

Retraction

Retracted: Analysis on the Particularity of Higher Education Subject Development under the Background of Artificial Intelligence

International Transactions on Electrical Energy Systems

Received 12 December 2023; Accepted 12 December 2023; Published 13 December 2023

Copyright © 2023 International Transactions on Electrical Energy Systems. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Wang, "Analysis on the Particularity of Higher Education Subject Development under the Background of Artificial Intelligence," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 8109117, 13 pages, 2022.

Research Article

Analysis on the Particularity of Higher Education Subject Development under the Background of Artificial Intelligence

Yancai Wang 

School of Teacher Education, Shaoguan University, Shaoguan 512005, Guangdong, China

Correspondence should be addressed to Yancai Wang; wyc@sgu.edu.cn

Received 22 July 2022; Revised 10 August 2022; Accepted 5 September 2022; Published 11 October 2022

Academic Editor: Raghavan Dhanasekaran

Copyright © 2022 Yancai Wang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Subject development plays a crucial role in higher education (HE), improving student academic performance. The HE continuously requires conceptual and empirical development to deliver valuable content to the students. The subject reforms offer quality, accessibility, affordability, accountability, and equity to accomplish continual learning. The changes in higher education subjects require a continuous assessment to understand the relationship between the reform and student performance. The subject development quality is evaluated using machine learning (ML) and artificial intelligence (AI) techniques. The existing researchers use intelligent techniques to identify student academic performance. However, the exact relationship between student performance and subject changes fails to address. Therefore, higher education learning (HEL) requires improvement to manage the Higher Education Subject Development (HESD). To achieve the research goal, AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM) network is introduced in this work. The network model uses the Hebbian supervised learning (HSL) process to create the training model. The learning process has a network parameter updating procedure that reduces the total error and deviation between the academic details. In addition, the neural model uses the memory cell that stores every processing information that recalls the output patterns with maximum accuracy. The output pattern identifies the student's academic performance, which helps to analyze the quality of the subject development in institutions. The created system ensures 98.78% accuracy, showing that subject development correlates highly with student academic performance.

1. Introduction of Higher Education Subject Development

Higher education management (HEM) [1, 2] concepts and elements have been altered at most institutions and colleges. The HEM is essential to postsecondary learning because it establishes the learning plan and manages the techniques, materials, and structure [3]. The HEM system regularly evaluates the educational system to raise the standard of instruction and increase its relevance. Therefore, proper guidelines and reviews should be developed to improve the education subjects [4]. The continuous improvement in the education subjects ensures the teaching and learning quality. The learning quality is maintained by creating the Higher Education Subject Development (HESD) program [5, 6] with particular policies and University Qualification Framework (UQF). Once the HESD is developed, it has to be

evaluated using various assessments before approving the subject changes. The frequent subject assessments [7] help to maintain the system's flexibility. In addition, the newly developed subject framework has been given to the students or graduates to get feedback to manage the education standards. In the HESD case, student performance plays a significant role because they are the actual participants in the learning [8, 9].

The performance of participant is evaluated with different dimensions such as written work, examination, presentation, and group activities. Among the various dimensions, student class participation has half importance in improving the HE standards. The teachers continuously monitor student participation, contribution, and learning ability during the class. If the subjects have more interest, then students have a power-packed performance in those subjects. However, student observation and assessment are

challenges because they require enormous student attributes. Student performance is not only determined via the cumulative grade point but also depends on student interactions, comments, and class flow. The student who frequently participates in the classroom is attaining positive factors. Students' learning, listening, and teaching abilities impact the student's academic performance. Therefore, HESD requires a quality instructor and effective student to improve the overall learning system flexibility reliability and significantly.

The HESD requires the student perspective and feedback to enhance the subject's nature and teaching quality [10]. In most situations, students are ambiguous and feel inadequate in understanding the concepts that will affect the HESD quality. Therefore, several researchers use machine learning and intelligent techniques [11, 12] to investigate student learning performance. The research analysis utilizes the student's academic attributes as input and output patterns are derived [13, 14]. However, the existing systems fail to ensure the particular subject's [15] related output. In addition, the enormous amount of data [16] is challenging to handle by the traditional performance analysis performance. The research issues are resolved with the help of the AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM). The model uses the memory cells that store every processed input, which helps to understand the student's learning ability. According to the students' learning ability, the HESD has been investigated effectively.

This research examines the rise of intelligent techniques in higher education teaching and learning. It examines the educational consequences of new technology on how students learn and how educational institutions change and adapt. Researchers examine recent technological developments and higher education's rising use of new technologies in order to forecast how higher education will change once artificial intelligence is an integral part of our institutions' fabric as importance contribution in this research. For institutions of higher education and students, the use of these technologies for teaching, learning, student assistance, and administration presents significant problems.

The remaining paper is arranged as Section 2, discussing the review analysis of the higher education system. Section 3 explores the AA-BAM approach's working process to identify the student performance to the HESD and the system's efficiency discussed in Section 4. Conclusion described in Section 5.

2. Review Analysis of Higher Education

Ho et al. [17] explored machine learning techniques in higher education to improve remote learning during the COVID-19 situation. This work uses the Hong Kong self-funded university student information for analyzing the emergency remote learning (ERL) during the pandemic. During the analysis, around 425 students' data are collected, which are analyzed according to the multiple regression techniques that investigate the student learning satisfaction and ensure 65.2% accuracy. The remote learning-based

attained results are compared with the traditional classroom learning in which the ERL process faces difficulties while accessing the Internet and learning devices.

Kuleto et al. [18] analyzed the difficulties and importance of artificial intelligence (AI) approaches and machine learning (ML) in higher education institutions (HEI). The study was conducted in Serbia, in which different information and reference points were collected from commercial sources, multiple academics, and scientific units. This study uses around 103 students' information, which is investigated by applying the ML and AI techniques. During the analysis, the correlation matrix and theoretical dimensions are computed with the help of regression analysis. The correlation values are used to effectively examine the student's skills and learning.

Rodríguez-Hernández et al. [19] predicted student academic performance by applying the artificial neural network (ANN). The system aims to predict higher studies student performance and academic performance and the predictors involved in academic performance. During the analysis, Colombia's public and private university's student information is gathered; around 162,030 student educational details are utilized to investigate the performance. The ANN recognizes the student performance from 71% to 82%. After identifying the student's performance, school characteristics, prior academic achievement, and school characteristics have been analyzed. The derived student learning characteristics give recommendations by applying the ANN in higher education.

Giannakas et al. [20] developed deep learning approach (DLA)-based classification framework for identifying the student's team-related academic performance. The deep neural network (DNN) uses the two hidden layers for analyzing the student's academic performance to identify the positive and negative impacts on team learning. The DLA uses various activation functions such as tanh, rectified linear unit (ReLU), and sigmoid to compute the output value. This classification process is optimized with the help of AdaDelta and AdaGrad, which minimize the deviations between the outputs. The system uses the Shapley Additive Explanations (SAE) to interpret with the DLA approach to derive the various features used to improve the overall classification accuracy. The author uses the 74 teams and 30000 entries to evaluate the introduced system efficiency, and the system ensures 80.76% and 86.57% accuracy.

Zhang et al. [21] applied the Sparse Attention Convolutional Neural Network (SACNN) approach to predicting the student grade in Chinese higher education. The SACNN approach uses the sparse attention layer to identify the course target and response. The network utilizes temporal features to investigate the student learning process. Fully convolution neural networks process the extracted features to predict the grade from the achieved features. The author uses the 137-course details, and 1307 students' information is processed to predict the student grades. The collected information was evaluated with the help of hold-out evolution in which the introduced system attains 85% of prediction accuracy. According to the grade performance,

learning efficiency and course relationship are evaluated to improve the learning efficiency.

Hai-tao et al. [22] developed school students' academic performance by applying the graph convolutional neural network (GCNN). This study uses the Chinese-Foreign Cooperation in Running School (CFCRS) student information to analyze their academic performance. The collected CFCRS information is investigated by applying the GCNN that uses the fully connected layer to explore the feature matrix. The computed output values are processed by the Pearson correlation coefficient (PCC) to estimate the student similarities. According to the computations, student learning efficiency is predicted with 81.5% accuracy.

Olabanjo and Wusu [23] recommended radial basis function neural (RBFN) model to identify secondary school student (SSS) academic performance. The author uses the school repository information to predict the SSS performance. The dataset consists of student characteristics and raw scores collected from 1 to 6 years; the dataset also includes teacher ratings. The gathered information is categorized according to the subjects such as Major, English, and Mathematics. The student details are processed using principal component analysis (PCA) to remove the irrelevant information. Then, noise-removed details are investigated RBFN, which predicts the student performance with 93.49% accuracy. According to the results, student's learning performance is improved.

Dogadina et al. [24] introduced hybrid model-related optimized neural networks (HMONN) for evaluating high school student (HSS) education. The system intends to assess the student homework performance by considering different criteria such as school exercises, assignment criteria, and time. The collected information is processed by neural models that predict student performance. During the analysis, the network uses the backtracking optimization algorithm (BOA), genetic algorithm (GA), and particle swarm optimization (PSO) are incorporated to find the homework completion time.

The above analysis and discussions clearly show that ML and AI algorithms are widely utilized in higher education learning (HEL) to improve student performance. The existing systems concentrate on student's entire academic performance and grading effectively. However, the existing methods fail to explore the particularity of Higher Education Subject Development (HESD). Therefore, the HEL requires improvement in the subjects to improve student performance. AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM) network is introduced to address this issue. The AA-BAM approach investigates each change in HEL subjects, and student's adaptations are evaluated in a particular period to justify the HESD. Then, the detailed description and working process of the AA-BAM-based HESD process are discussed below.

3. AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM) Network-Based HESD

3.1. Higher Education Subject Development (HESD). This section reviews, delivers, and develops the Higher Education

Subject Development (HESD) system using the AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM) approach. The HESD utilizes the set of policies and procedures, which regulate the changes and development in higher education (HE) subjects. The successful usage of HESD policies helps manage the quality of teaching and learning. The HESD should be incorporated with the universities/college's guidelines to improve the student's learning efficiency. The HE subject improvement and development must satisfy the following criteria:

- (i) Appropriate level: subjects are created level by level; they should be adopted to the Academic Qualifications Framework (AQF).
- (ii) Appropriate assessment: institutions or universities are needed to assess to compute the workload and student performance. The evaluation should be indicative, and the computations are proportional to the entire subject. The assessment process must be flexible.
- (iii) Learning outcome: learning process and outcomes are related to the AQF.
- (iv) Student attributes: subjects must be developed according to the student's learning attributes.

According to the above criteria, the HE teachers and staff register their policies in institutions. Then, the subject outlines are assessed for delivering valuable notes to the students. In addition, the HESD must consist of proper resources to satisfy the subject requirement. The developed subjects need to be incorporated with the UQF that has to be approved by the Teaching Committee (TC). Once the TC supports the subjects in HE, the internal subject review process is performed in the end of semester review, subject reports, and information distribution. The developed subject-related examinations are conducted, and the results are evaluated at the end of the semester. During this process, feedback of student and teacher is collected to understand the complexity of new subjects. The staff generated a summative subject report (SSR) according to the subject coordinator. The developed SSR is submitted to the senior faculty and institution dean to explore the subject's improvement. The designated representative investigates the generated SSR report to identify the implications and significance of the subjects. Then, the quality administrator (QA) assesses the SSR and stores it in the database for further subject improvement. According to the reports and feedback, students are trained further, and the subjects are changed to improve their learning ability. From the analysis, student performance in particular subjects played an important role because it determined the HESD efficiency. The collected student academic information is investigated by applying ML and AI techniques. The existing techniques fail to address the HESD-related feedback and performance, which reduces the learning efficiency. The discussed issues are overcome by applying the AA-BAM network to the student academic features. A detailed explanation of the AA-BAM process is discussed in the below section. SSR

TABLE 1: Dataset attribute information.

Attribute number	Attribute name	Information
1	Student ID	Identification number for students
2	Age	(1–18 to 21; 2–22 to 25; 3-above 26)
3	Sex	1 for female and 2 for male
4	Institute type	1: private; 2: state; 3: other
5	Subsidy type	1: no; 2–25%; 3–50%; 4–75%; and 5: full
6	Extra work	1: yes; 2: no
7	Sports activity	1: yes; 2: no
8	Salary (if available)	1: USD 135 to 200; 2: USD 201 to 270; 3: USD 271 to 340; 4: USD 341 to 410; and 5: above 410 USD.
9	Transportation	1: bus; 2: private car; 3: bicycle; and 4: others
10	Accommodation	1: rental; 2: dormitory; 3: with family; and 4: others
11	Number of siblings	1: 1; 2: 2; 3: 3; 4: 4; 5: 5 or above
12	Parent status	1: married; divorced; 2, 3: died any one
13	Study hours for the week	1: none; 2: above 5 hr; 3: 6 to 10 hr; 4: 11–20 hr; 5: more than 20 hr
14	Nonscientific books reading time	1: none; 2: sometimes; and 3: often
15	Scientific books reading time	1: none; 2: sometimes; and 3: often
16	Attendance of conference related to department	1: yes and 2: no
17	Project impacts for success	1: positive; 2: negative; and 3: neutral
18	Class presence	1: always; 2: sometimes; and 3: never
19	Midterm exam one preparation	1: alone; 2: with friends; and 3: not
20	Midterm exam two preparation	1: closest to the exam, 2: regular, and 3: never
21	Class notes taking	1: never; 2: sometimes; 3: always
22	Class listening	1: not ever; 2: occasionally; 3: continuously
23	Discussions regarding improvement	1: never; 2: sometimes; 3: always
24	Schoolroom dismissive	1: not valuable; 2: useful; and 3: not appropriate
25	Collective score points	1: above 2.00; 2: 2 to 2.49; 3: 2.50 to 2.99; 4: 3 to 3.49; and 5: above 3.49
26	Expected collective grade points	1: above 2.00; 2: 2 to 2.49; 3: 2.50 to 2.99; 4: 3 to 3.49; and 5: above 3.49
27	Course ID	-
28	Score	7: AA; 6: BA; 5: BB; 4: CB; 3: CC; 2: DC; 1: DD; 0: be unsuccessful

may be integrated into teaching and learning activities so that students' progress is constantly monitored. High-accuracy algorithms have been used to accurately forecast the likelihood of a student failing an assignment or withdrawing from a course.

3.2. Student Data Collection. This work uses the Higher Education Students Performance Evaluation (<https://www.kaggle.com/datasets/csafriz2/higher-education-students-performance-evaluation>) [25] dataset. The dataset was gathered from the student of Engineering and Educational Sciences in 2019. The dataset was used to evaluate the student performance by applying ML and AI techniques. The dataset consists of 32 attributes that include student personal information (name, age, family background, scholarship type, sex, partner details, transportation, and attendance), and academic information (study hours, reading books, frequency of reading, writing, preparation strategies, notes, flip-classroom, course ID, cumulative grading points, and output grade). The dataset has this information along with the output label, and the attribute information is illustrated in Table 1.

The above attributes are considered while developing the student dataset, which is more valuable in exploring the importance of the HESD. Once the dataset is obtained, it has

been processed by applying the introduced AA-BAM approach to predict student performance.

3.3. Student Performance Prediction toward HESD. The first step of the HESD-related student performance prediction is data preparation and preprocessing. The data preprocessing utilizes machine learning techniques for changing the raw input data into the computation format. The preprocessing changes the data into a machine-processable format that helps to predict and interpret the data features. The main reason for selecting this step is to identify the noisy, inconsistent, and missing values in the heterogeneous data. Increasing sophistication in the field of artificial intelligence has prompted educational reforms that have modernized higher education, reimagined how schools are operated, and improved the way teachers are trained. Lifelong education, a borderless education system, intelligent campus building, and so on are all included in the new technologies used to achieve these goals. It is through the use of artificial intelligence that we are not only improving our ability to educate. By speeding up the transition from educational system innovation to governance innovation, China's higher education quality improves over time.

Therefore, the data preprocessing procedure is incorporated in this study to enhance the overall system

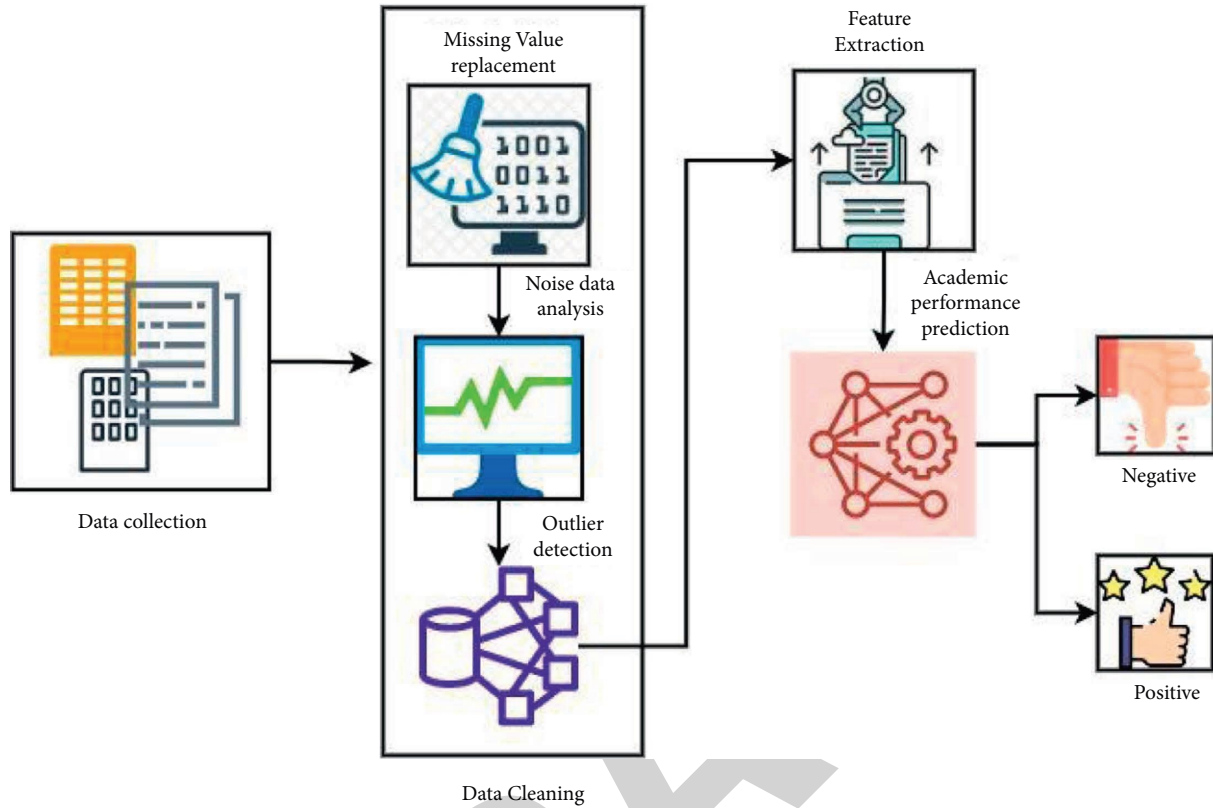


FIGURE 1: Student academic performance analysis structure.

performance and data quality. The missing values in the dataset reduce the overall statistical data analysis, and the outlier and inconsistent data reduce the model learning efficiency, which causes false predictions. The preprocessing step consists of data collection, cleaning, and outlier identification. The overall data preparation, preprocessing, and student performance prediction process are illustrated in Figure 1.

Initially, the data cleaning is performed to remove the outliers, missing values, noise data, and inconsistency. The missing value should be addressed first to improve the data quality, done manually or by applying numerical methods. Suppose the dataset is high in dimension, the tuples are ignored; the missing values need to be filled. In this work, a median filter is applied for computing the missing values. If the dataset has an odd number of records, the filter selects the median value as the missing value. Consider the dataset has n records, and then, the missing value is replaced by computing $(n + 1)/2$ and the estimated using the value. If the dataset has even records, then the missing values are replaced by estimating the $((n/2) + 1)$ value. After replacing the missing values, noise or variance values are removed from the dataset. The variance data are eliminated by applying the discretization process, which minimizes the discrete and continuous data cardinality. During this process, similar data are grouped to minimize the distinct value involvement. It also enhances the overall data utilization and manages the response time while handling the student data without affecting the model quality. The

binning process manages the attribute relationship and enhances the overall student performance analysis system. During the analysis, the binning boundaries are identified according to the attributes involved in the dataset. The main motive for picking the binning procedure is that it is utilized for investigating both categorical and numerical attributes in the dataset. Data have been sorted and divided into equal bins in the binning process. Then, inconsistent data have to be removed from the dataset to enlighten the data quality.

The widespread adoption of AI has radically altered traditional educational concepts and practices. More college education is being transformed by artificial intelligence for quality administrators (QA). The study and use of artificial intelligence by quality administrators (QA) is critical to their professional growth. To better prepare students for the new era of intelligence, it is vital to teaching students how to take tests on their own and use social skills.

The inconsistent or outlier data have been removed by applying the centroid-based clustering procedure. The clustering process utilizes the K-means clustering procedure to explore every data in the dataset. The clustering algorithm works according to the unsupervised learning procedure. The cluster analysis selects the centroids or K-center points iteratively, and the attributes are allocated to the closest centroid. The algorithm selects the best center point and reduces the cumulative square distance between the attribute to the centroid value. The dataset has a set of attributes such as $(x_1, x_2, x_3, \dots, x_n)$, which has d -dimensional vector that

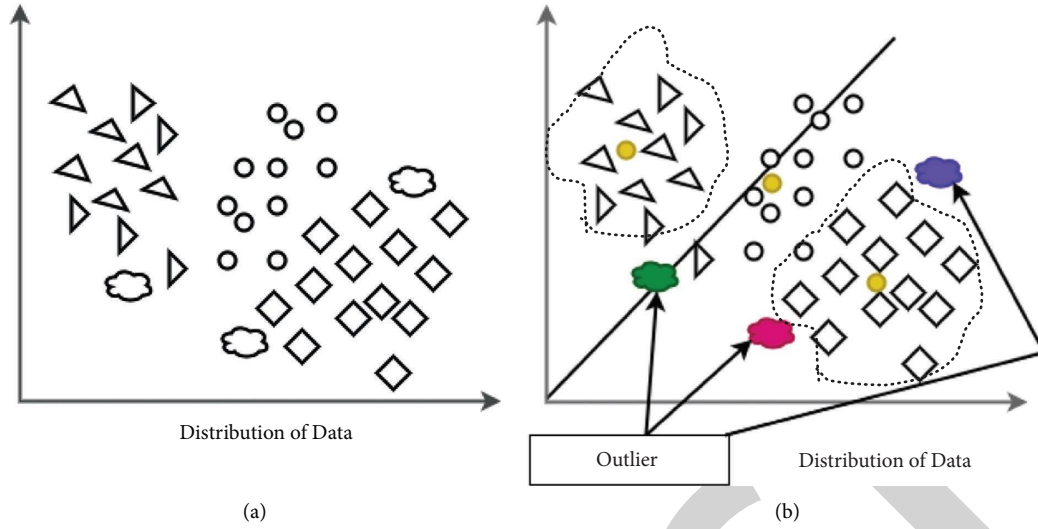


FIGURE 2: Centroid clustering-based outlier elimination (a) Before Clustering, (b) After Clustering.

has to be partitioned into the different sets that are defined as $s = \{s_1, s_2, \dots, s_k\}$. The K-means clustering procedure reduces the outliers by reducing the variance. Then, the objective of the clustering is attained by applying the following equation:

$$\text{clustering objective} = \operatorname{argmin}_s \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2. \quad (1)$$

In equation (1), the k is defined as the number of clusters, x is the attributes that belong to the set or cluster, and the μ is the mean value of the data in the particular set S_i . This process continuously examines the data points, and the cluster members are predicted. For every time, the centroid value has to be recomputed that is done by using the following equation:

$$m_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \in S_i^{(t)}} x_j. \quad (2)$$

The exploration of each attribute x_j in the dataset and centroid values are estimated by reducing the variance value. The clustering process investigates each data point, and similar attributes are grouped. The similarity between the cluster center and other data points is used to identify the outliers in the list. According to the discussion, the predicted outliers are illustrated in Figure 2.

After identifying the outlier from the dataset, data points have been investigated by applying the AA-BAM network model to predict student performance. The AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM) is one of the recurrent neural network (RNN) types that utilize the extensive possibilities to predict the HESD between the students. Here, the cleaned student's information is processed by applying the layer of networks that predicts the features or attributes from the data. The extracted features are explored using the memory network that can process and

store every piece of information. In addition, the network has feedback signals that can process the multiple functions effectively.

The AA-BAM approach is a supervised learning system with hetero-associative memory while processing the student's inputs. The network processes the inputs and gives the output in a different size because it works according to the human brain function. The memory layer helps to recognize the previously processed information. The network receives inputs from one form and has been analyzed using different layers, generating output patterns. The main reason for choosing the memory-related network is to save the hetero-related pattern that can retrieve the exact output pattern, even if it has incomplete or noisy inputs. The adaptive memory-associated neural network structure is illustrated in Figure 3.

Considered the student attributes X with n -dimensional vector and respective outputs Y are recalled from memory set with m -dimensional vector. The recalling process worked in the backward direction; therefore, Y is denoted as input for getting the student performance. The outputs are estimated by using the learning or storage process. The model uses the network parameter called weight matrix (W) during the learning process. Then, the synaptic weight values are calculated using

$$W = \sum_{m=1}^M X_m Y_m^T. \quad (3)$$

The computed W values are applied to the inputs, and the activation function is applied to estimate the output value. The learning process uses the set of information and network parameters to generate the output pattern. Then, the testing phase is initiated to identify the student's new input. Here, the associative memory model recalls the output value for given inputs by examining the student's academic information and the corresponding output estimation illustrated in

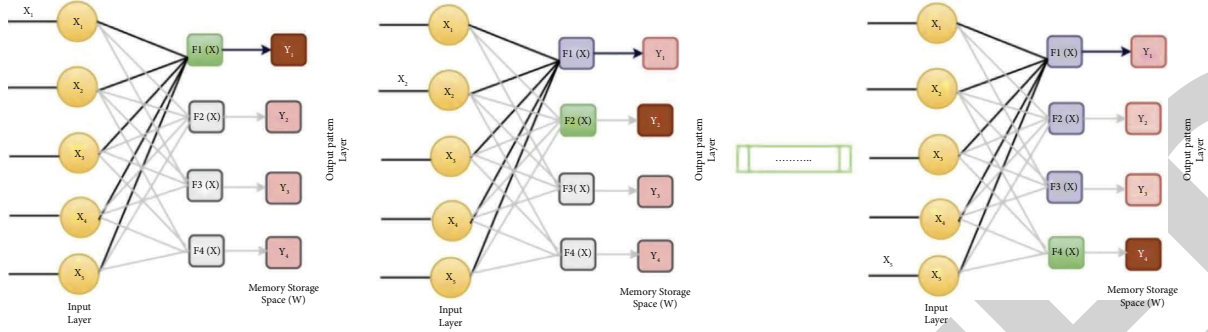


FIGURE 3: Memory-associated neural network structure.

TABLE 2: Steps for associative memory network output computation.

Input: Student academic attributes $x_1, x_2, x_3, \dots, x_n$
Output: Academic performance Y
Step 1: initialize $X(0) = X, p = 0 // X$ -input, p -iteration
Step 2: compute the output for iteration p for a given input $Y(p) = \text{sign}[W^T X(p)]$
Step 3: update the student input vector $X(p)$ $X(p+1) = \text{sign}[WY(p)]$
Step 4: repeat the process to meet the convergence, which means the input and output values are unchanged

$$Y_m = \text{sign}(W^T X_m); \quad m = 1, 2, 3 \dots M, \quad (4)$$

$$X_m = \text{sign}(WY_m); \quad m = 1, 2, 3 \dots M. \quad (5)$$

In equations (4) and (5), W is denoted as the weight value for the given input X_m , and Y_m is the output for the input X_m . After recalling the output pattern, the student's performance should be retrieved using the retrieval procedure. The strength of associative memory network output computation connections can alter over time in response to changes in the stimulation pattern. Neurons can also make new connections with other neurons, and whole groups of neurons can migrate from one location to another. Learning in the brain is assumed to be based on several mechanisms. Learning and memory are underpinned by associative memory network output computation, a fundamental biological function. Numerous learning rules detailing how activity and training experience alter synaptic efficacies have been computed, as a result, using associative memory network output computation. For every unknown student input X , the memory layer analyzes and retrieves the input-associated output. The output is estimated according to the steps defined in Table 2.

According to the above algorithm, the given student inputs are processed to get the output patterns. The memory-associated network learns the data points from different types of data that must be changed to the bipolar pattern. Here, the inputs are processed in terms of binary elements such as -1 's and 1 's. The dataset information may contain the multiple patterns processed by arranging the 2-D

patterns embedded in the column for the output. As defined in Figure 1, the memory network has a memory cell that relates every input with the respective output. The neural model encodes the X input to the Y output using pattern mapping. The mapping process has equal dimensions for both input and output values. At the time of mapping, the network has input, an output layer, and respective network parameters such as synaptic weight. As shown in Figure 1, the network has n neurons that can process the input in the input layer to get the output value. Initially, the input x is forwarded to the memory cell m incorporated in the output layer. The input and output patterns determine the associative network layer size. Here, the network has five neurons and four memory cells for processing the inputs. The introduced network has a memory unit that computes the outputs according to several inputs. Each neuron has a specific weight involved in the output estimation process.

According to the input, the output patterns are recalled to identify the student's performance. After computing the output value for each input, the output layer weighted summation result is estimated and fed into the bipolar threshold function. Then, the network produces the negative (-1) and positive ($+1$) values as the output. The network manages the entire processing parameters, such as input, synaptic weights, memory function, and cells, which helps to improve the overall output pattern identification. The network uses the Hebbian supervised learning (HSL) algorithm to enhance the system performance. The learning process is utilized to recall the output pattern for the given input. During the learning process, the X and Y dot products are computed, producing the correlation matrix W . Here, the W is defined and the recollected output for a given input. The recall process is done by performing the dot product WX_k or WY_k . This analysis keeps most of the weight value and discards the weight values when it has zero. The recall process has $W_{n \times m}$ that is obtained from the input and output patterns. During the student performance analysis, the system must handle the classification problem due to the incomplete data and weak classifier. The research problem is overcome by applying the boosting algorithm. The boosting process is used to change the weak learners into strong learners. The boosting algorithm generates the training or learning model using the training data. Then, errors are identified from the created model, which helps to reduce the

error rate in student performance analysis. This work uses the adaptive boosting (AdaBoost) algorithm to make decisions regarding student performance. The training model was developed by considering the equal weights of the entire data points. The training process is performed to get the minimum error rate. Suppose the network has n data points, then each neuron has $1/n$ as an equal weight value in every node. After computing the equal weight value, Gini Index (GI) value for each feature should be estimated:

$$GI = \frac{\sum_{i=1}^n \sum_{j=1}^n |x_i - x_j|}{2 \sum_{i=1}^n \sum_{j=1}^n x_j} \quad (6)$$

In equation (6), x_i, x_j is represented as the student's academic attributes. All student attributes are explored to get the GI value. The GI is partially represented as the relative mean absolute difference (RMAD), equivalent to the Lorenz curve. The computed GI value identifies the difference between the two features, which identifies the student involvement in learning. The GI had values between 0 and 1; it helps to identify the positive and negative impact of the HESD. After identifying the GI value, the importance of the classifier must be analyzed by computing the error rate (equation 7).

According to the RMAD, the student's academic attributes, assessment scores, final results, and other learning factors are investigated to alert the student interventions. Students' privacy concerns can be alleviated by minimizing the requirement for invigilators or having access to their accounts because of the high level of accuracy (93%).

$$\text{Importance} = \frac{1}{2} \log \frac{1 - TE}{TE} \quad (7)$$

In equation (7), TE is denoted as the total error, estimated by computing the summation of the misclassified data points corresponding sample weight value. After calculating the classifier importance and TE value, the deviation between the actual and computed output is estimated. If the training model has the error value, then the network parameter weight value has been updated. Then, the new weight value is estimated using

$$Nw = \text{old weight} * e^{\pm \text{Importance}} \quad (8)$$

In equation (8), Nw is defined as the new weight value computed from the old weight value and importance. If the importance has a negative value, then the AA-BAM approach correctly classifies the student learning performance toward HESD. Suppose the importance value produces the positive, then the samples have been misclassified. This process is repeated continuously until to get a lower error rate. The effective utilization of the memory cell and AdaBoost algorithm improves student performance in HESD. According to the student performance, particular subject development in HE feedback is collected from teachers. The classifier predicts the positive and negative feedback depending on the cumulative grading points and student involvement. The collected reviews are examined, and the

committee gives the amending outlines for improving the HESD performance.

3.4. HESD Amending Guidelines. The subject development importance should be examined according to the student results classified from the AA-BAM. The feedback and results of HESD require minor and significant amendments. After making the amendments, the committee members re-evaluate the developed subjects to be incorporated into higher education.

In higher education, artificial intelligence has fulfilled the role of low-level instruction. The use of the AA-BAM network in higher education institutions is becoming increasingly widespread. Instructors and students may better understand each other's learning situations through data collecting, analysis, categorization, and matching. Teaching approaches that encourage students' creativity, collaboration, emotional intelligence, and other social skills will be developed so that instructors have new tools to use. Allowing students to leave the classroom and no longer be bound by objectives and assignments improves the trajectory of higher education growth.

3.4.1. Minor Amendments

- (i) The student performance assessment time needs to be extended to improve the student learning efficiency.
- (ii) Subject task and assessment workload calculator must be utilized for a different task, broad content, and model for evaluating the student performance. During the assessment, the subject coordinator's permission needs to be received, and the task weight values are unchanged.
- (iii) The subject coordinator needs to assess the lecturer's notes, reference list, and textbook changes for accepting and rejecting the changes. According to the student score, the subject development process has taken almost 1 to 2 months to approve the HESD.
- (iv) The contextualization elements are updated continuously because it does not impact the subject objectives.

Suppose the student attains negative feedback or marks; the HESD requires significant amendments. After performing the amendment, students are instructed to learn the new subjects, and their performance is evaluated to understand the HESD importance.

3.4.2. Major Amendments

- (i) Alter the corequisite or prerequisite of the subject. The lecture must give a copy of the subjects to the subject coordinator to enhance the learning process. The subject changes are done based on expert accreditation. It may take 1 to 2 months to prepare.

- (ii) Helping students in big courses to properly advance through their learning experience to reach targeted results, conducting evaluations, and providing constructive individualized feedback remained problems required for subject-related examinations.
- (iii) Outline of the subject, code, and name of the subject should be considered. The subject coordinator takes charge of updating the subject concept, and the changes should be in the rationale. This process has also taken almost two months.
- (iv) The subject teaching framework, answer formation, and practical analysis should be reviewed by the Teaching and Learning Committee and the Subject Coordinator. According to the importance of the concept, the committee members may accept and reject the subjects. In this stage, extra support has to be needed to improve the overall learning process.

After making the appropriate amendment, the changes involved in the subject, proposal, and framework should be updated with the lecturer, Dean of Faculty, Subject Coordinator, stakeholders, program director, head of the department, and library. These members update the subject ideas, and master copies are managed for further assessment.

4. Results and Analysis

Information from the Kalboard 360 Learning Management System (LMS) is used to compile this data collection. Using cutting-edge technology, Kalboard 360s multi-agent LMS is meant to make learning easier. A system allows students to admittance instructional information in real time from somewhat Internet-connected device. Using a technology called experience API, learner activity data are gathered. Training and learning architecture (TLA) keeps track of how much a student has learned and what actions they have taken, such as reading, viewing, and training video. Learners, activities, and objects that characterize a knowledge experience may be identified using the involvement API. Of 480 student records and 16 different characteristics, 150 student records have been considered to make up the dataset in this study. It may be divided into three primary groups: (1) gender and nationality of demographic characteristics; (2)

educational level, grade level, and sector of schooling; (3) behavioral characteristics like raising their hands in class, opening up resources, and responding to parent surveys are examples.

This section discusses the efficiency of the AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM) Network-based HESD. The detailed analysis of the statistical findings and AA-BAM approach-related student performance is evaluated. Here, Kaggle dataset information is utilized for investigating the student performance on HESD; around 60% of data is used for training purposes and 40% for testing analysis. The collected student academic information is processed by the AA-BAM approach that identifies the positive and negative impact of the subject development on the learning system. To compare and draw conclusions from the data, this article will use research methodologies and analysis tailored to specific challenges. According to surveys, almost all students (approximately 85–75%) agree that the future of higher education may be brightened by the implementation of artificial intelligence (AI). Students cannot keep up with today's fast-paced culture unless we help them develop self-directed learning skills using active learning for the rapid growth of higher education under AI.

The introduced neural classifier resolves the weak learner involvement and binary classification problem. The developed neural model should consume the minimum error rate, which means the system consumes a minimum deviation between the actual and predicted values. The low square value means the computed output values are more relevant to the output patterns. The error values are calculated by applying the following equation:

$$\text{mean square error rate} = \frac{1}{n} (y_{ij} - t_{ij})^2. \quad (9)$$

In equation (9), y_{ij} is defined as the computed output value, and it has to be compared with the target output t_{ij} . The calculated error values are close to error, which means the introduced algorithm successfully predicts the output with maximum accuracy. In addition, accuracy, sensitivity, specificity, and correlation metrics are utilized to evaluate the effectiveness of the introduced system. These metrics are estimated using the following equations:

$$\text{sensitivity} = \frac{\text{true positive}}{\text{true positive} + \text{false negative}}, \quad (10)$$

$$\text{accuracy} = \frac{\text{true positive} + \text{true negative}}{\text{false positive} + \text{false negative} + \text{true positive} + \text{true negative}}, \quad (11)$$

$$\text{correlation analysis} = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (12)$$

In equations (10–12), true positive (TP) is defined as the AA-BAM approach correctly identifying the student

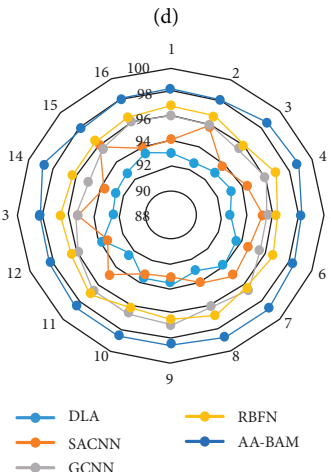
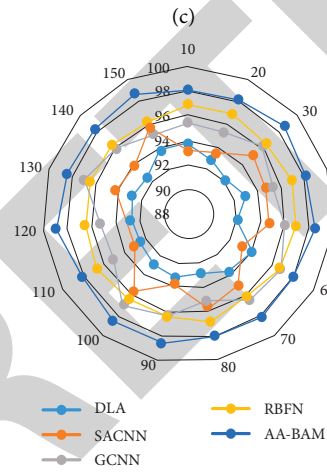
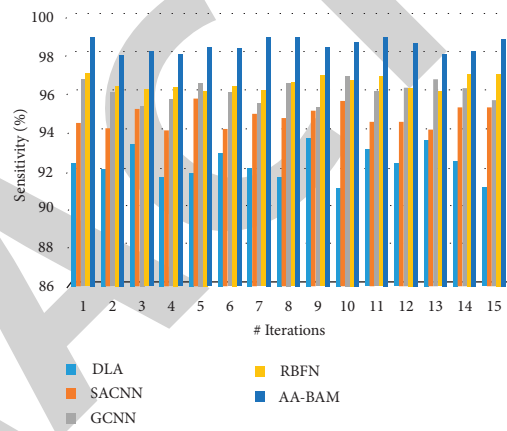
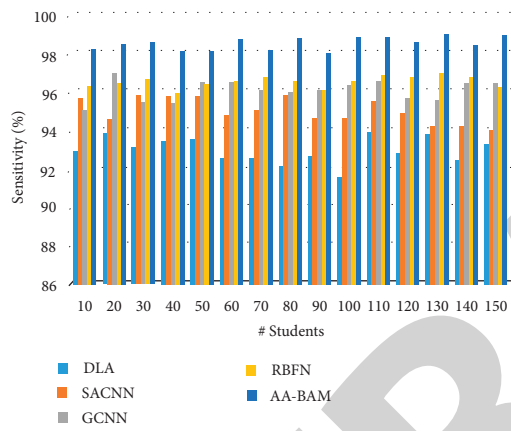
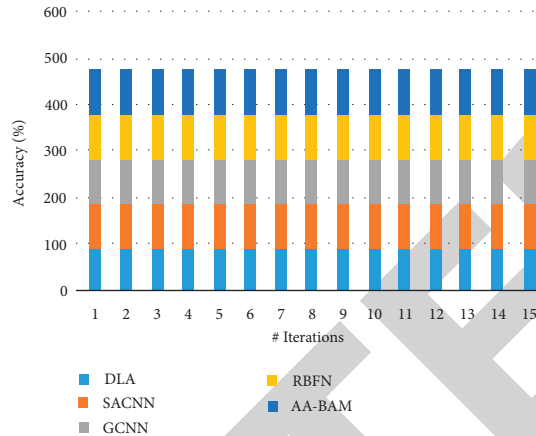
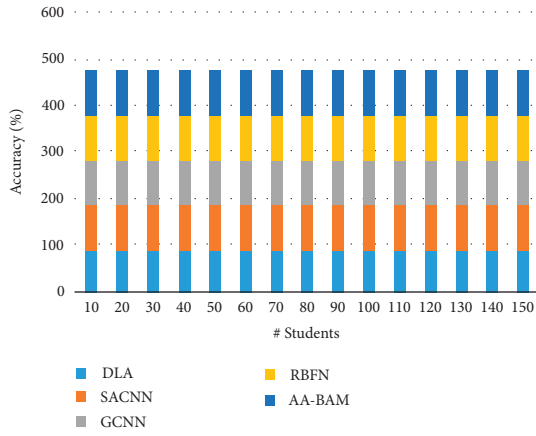


FIGURE 4: Continued.

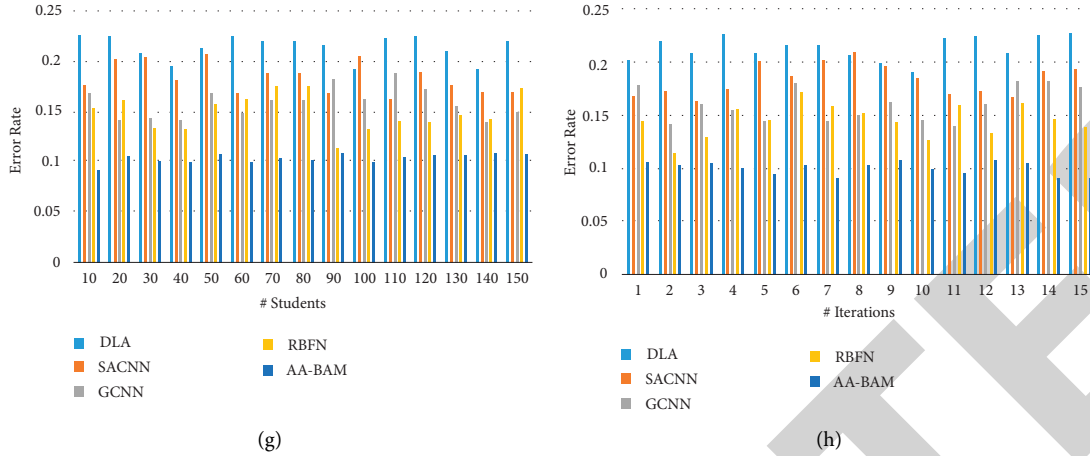


FIGURE 4: (a, b) Accuracy analysis; (c, d) sensitivity analysis; (e, f) correlation analysis; (g, h) error rate analysis of AA-BAM.

TABLE 3: Spearman's rho correlation analysis.

Actual value (x)	Computed value (y)	Rank of x	Difference between rank x and mean of x	Rank y	The difference between rank y and mean of y	Sum difference
45	41	5.00	1.50	4.00	0.50	0.75
44	42	4.00	0.50	5.00	1.50	0.75
33	34	2.00	-1.50	3.00	-0.50	0.75
35	26	3.00	-0.50	1.00	-2.50	1.25
63	74	6.00	2.50	6.00	2.50	6.25
30	33	1.00	-2.50	2.00	-1.50	3.75

performance from their learning attributes. True negative (TN) means wrongly identifying the student's performance, false positive (FP), which eliminates the wrong information while analyzing the student's performance. False negative (FN) means rightly rejecting the false student attribute. The discussed system was developed using the Python tool. During the analysis, academic-related features such as study hours, reading frequency, cumulative grade points, and classroom flips are utilized. The obtained results are compared with the existing algorithms such as deep learning approach (DLA) [20], sparse attention convolution neural network (SACNN) [21], graph convolutional neural network (GCNN) [22], and radial basis function neural model (RBFN) [23]. Then, the obtained results are illustrated in Figure 4.

Figure 4 illustrates the efficiency analysis of the introduced AA-BAM algorithm with the existing method-based student performance analysis system. Here, the AA-BAM approach attains 98.78% of accuracy, 98.41% of sensitivity, and 98.57% of correlation values for different students' academic records. The analysis is extended for different iterations, and the introduced AA-BAM approach attains high results such as 98.54%, 98.52%, and 98.41% of correlation analysis values. The above results clearly show that the introduced AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM) approach successfully recognizes student performance from data collection. During the analysis, the recommended AA-BAM approach uses the student

academic features collected from the Kaggle dataset. The attributes in the dataset were successfully processed by the data preprocessing and bidirectional associative memory network function. A combination of statistical and clustering algorithms is utilized in the data preparation and cleaning procedure. The effective utilization of the mean filter helps to remove the noise and inconsistent data. The less inconsistent values help to improve the overall student performance analysis. In addition, the associative memory network uses the memory cell (m) that predicts the output pattern $\text{sign}[W^T X(p)]$ for every input effectively. The network uses the training model to identify the matching patterns that effectively recognize student performance. The training model is generated according to the AdaBoost algorithm that reduces the weak learner's involvement in the classification process. The boosting procedure continuously updates the network weight value, $Nw = \text{old weight} * e^{\pm \text{Importance}}$. The computed weight values are incorporated with the input to get the output pattern. Here, the student information is explored in the initial stage to reduce the inconsistent and outlier data by applying the centroid-based clustering algorithm. During this process, the K-means clustering algorithm estimates the distance between the data and the centroid. According to the distance measure, similar data are grouped; this process minimizes the error rate. The training model is created by using the supervised learning model, which is done by utilizing the Gini Index ($\sum_{i=1}^n \sum_{j=1}^n |x_i - x_j| / 2 (\sum_{i=1}^n \sum_{j=1}^n x_j)$). The GI value is

continuously checked to reduce the difference between computed and target output values. In addition, the summation of the misclassified data points with corresponding sample weight values is estimated via equation (7). These two parameters are widely applied to improve the overall student academic performance analysis. The dataset covers almost students' entire academic information that helps to identify the variations involved in the student learning activities. According to the derived student academic performance, the HESD efficiency is analyzed to get how the student performance is interrelated with the subject change. The HESD and student performance relationship are analyzed using Spearman's Rho correlation analysis (SRC). The SRC is one of the effective nonparametric tests that help to identify the strong association between student learning performance and subject change. If the SRC relation (r) has the value of one, both attributes have a strong relationship, and -1 means that it has a negative correlation analysis. The SRC value is estimated using the following equation:

$$\text{SRC} = 1 - \frac{6\sum D^2}{N^3 - N} \quad (13)$$

In equation (13), D is defined as the difference between the two observations, and n is the quantity of observations. Here, the efficiency is assessed for 250 students' academic records, and the results are illustrated in Table 3.

Table 3 shows the relationship between the student's academic attributes and subject development in higher education. Here, the analysis uses the expected outcome of the student attribute with the target attribute. The correlation analysis uses the rank value and means value for x that identifies the relationship between the two attributes in the computation. From the analysis, the system ensures the 0.77% value related to a positive value, which means that the student performance also creates the subject development in the HE. Therefore, in higher education system, student performance has been creating a significant impact on the HESD. If the calculated student performances are more significant to the subject development, then it requires minor reforms in the subject development. Students are surveyed using HESD to uncover the underlying factors contributing to failure or success. It was decided to use Spearman's correlation coefficient model to examine the traits of success and failure that are most closely linked. Results suggest a significant association exists between exogenous variables such as students' desire to excel in their education and the job environment. Students' performance is highly influenced by factors specific to the institutions, such as the clarity and understanding of the ability of test papers and study resources. In light of these findings, this research should take a comprehensive and inclusive approach to develop and execute strategies targeted at enhancing student performance and avoiding obstacles that impede student achievement. Else, significant changes are required, which are described in Section 3.4. According to the results, subject development changes are made to improve the overall academic performance. Hence, it is suggested to understand the broader context of development, research, and assess the changing nature of industry

demand, grab new possibilities, meet new problems head-on, and collaborate to advance higher education in the new millennium.

5. Conclusion

Thus, the paper analyzes the AdaBoost Adaptive-Bidirectional Associative Memory (AA-BAM)-based Higher Education Subject Development (HESD). This work uses Higher Education Students Performance Evaluation dataset information to evaluate the relationship between student performance and subject development. The collected student details are investigated by applying the preprocessing procedure that eliminates the irrelevant, missing data, and outlier information. During this process, each data point's distance and characteristic are examined to form the cluster. This centroid-based clustering procedure reduces outlier involvement. Then, memory associative neural network is utilized to save the processed information. The memory cells are more helpful in recalling the output patterns relevant to the inputs. In addition, Hebbian supervised learning (HSL) is incorporated to improve the overall student performance detection efficiency by creating the training model. The subsequent development of training data reduces the difficulties in extensive volume data and subject-based improvement. The created system successfully recognized the student performance up to 98.78%. According to the student performance, the HESD subjects are amended to improve the learning quality. However, this system requires improvement while handling students' entire academic features. The large volume of data has to be reduced by applying the dimensionality reduction technique. The selected features help to improve the overall HESD performance.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

References

- [1] J. Martins, F. Branco, R. Gonçalves et al., "Assessing the success behind the use of education management information systems in higher education," *Telematics and Informatics*, vol. 38, pp. 182–193, 2019.
- [2] S. Quarchioni, S. Paternostro, and F. Trovarelli, "Knowledge management in higher education: a literature review and further research avenues," *Knowledge Management Research and Practice*, vol. 20, no. 2, pp. 304–319, 2022.
- [3] D. A. Housel, "An exploratory study of instructors who became administrators of post-secondary ESOL programs in the United States," *The Journal of Continuing Higher Education*, pp. 1–15, 2022.
- [4] S. Subhash and A. Elizabeth, "Cudney Gamified learning in higher education: a systematic review of the literature," *Computers in Human Behavior*, vol. 87, pp. 192–206, 2018.

- [5] H. J. Machumu, *Constructivist-based Blended Learning Environments in Higher Education: Student and Teacher Variables in the Tanzanian Context*, Vrije Universiteit Brussel, Brussels, Belgium, 2018.
- [6] P. R. Kitula and O. Evans, "Effectiveness of implementing continuous assessments in Tanzanian universities," *International Journal of Contemporary Applied Researches*, vol. 5, no. 7, pp. 1–18, 2018.
- [7] A. S. Mikhaylov and M. Anna Alekseevna, "University rankings in the quality assessment of higher education institutions," *Calitatea*, vol. 163, pp. 111–117, 2018.
- [8] D. Wang, Y. Sun, and T. Jiang, "The assessment of higher education quality from the perspective of students through a case study analysis," *Frontiers of Education in China*, vol. 13, no. 2, pp. 267–287, 2018.
- [9] C. Adachi, J. H.-M. Tai, and P. Dawson, "Academics' perceptions of the benefits and challenges of self and peer assessment in higher education," *Assessment and Evaluation in Higher Education*, vol. 43, no. 2, pp. 294–306, 2018.
- [10] A. Armellini, V. T. Antunes, and R. Howe, "Student perspectives on learning experiences in a higher education active blended learning context," *TechTrends*, vol. 65, no. 4, pp. 433–443, 2021.
- [11] R. Alamri and B. Alharbi, "Explainable student performance prediction models: a systematic review," *IEEE Access*, vol. 9, pp. 33132–33143, 2021.
- [12] A. Rivas, A. Gonzalez-Briones, G. Hernandez, J. Prieto, and P. Chamoso, "Artificial neural network analysis of the academic performance of students in virtual learning environments," *Neurocomputing*, vol. 423, pp. 713–720, 2021.
- [13] D. Aggarwal, S. Mittal, and V. Bali, "Significance of non-academic parameters for predicting student performance using ensemble learning techniques," *International Journal of System Dynamics Applications*, vol. 3, pp. 38–49, 2021.
- [14] S. F. Shetu, M. Saifuzzaman, S. Sultana, and R. Yousuf, "Student's performance prediction using data mining technique depending on overall academic status and environmental attributes," in *Proceedings of the International Conference on Innovative Computing and Communications*, Springer, Berlin, Germany, 2021.
- [15] J. Annala, M. Mäkinen, J. Lindén, and J. Henriksson, "Change and stability in the academic agency in higher education curriculum reform," *Journal of Curriculum Studies*, vol. 54, no. 1, pp. 53–69, 2022.
- [16] J. F. Duque, "A comparative analysis of the Chilean and Colombian systems of quality assurance in higher education," *Higher Education*, vol. 82, no. 3, pp. 669–683, 2021.
- [17] I. M. Ho, K. Y. Cheong, and W. Anthony, "Predicting student satisfaction of emergency remote learning in higher education during COVID-19 using machine learning techniques," *PLoS One*, vol. 16, no. 4, Article ID e0249423, 2021.
- [18] V. Kuleto, M. Ilić, M. Dumangiu et al., "Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions," *Sustainability*, vol. 18, Article ID 10424, 2021.
- [19] R. Hernández, C. Felipe, M. Musso, E. Kyndt, and E. Cascallar, "Artificial neural networks in academic performance prediction: systematic implementation and predictor evaluation," *Computers and Education: Artificial Intelligence*, vol. 2, Article ID 100018, 2021.
- [20] F. Giannakas, C. Troussas, I. Voyiatzis, and C. Sgouropoulou, "A deep learning classification framework for early prediction of team-based academic performance," *Applied Soft Computing*, vol. 106, Article ID 107355, 2021.
- [21] Y. Zhang, A. Rui, J. Cui, and X. Shang, "Undergraduate grade prediction in Chinese higher education using convolutional neural networks," in *Proceedings of the LAK21: 11th International Learning Analytics and Knowledge Conference*, Association for Computing Machinery, New York, NY, United States, 2021.
- [22] P. Hai-tao, H. Zhang, Y. Bi-Zhen et al., "Predicting the academic performance of students in Chinese-foreign cooperation in running schools with graph convolutional network," *Neural Computing and Applications*, vol. 33, no. 2, pp. 637–645, 2021.
- [23] O. Olabanjo and A. Wusu, *A Machine Learning Prediction of Academic Performance of Secondary School Students Using Radial Basis Function Neural Network*, 2022.
- [24] E. P. Dogadina, M. V. Smirnov, V. O. Aleksey, and V. S. Stanislav, "Evaluation of the forms of education of high school students using a hybrid model based on various optimization methods and a neural network," *Informatics*, vol. 8, no. 3, p. 46, 2021.
- [25] N. Yılmaz and B. Sekeroglu, "Student performance classification using artificial intelligence techniques," in *Proceedings of the 10th International Conference on Theory and Application of Soft Computing, Computing with Words and Perceptions—ICSCCW-2019*. ICSCCW 2019, Springer, Berlin, Germany, 2020.