, and 0.86, respectively, compared to the existing methods. According to the analysis, the RR-BGRAC achieves a 69.29ms reduction in time complexity and a 147kB reduction in space complexity compared to [1], [2], [9], and [11].

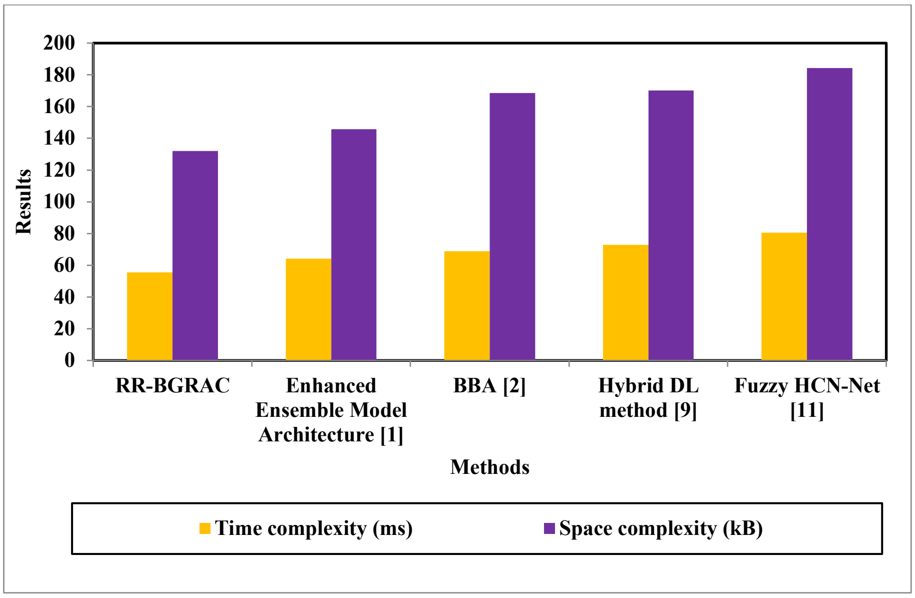


Fig. 14: Overall Performance Results of Time Complexity and Space Complexity Using the University Employability Dataset.

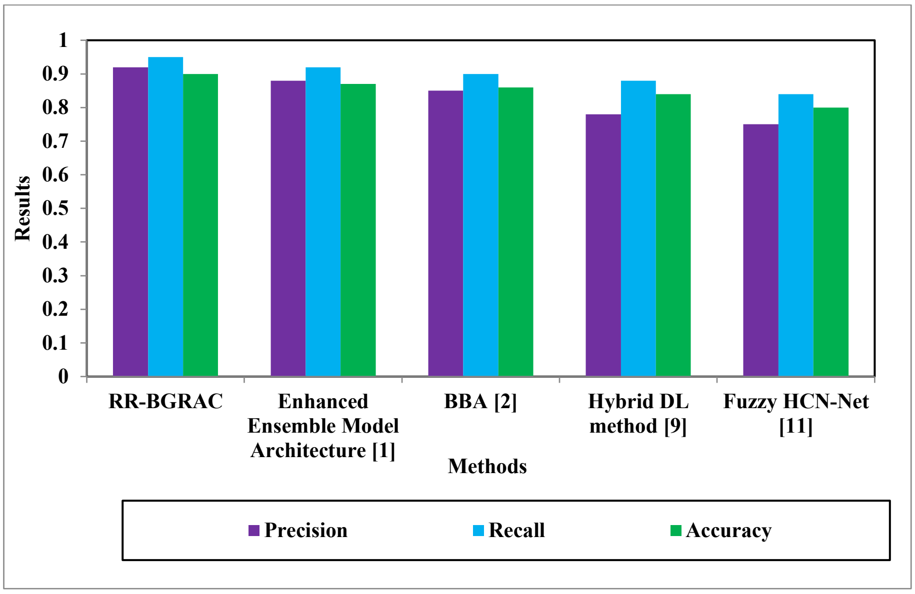


Fig. 15: Overall Performance Results of Precision, Recall, and Accuracy Using the University Employability Dataset.

Figures 14 and 15 illustrate the overall performance results for various parameters across five methods. This outcome clearly indicates that the performance of all parameters using the proposed RR-BGRAC, in terms of precision, recall, and accuracy, is significantly improved by 0.92, 0.95, and 0.9, respectively, compared to existing methods. According to the analysis, the RR-BGRAC achieves a 69.29ms reduction in time complexity and a 147kB reduction in space complexity compared to [1], [2], [9], and [11].

5. Discussion

Proposed RR-BGRAC is employed in various applications, including corporate training and student mental health, for performing semantic analysis through academic performance and job postings. Deep learning offers a robust, data-driven approach to corporate training, generating highly personalized and responsive learning experiences. Deep learning methods are employed to analyze a student's academic background and sentiment data to predict skill gaps and areas of improvement. Deep learning techniques are utilized to help educational institutions identify and support students facing mental health challenges. Corporate trainers design specific programs to address these weaknesses, whether they involve technical skills or soft skills that impact mental well-being. By incorporating student data from their academic careers, companies can better customize and target training.

5.1. Limitations and future work

Educational data is particularly sensitive and complex. To achieve academic performance and job placement, several implementation challenges are considered, including data privacy, system integration, and ethical concerns, when using deep learning. Education technology (EdTech) platforms collect vast amounts of student data, ranging from personal identifiable information to academic and behavioral records, which poses significant privacy risks. To improve academic and career outcomes, various systems, including Learning Management Systems (LMS), career services platforms, and student information systems, pose a significant issue in system integration.

In the future, university systems will be integrated with novel deep learning for sentiment analysis of student feedback to enhance academic-oriented placement. Additionally, the project's costs will be considered for deep learning systems.

6. Conclusion

Historical student data can be utilized in training predictive models. These models aid in forecasting the feasibility of placing a student, based on factors such as grades, skills, and internship experiences. However, the scope of optimizing placement strategies is limited as they depend on manual detection, which cannot be accounted for or made feasible manually. Hence, optimizing the placement strategy is essential. This work proposes an effective deep learning (DL) method for sentiment analysis on student feedback, called the Ridge Regularized Bidirectional Gated Recurrent Attention-based Classifier (RR-BGRAC). The different processes involved in the design are feature engineering and classification. First, raw samples from the Student Feedback Sentiment Analysis dataset are preprocessed using Ridge Class-based Regularization. Next, with the processed information, exploitation and exploration are involved in selecting prominent features using the Bidirectional Gated Recurrent Attention-based Round-robin Feature Selection model. Finally, the extracted features are provided as input to the Softmax-activated Student Feedback Sentiment Analysis Classifier, which outputs the job role based on the student's feedback through sentiment analysis. The proposed RR-BGRAC method is simulated using Python and the Student Feedback Sentiment Analysis dataset. The simulation results validated that the RR-BGRAC method outperforms state-of-the-art methods in terms of key performance metrics, including training time, precision, recall, and accuracy.

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