Bayesian Asymmetric Quantized Neural Networks Students Behaviour Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness with Snow Geese Algorithm

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Abstract. Data-driven models are used in Students' Behavior Prediction with Feedback Generation to predict learning demands and student behaviors. It offers individualized feedback to boost classroom involvement and teaching effectiveness by assessing engagement patterns and performance. The goal is to improve student outcomes and customizes instructional tactics to meet the needs of each individual student. To overcome these problems, Bayesian asymmetric quantized neural networks with Snow Geese Algorithm (BAQNN-SGA) is proposed. In this, input data is taken from a dataset such as OULAD datasets. It pre-processed data using Savitzky-Golay Denoising method (SGDM), Following that, Students Behaviour Prediction for Enhancing Classroom Engagement and Teaching Effectiveness is then the features extracted using Adaptive Quantization for a Discrete Wavelet Transformation's Coefficients (AQDWTC), Following that Feature selection using Giant Trevally Optimizer (GTO) and classification Bayesian asymmetric quantized neural networks (BAQNN) and the optimization using Snow Geese Algorithm (SGA) for detecting the type of Students Behaviour Prediction and to find the Low achiever, Medium, High achiever Engagement. The introduced system is executed in python. The efficiency of the proposed BAQNN-SGA is analysed using a datasets and attains 99.9% accuracy, 99.8% recall and attains better results compared with the existing methods. This indicates the approach's superior efficiency and potential for further development in the field.

Keywords: Savitzky-Golay Denoising method (SGDM), Adaptive Quantization for a Discrete Wavelet Transformation's Coefficients (AQDWTC), using Giant Trevally Optimizer (GTO), Bayesian asymmetric quantized neural networks (BAQNN) and Snow Geese Algorithm (SGA).

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1 Introduction

The Motivation to study is essential for effective learning. Personalized learning in the classroom can be supported by artificial intelligence (AI) technology. Artificial intelligence (AI) systems can serve as policymakers' advisors, intelligent tutees, intelligent tutors, or intelligent learning tools. There are several different types of intelligent tutoring systems, including recommendation, personalized, and adaptive learning systems. Research has demonstrated that effective tutoring programs can enhance pupils' academic performance [1]. There is growing interest in identifying students who are likely to perform badly in STEM programs so that attrition can be avoided in a timely manner. To forecast pupils' success or failure, a variety of data sources have been used, frequently incorporating demographic data regarding underrepresented groups. Log data on student learning activities is collected by LMSs such as Sakai, Blackboard Learn, Desire2Learn, and Canvas. This allows researchers to monitor user behaviour and analyse data from different angles [2]. This project aims to produce a solution artifact that quantifies instructors' efficacy in the classroom by utilizing machine learning techniques. Researchers can build up learning opportunities and track learning progress with this artifact, which makes use of a case a collection from the machine learning repository at UCI. This creative method improves teachers' effectiveness in the classroom [3]. The ability of smart devices and technology to provide online peer feedback has drawn a lot of interest due to its potential to enhance writing skills. With the use of this technology, students can more easily engage in critical discourse and reasoning processes while also giving excellent anonymous feedback. Yet, student participation in the learning process is essential for the effectiveness of online peer review. Low percentages of feedback might be included into revisions, according to some studies, and learners with little subject expertise might find it difficult to understand feedback. Critical feedback may also be impeded by emotional obstacles. Participating actively in peer feedback is therefore essential [4-5]. In order to evaluate the study examines teaching and learning in a large, fully online university course student engagement as a novel way to measure quality. The study was carried out in an Italian university and examined the behavioural, utilizing reflective diaries and Moodle log data to track students' emotional and cognitive participation in a mandatory course kept by the students [6-7].

Novelty and contribution

The Novelty and contribution of this paper is given below:

- In this manuscript, a Bayesian Asymmetric Quantized Neural Network [18] with Snow Geese Algorithm for Students Behaviour Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness (BAQNN-SGA) is proposed.
- The objective of using Savitzky-Golay Denoising Method (SGDM) [13] for pre-processing is a common smoothing and denoising technique that improves data quality by lowering noise while maintaining crucial signal characteristics.
- The objective of employing Students Behaviour Prediction is feature extracted using Adaptive Quantization for a Discrete Wavelet Transformation's Coefficients (AQDWTC) [14] dynamically modifies the quantization step size according to the local properties of the signal.

- The objective of employing Students Behaviour Prediction is feature selection using Giant Trevally Optimizer (GTO) [15] to ensure that relevant and significant features are chosen for student performance, the study presented a feature selection approach to eliminate irrelevant features from predictive models.
- The Students Behaviour Prediction for classification using Bayesian asymmetric quantized neural networks (BAQNN) with Snow Geese Algorithm (SGA) [16-17] improving accuracy and robustness. This approach aims to leverage diverse feature extraction and global optimization for precise and reliable detection of various Students Behaviour Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness to find Low achiever, Medium, High achiever Engagement.

Section 2 surveys the existing literature, Section 3 proposes a method, Section 4 discusses the findings and observations, and Section 5 concludes with recommendations for future research.

2 Literature Survey

The papers related to Students Behavior Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness using deep learning methods is given below:

In 2023 Alruwais, et a1. [8] has introduced an Extreme Gradient Boosting (XGBoost) for Students Behaviour Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness. The goal of the study is to identify the optimal algorithm for forecasting classroom participation from students. Several pre-processing methods and machine learning classification algorithms were used to process the VLE data. The accuracy of the CATBoost model was superior to other models, indicating the complexity of student involvement.

In 2024 Alnasyan, et a1. [9] has introduced a Factorization Deep Product Neural Network (FDPN) for Students Behavior Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness. In order to help teachers discover the strengths and limitations in their students' achievement, deep learning approaches have become essential for forecasting student performance. According to an analysis of 46 research examined between 2019 and 2023, CNN-LSTM models and DNNs are the most widely utilized techniques in MOOCs; the most well-liked model is OULAD, or the Open University Learning Analytics Dataset significant predictors were found to be learning behaviour and activity aspects, indicating that student engagement with the learning environment is critical to success.

In 2024 Kukkar, et a1. [10] has introduced a Recurrent Neural Networks and Long Short Term Memory networks (RNN-LSTM) for Students Behavior Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness. The paper presents a novel approach that uses machine learning models to predict students' academic progress by combining academic, demographic, emotional, and VLE sequence data.

In 2024 Hassan, et a1. [11] has introduced a Semantic-based Modelling Framework for Student Outcome Prediction (SMFSOP) for Students Behaviour Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness. The study suggests a framework known as SMFSOP, which automatically connects student actions to the Community of Inquiry model, a standardized behavioural model. This approach is applied to forecast results and group pupils. Data collection, pre-processing, automatic mapping, clustering, and prediction are the three stages of the framework. Three real-world datasets are used to test the system and make sure it is applicable.

In 2023 Gámez-Granados, et a1. [12] has introduced a Joint neural network (JNN) for Students Behavior Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness. In order to solve the problem of identifying reinforcement or extension activities, the research suggests utilizing FlexNSLVOrd, an optimized ordinal classification method, to forecast students' success in remote courses.

2.1 Problem Statement

Utilizing data-driven models, learning demands and actions of students are predicted with the goal of improving teaching effectiveness and classroom engagement by providing personalized feedback. But it's still difficult to forecast student behavior with any degree of accuracy and to increase participation. Using data from datasets like OULAD to enhance prediction accuracy and teaching strategies, the suggested method uses Bayesian asymmetric quantized neural networks optimized with the Snow Geese Algorithm (BAQNN-SGA) to address these problems.

3 Proposed Method

Fig 1 illustrates the operation. The proposed method consists of five process (1) Image Acquisition, (2) pre-processing (3) Feature Extraction (4) Feature selection (5) classification and optimization.

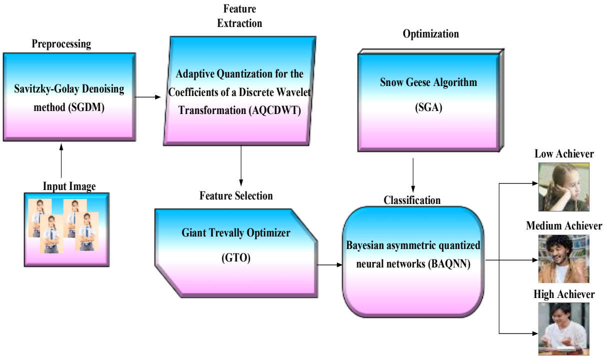

Fig 1. Workflow diagram of proposed BAQNN-SGA method

A. Image Acquisition

In this input images are taken from a datasets such as OULAD dataset. These images are collected from the Students Behavior Prediction images, so that, these images are full of noises, to remove these noises pre-processing techniques are used, they are given below:

B. Pre-processing using Savitzky-Golay Denoising Method (SGDM)

Following data collection, pre-processing was done on the downloaded data files to keep students' identities private, eliminate redundant data, link students to their social and educational activities, and label students. Input Students Behaviour Prediction images are full of noise so Savitzky-Golay Denoising Method (SGDM) [13]. In signal processing, the Savitzky-Golay (SG) filter is a common smoothing and denoising technique that improves data quality by lowering noise while maintaining crucial signal characteristics. Data preprocessing involves cleaning, converting, and formatting datasets to enhance analysis accuracy and reliability. Properly handling missing values is crucial, as neglect can lead to biased or erroneous results. Time-series data, which is frequently used in applications like student behaviour prediction, is one area in which it is quite helpful. Using a linear least-squares approach, A non-causal FIR smoothing filter is the Savitzky-Golay filter that successfully preserves a signal's high frequency components without changing its original properties is given in equation (1):

$$x_j = \sum_{m=-mK}^{mQ} B_n y_{j+m} \tag{1}$$

where, mK is the quantity of samples regarded as being on the left side of the data point j, Conversely, the quantity of samples to the right of position i is shown by mQ, The data point gets replaced by the S-G filter x_j, x_j the smoothed or filtered value at index j, y_{j+m} is the data point at index $j+m$, B_n Coefficients used in the smoothing or filtering process, mK number of points to the left of j in the window, mQ number of points to the right of j in the window.

A polynomial of a given degree is fitted to a moving window of data points in order to create the Savitzky-Golay filter, which smooth's the data. While eliminating noise, this method aids in keeping significant trends and patterns in the data. By mitigating the effects of measuring mistakes and random noise, underlying trends can be seen more clearly. Enhance the quality of the input data for machine learning models and produce predictions and insights about student behaviour that are more accurate by applying the Savitzky-Golay filter. After data pre-processing, the OULAD dataset was assessed using the learning environment. The data was then divided based on normalization approaches and handling of missing values. The outcomes of this pre-processing included the selection of features and classification. Then the feature extraction is done.

C. Feature extraction using Adaptive Quantization for a Discrete Wavelet Transformation's Coefficients (AQDWTC)

After pre-processing the feature extraction is carried out. The feature extraction using Adaptive Quantization for a Discrete Wavelet Transformation's Coefficients (AQDWTC) [14]. For Discrete Wavelet Transformation (DWT) coefficients, adaptive quantization dynamically modifies the quantization step size according to the local properties of the signal. The DWT compression by the JPEG200 standard algorithm. In applications such as image and signal processing, this method improves compression efficiency by lowering the number of bits required for representation while maintaining important information, resulting in more precise signal reconstruction is given in equation (2):

$$T_{i,l}^{K} = \sum_{m=0}^{M-1} T_{i=1,m}\, g_{m-2l} \qquad (2)$$

where, m is the numbers of counts for an original discrete signal, L is the numbers of DWT coefficients for the transformed signal within a range from 0 to $(M-1)/2$, $T_{i,l}^{K}$ Coefficient at scale i and position l, $T_{i=1,m}$ Coefficient at the previous scale $i=1$ and position m, g_{m-2l} Filter coefficient, $\sum_{m=0}^{M-1}$ Summation over M terms. After scaling and splitting the signal into its low- and high-frequency components, 2D images undergo wavelet modification, which is followed by quantization with a fixed step size. The quantization DWT coefficients at each iteration can be described in equation (3):

$$\hat{T}_i^{GG} = \left\lfloor \frac{T_i^{GG}}{\Delta_i^{GG}} \right\rfloor \qquad (3)$$

where, $\hat{T}_i^{GG}$ Quantized high-high frequency coefficients at scale i, T_i^{GG} Original high-high frequency coefficients at scale i, Δ_i^{GG} Quantization step size for the high-high frequency sub band at scale i .For each sub range, fixed quantization steps are used in JPEG2000 to conduct DWT coefficient quantization. By allocating more bits to significant coefficients and fewer to less important ones, adaptive quantization improves compression efficiency and data representation by adjusting the precision of discrete wavelet transformation coefficients based on their significance. This method may result in less effective compression because it ignores the image's local properties and structural details. Feature selection is given below.

D. Feature selection using Giant Trevally Optimizer (GTO)

After that, the extracted features are given to the feature selection. Feature selection using Giant Trevally Optimizer (GTO) [15]. In order to ensure that relevant and significant features are chosen for student performance, the study presented a feature selection approach to eliminate irrelevant features from predictive models. The GTO method uses a met heuristic computation based on the reasons behind the chasing behaviours of the monster trevally to solve the P-OPF problem. The GTO approach makes use of numerical simulations of the foraging travels of mammoth trevallies in order to improve the algorithm's exploration capacity and ensure a safe separation from nearby optimal points. The state that was used in the described is given in equation (4):

$$Y(s+1) = Best_o \times W + (Maximum - Minimum) \times W + Minimum \times Levy(Dim) \tag{4}$$

where, $Y(s+1)$ is denoted as the massive trevally's position vector in the next iteration, $Best_o$ refers to the prominent position attained, W refers to a random number that ranges from 1, $Levy(Dim)$ refers to the Need flight. At this point, the algorithm determines the best hunting location inside the search space based on food accessibility. After the reproduce this behaviour is given in equation (5):

$$Y(s+1) = Best_o \times \mathrm{B} \times W + Mean_{Info} - Yj(s) \times W \tag{5}$$

where, B perhaps a parameter that regulates changes in position, $Yj(s)$ indicates the position at that moment, and W might be any number at all. The framework uses Snell's equation for visual twisting to mimic a trevally attacking its victim and impairing its vision due to light refraction. The trevally attack is given in equation (6):

$$Y(s+1) = \mathrm{K} + U + G \tag{6}$$

where, $Y(s+1)$ represents a different stance, K is the dispatch speed, U is the damage to the visual, and G is the jumping incline work. Allowing the computation to proceed from the level of research to the step of misuse in this way. A meta heuristic algorithm called the gigantic Trevally Optimizer (GTO) was developed in response to the hunting habits of gigantic trevally fish. By imitating the fish's predatory strategies, it effectively chooses features, enhancing tasks related to optimization and classification. GTO's dynamic and adaptive search process improves performance in challenging issues. Then the classification is done.

E. Classification using Bayesian Asymmetric Quantized Neural Networks (BAQNN)

After the feature selection the classification is done using Bayesian Asymmetric Quantized Neural Networks (BAQNN) [16]. M-ary QNN ignores model uncertainty, which lowers test time costs. By adjusting for weight uncertainties brought on by randomness in heterogeneous contexts, the Bayesian approach can enhance M-ary QNN. A novel robust quantization and distribution estimation in M-ary using a Bayesian neural network quantized neural networks (QNN). By considering Rather than using fixed values to represent parameters, a Bayesian neural network (BNN) incorporates Bayesian probability theory into neural networks, enabling uncertainty estimates in predictions and the loss function for cross-Entropy is provided in equation (7):

$$K_{MKK}(\hat{x}, x) = -\log O(x|y) = -\sum_{m=1}^{M}\sum_{L=1}^{L} x_{ml} \log \hat{x}_{ml} \tag{7}$$

where, $K_{MKK}(\hat{x}, x)$ denotes the notation likely refers to the negative log-likelihood $_{MKK}$ loss between the true labels x and the predicted probabilities $\hat{x}$, $-\log O(x|y)$ term represents the negative logarithm of the predicted probability $O(x|y)$ represents the true label x given the input y, M is the many data points there are in the dataset, L denotes number of classes, x_{ml} is true label for the mth data point for the Lth class, $\hat{x}_{ml}$ represents the predicted probability that the mth data point belongs to the Lth class. Estimates model and variation parameters maximized for classification minimizes to align posterior and prior replaces back propagation with Monte Carlo estimator. Applying the re-parameterization approach, a differentiable function is used to find S samples are given in equation (8):

$$G_{ji}^{(t)} = h_{\sigma_{ji}}\left(\in^{(t)}\right) \tag{8}$$

where, $G_{ji}^{(t)}$ represents the sampled weight for the $t-th$ sample, $h_{\sigma_{ji}}\left(\in^{(t)}\right)$ is the parameterized by σ_{ji}, transforms a random variable $\left(\in^{(t)}\right)$, $\in^{(t)}$ represents the random noise sample, often drawn from a standard distribution. Four layers made up the multilayer perceptron: an output layer with one unit and sigmoid activation for binary classification, two hidden layers, each with 32 units and ReLU activation, and an input layer with 16 units. The use of dropout layers prevented over fitting.

Bayesian Asymmetric Quantized Neural Networks leverage asymmetric quantization to increase efficiency and Bayesian techniques to manage uncertainty. In neural network models, they provide a compromise between computational resource requirements and accuracy. Then the optimization is done.

a) Optimization using Snow Geese Algorithm (SGA)

In this, SGA [17] is used to optimize the weight parameters of BAQNN such as weight for improving accuracy. In order to maximize energy efficiency, snow geese display cooperative flight behaviours such as herringbone and straight line patterns. The population's fluctuating conditions are taken into account by the optimization process is given in equation (9):

$$Y_j^{s+1} = \frac{\sum_{j=1}^{m} Y_j^s . G\left(Y_j^s\right)}{n.\sum_{j=1}^{m} . G\left(Y_j^s\right)} \tag{9}$$

where, Y_j^{s+1} is the weighted average position of the population, Y_j^s illustrates the location of the $j-th$ individual in the population, $G\left(Y_j^s\right)$ is the value of the fitness function connected to the $j-th$ individual, G represents the sampled weight, m is the entire number of people that make up the population. The emphasis switches from exploration to exploitation throughout the meta-heuristic algorithm's development, increasing the possibility of local optima and early convergence. To avoid such traps, the SGA makes use of the randomness inherent in Brownian motion. By altering their locations and velocities in response to energy and aerodynamic factors, the Snow Geese Algorithm (SGA) is a computer optimization technique that mimics the migratory behaviour of snow geese with the goal of optimizing energy efficiency and solution discovery. In the next section the results and discussions are discussed.

4 Results and Discussion

To This section presents the findings and discussion of the introduced scheme. Python is used to carry out the results and discussion of the method. *A. Dataset Description*

To classify the Students Behaviour Prediction with feedback generation for Enhancing Classroom Engagement and Teaching Effectiveness, a datasets are taken, they are OULAD dataset and its descriptions are given below:

a) OULAD Dataset [8-12]

With its concentration on distant learning in higher education through VLE platforms, OULAD provides anonym zed statistics on seven Open University courses. 10,655,280 entries from 32,593 students are included, encompassing VLE interaction logs and evaluation outcomes from 2013 and 2014. The dataset also contains information on the students' location, age, handicap, gender, and level of schooling. The results of student evaluations and their interactions with the online learning environment are also given. In the OULAD dataset three classes they are Low Achiever, Medium and High Achiever.

B. Performance analysis of proposed method

Fig 2. shows the performance analysis of Loss and Training Accuracy for OULAD dataset with 99.9% accuracy. One important measure of the model's learning efficiency during training is the loss function, where a lower value indicates better performance. Training accuracy, evaluated on the training set, provides valuable insight into how well the model is assimilating the material it has encountered.

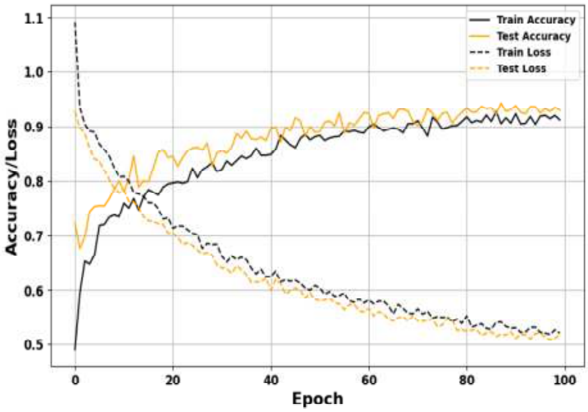

Fig 2. Loss and Training Accuracy for OULAD datasets

Fig 3 shows the performance analysis of Confusion matrix for OULAD dataset. The suggested method performs exceptionally well in identifying true instances and minimizing errors across all datasets, as confirmed by the confusion matrix analysis. This results in high accuracy, precision, recall, and overall robust performance in Predicting Student Behaviour.

Fig 3. Matrix of confusion for OULAD dataset

Fig 4 shows the ROC curves for the proposed approach, which is compared with existing methods such as XGBOOT [8], FDPN [9], RNN-LSTM [10], SMFSOP [11], JNN [12] in OULAD dataset. The ROC curve is a plot of the true positive rate against the false positive rate at various thresholds. It helps evaluate a model's classification performance; the area under the curve (AUC) shows the overall accuracy. Greater model performance is indicated by a higher AUC.

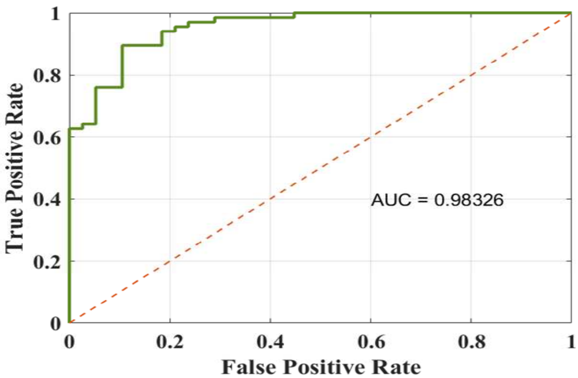

Fig 4. ROC curves for proposed approach

Table 1. Performance comparison of OULAD dataset

Methods	Acc (%)	Pre (%)	Spe (%)	Recall (%)	F1-score (%)	PT (%)	Error (%)
XGBOOT [8]	98.5	96.88	96.4	87.61	96.48	0.1	0.8
FDPN [9]	87.52	76.7	87.9	83.6	88.69	0.1	0.5
RNN-LSTM [10]	89.69	91.5	86.60	86.78	86.68	0.1	0.6
SMFSOP [11]	79.73	85.6	89.97	89.23	87.9	0.1	0.9
JNN [12]	87.55	77.7	87.9	83.64	86.68	0.1	0.3
Proposed-BAQNN-SGA	**99.89**	**98.40**	**99.38**	**96.30**	**95.35**	**0.1**	**0.1**

Here, Acc signifies Accuracy, Pre signifies the precision, Spe signifies the specificity, Sen signifies the sensitivity, Err signifies the Error. The above Table 1 illustrations the qualified analysis of the proposed method against existing methods such as existing methods such as XGBOOT [8], FDPN [9], RNN-LSTM [10], SMFSOP [11], JNN [12] in OULAD dataset. The proposed method attains the highest accuracy (99.89%), precision (98.40%), spe (99.38%), Recall (96.30%) and F1-Score (95.35%) respectively. It likewise validates the lowest processing time (0.1) and error rate (0.1), demonstrating its efficiency and reliability. Table 3 shows the Based on student groupings, decisions are made.

Table 2. Based on student groupings, decisions are made.

Steps	Grade	Effort
1	A^+	Excellent performance. Continue current study habits.

2	A,A^-	Good performance. Focus on improving CT and Quiz scores
3	B^+,B	Average performance. Enhance attention in CT, quizzes, and labs.
4	Below B grade	Needs significant improvement. Prioritize practice in lessons, and pay close attention to CT, lab work, quizzes, and attendance.

Table 2 lists the choices made depending on the effort and grades of the students. Higher scoring students (A+, A, and A-) are considered good but could require some assistance. Lower-grade children need extensive practice and all-encompassing care, whereas medium-level pupils (B+, B) need attention in various areas.

5 Conclusion

In In this manuscript, a Bayesian Asymmetric Quantized Neural Networks with Snow Geese Algorithm (BAQNN-SGA) is proposed. In this, input data is taken from a dataset such as OULAD dataset. It pre-processed data using Savitzky-Golay Denoising method (SGDM), Following that, Students Behaviour Prediction for Enhancing Classroom Engagement and Teaching Effectiveness is then the features extracted using Adaptive Quantization for a Discrete Wavelet Transformation's Coefficients (AQDWTC), Following that Feature selection using Giant Trevally Optimizer (GTO) and classification Bayesian asymmetric quantized neural networks (BAQNN) and the optimization using Snow Geese Algorithm (SGA) for detecting the type of Students Behaviour Prediction and to find the Low achiever, Medium, High achiever Engagement. The introduced system is executed in python. The efficiency of the proposed BAQNN-SGA is analysed using a datasets and attains 99.9% accuracy, 0.1% error rate and 0.1s PT and attains better results compared with the existing methods. This demonstrates the approach's superior efficiency and the potential for future progress in the field. Future work will improve model robustness and generalizability by increasing the dataset, incorporating real-time processing, and developing a user-friendly interface for clinical applications.

References

1. Huang, A. Y., Lu, O. H., & Yang, S. J.. Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. Computers & Education, 194, 104684, (2023)

2. Arizmendi, C. J., Bernacki, M. L., Raković, M., Plumley, R. D., Urban, C. J., Panter, A. T., ... & Gates, K. M. Predicting student outcomes using digital logs of learning behaviors: Review, current standards, and suggestions for future work. Behavior research methods, 55(6), 3026-3054, (2023)
3. Sabharwal, R., & Miah, S. J. Evaluating teachers' effectiveness in classrooms: An ML-based assessment portfolio. Social Network Analysis and Mining, 14(1), 28.
4. Jin, X., Jiang, Q., Xiong, W., Feng, Y., & Zhao, W. (2024). Effects of student engagement in peer feedback on writing performance in higher education. Interactive Learning Environments, 32(1), 128-143, (2024)
5. Meyer, J., Jansen, T., Schiller, R., Liebenow, L. W., Steinbach, M., Horbach, A., & Fleckenstein, J.. Using LLMs to bring evidence-based feedback into the classroom: AI-generated feedback increases secondary students' text revision, motivation, and positive emotions. Computers and Education: Artificial Intelligence, 6, 100199, (2024).
6. Yang, N., & Ghislandi, P. Quality teaching and learning in a fully online large university class: a mixed methods study on students' behavioral, emotional, and cognitive engagement. Higher Education, 1-27, (2024)
7. Noetel, M., Parker, P., Dicke, T., Beauchamp, M. R., Ntoumanis, N., Hulteen, R. M., ... & Lonsdale, C. Prediction versus explanation in educational psychology: A cross-theoretical approach to using teacher behaviour to predict student engagement in physical education. Educational Psychology Review, 35(3), 73, (2023)
8. Alruwais, N., & Zakariah, M. Student-engagement detection in classroom using machine learning algorithm. Electronics, 12(3), 731, (2023)
9. Alnasyan, B., Basheri, M., & Alassafi, M. The Power of Deep Learning Techniques for Predicting Student Performance in Virtual Learning Environments: A Systematic Literature Review. Computers and Education: Artificial Intelligence, 100231. (2024)
10. Kukkar, A., Mohana, R., Sharma, A., & Nayyar, A. A novel methodology using RNN+ LSTM+ ML for predicting student's academic performance. Education and Information Technologies, 1-37, (2024)
11. Hassan, Y. M., Elkorany, A., & Wassif, K. SMFSOP: A semantic-based modelling framework for student outcome prediction. Journal of King Saud University-Computer and Information Sciences, 35(8), 101728, (2023)
12. Gámez-Granados, J. C., Esteban, A., Rodriguez-Lozano, F. J., & Zafra, A. An algorithm based on fuzzy ordinal classification to predict students' academic performance. Applied Intelligence, 53(22), 27537-27559, (2023)
13. Samann, F., & Schanze, T. An efficient ECG denoising method using discrete wavelet with Savitzky-Golay filter. Current Directions in Biomedical Engineering, 5(1), 385-387.
14. Sai, S. V. (2023). A Method of Adaptive Quantization for the Coefficients of a Discrete Wavelet Transformation. Optoelectronics, Instrumentation and Data Processing, 59(2), 167-176, (2019)
15. Li, S. Exploring the Impact of Time Management Skills on Academic Achievement with an XGBC Model and Metaheuristic Algorithm.
16. Chien, J. T., & Chang, S. T. Bayesian asymmetric quantized neural networks. Pattern Recognition, 139, 109463, (2023)
17. Tian, A. Q., Liu, F. F., & Lv, H. X. Snow Geese Algorithm: A novel migration-inspired meta-heuristic algorithm for constrained engineering optimization problems. Applied Mathematical Modelling, 126, 327-347, (2024)
18. Morarjee Kolla, Rupesh Kumar Mishra, S Zahoor ul Huq, Y. Vijayalata, M Venu Gopalachari, KazyNoor-e-Alam Siddiquee, CNN-Based Brain Tumor Detection Model Using

Local Binary Pattern and Multilayered SVM Classifier, Computational Intelligence and neuroscience, 1, 9015778, (2022)