Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 14 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i14.56855

SPECIAL FOCUS PAPER

AI-Powered and Mobile-Integrated Assessment Models Using Random Forest: Redefining Examinations and Grading

Sukhmeet Kaur[1], Divya Goel[2] (✉), Sharmila Devi Ramachandaran[3], Saloni Devi[4], Babita Yadav[5], Anita Goyal[6]

[1]INTI International University, Nilai, Malaysia

[2]Jaypee Business School, Jaypee Institute of Information Technology, Noida, Uttar Pradesh, India

[3]Faculty of Business and Communication, INTI International University, Nilai, Malaysia

[4]The Business School, University of Jammu, Jammu, India

[5]Department of Business Management, Doctor Harisingh Gour Central University, Sagar, Madhya Pradesh, India

[6]Department of Computer Applications, Rayat Bahra University, Chandigarh, India

divyagoel.jmi@gmail.com

ABSTRACT

The proposed system applies a completely different method for examinations and grading by using the supervisor learning technique, namely Random type Forest algorithms. Leveraging the power of artificial intelligence (AI), the process of evaluation is becoming automatic, thereby increasing the efficiency and accuracy in the students' grading? this breakthrough technique is characterized by its hybrid supervised learning setup that exploits both labeled and unlabeled data to come up with a model that is extremely adaptive to unseen examination data. This not only substantially reduces the necessity of human intervention but also dramatically improves the model's ability to perform reliable predictions based on the prevalent patterns. This AI-driven assessment model can be further integrated into a mobile platform to enable real-time student engagement. The integration can benefit the students as the interactive mobile applications can enable the students to enhance their performance by providing instant outcome, and flexibility to take assessments. The mobile applications can contribute to skill enhancement by providing student assessment data related to quizzes, formative assessments or project-based learning assessments, for the random forest (RF) model. Interactive mobile applications can also assist faculty in tracking student performance and analyzing their progress along with improving the accessibility of data. The system, through a comprehensive evaluation of student responses, introduces a more customized and equitable grading system. That is, fundamentally, the traditional assessment methods are being reimagined, and at the same time, they ensure that educational environments globally are both scalable and fair.

KEYWORDS

artificial intelligence (AI)-driven assessment, machine learning, random forest (RF), semi-supervised learning (SSL), automated grading, examination evaluation, interactive mobile applications, student performance analysis, educational data mining, intelligent assessment, personalized grading

Kaur, S., Goel, D., Sharmila Devi, R., Devi, S., Yadav, B., Goyal, A. (2025). AI-Powered and Mobile-Integrated Assessment Models Using Random Forest: Redefining Examinations and Grading. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(14), pp. 57–69. https://doi.org/10.3991/ijim.v19i14.56855

This article is a revised version of a paper presented at the Annual Conference on Innovating for Impact, held on February 19–20, 2025, at the Manipal Dubai Campus, Dubai, UAE. Article submitted 2025-04-26. Revision uploaded 2025-05-28. Final acceptance 2025-06-02.

1 INTRODUCTION

In recent years, the landscape of education has undergone significant transformations, largely driven by the integration of technology and supervisor intelligence in various academic processes. One of the most notable advancements is the use of artificial intelligence (AI) in the assessment and grading of student performance. Traditional methods of evaluation, which rely heavily on manual grading and subjective judgment, often lack the scalability and efficiency needed to keep up with the growing demands of modern education. This is supervisor algorithms come into play, offering the potential to automate and optimize the evaluation process. Among the most effective ML algorithms for this task is the random forest (RF) algorithm, which has shown promise in various applications due to its robustness and ability to handle large datasets effectively [1]. The application of AI in assessments not only addresses issues related to human error and bias but also introduces a level of personalization that traditional methods cannot offer. By leveraging semi-supervised learning (SSL), which utilizes both labeled and unlabeled data, the system can continuously learn and improve its accuracy without requiring extensive amounts of labeled data, a common challenge in educational datasets [2]. SSL allows for the efficient use of available data, making it possible to create a system that can adapt to new and evolving patterns of student behavior and performance [3]. In this system, the grading process is automated, significantly reducing the time and effort required to grade assignments and exams [4]. The AI-driven model is designed to provide consistent and unbiased evaluations, ensuring fairness in grading while also allowing for a more holistic view of student performance over time [5]. Moreover, the adaptability of the model allows it to be applied across various types of exams, from multiple-choice questions to more complex essay-type assessments [6].

This advantage in the direction of the machine-graded result systems can lead to a significant change in the way academic institutions look at student feedback and performance analysis. Traditional grading has a tendency to focus on the evaluation of single student performances, while the AI-assisted tools may provide the complete picture of the student's progress by looking at the relationships between the answers provided by a student to various kinds of questions on different tests [7]. In this way, teachers are able to more efficiently pinpoint weak points in their students, which non-significantly, can lead to more successful corrective actions and individualized teaching [8]. Moreover, the use of machine learning in assessments can assist schools in more effective organization of their vast data through the conversion of them into manageable datasets, especially in cases where the teacher-to-student ratio is very high. With the boom in digital education and testing platforms within educational institutions, the importance of having distributed and trustworthy grading systems grows even more important [9]. Teachers can free up a lot of their time by turning the work of evaluation into automatic machines, as AI grading systems not only do teachers' paperwork but also considerably alleviate their other possible burdens, such as students' enthusiasm development and syllabus improvement [10]. Thus, the application of supervised learning algorithms such as RF will be a change that will transform the allowed directed evaluation towards the learning stage and strengthen the process of the evaluation.

These examination and grading systems not only are capable of to a higher degree the process but also present the principle of a more personal and fair student evaluation, a modern way different from the tradition system. The major innovations of the proposed system are that it adopts SSL for flexibility in grading, makes use of Random way Forest for constant and reliable assessment classification, and employs bias reduction mechanisms for evaluation fairness. The system is able to function by computerizing the grading as well as conforming, and of course, it is user-friendly, easy to operate and very beneficial in an environment that is a mix of people with different learning abilities and backgrounds. When executed and the information will be automatically extracted, organized, and stored, the system will yield, in practice, a significant improvement scalability, variability, and individuality of the manual grading process which will meet the needs of different levels of education.

2 LITERATURE SURVEY

The supervisor learning algorithms are definitely transforming the way grading is done with ensemble techniques such as the RF. Not only can these innovations change the traditional assessment process by making it even more fair, scalable, and personal, but also educational systems can be most benefited from these ways of administration. The field of education has recently identified a growing trend of using teacher algorithms of different kinds for automating the process of classifying and grading in academic institutions. Among the most prominent components, there is the use of AI-powered models integrated with mobile technology that are more efficient and unbiased when dealing with the problematic issue of determining the future of the educational system [11].

In brief, the work presented in one paper showed that it is possible to utilize smart learning approaches in grading virtually, indicating that educators' workload can be minimized without omitting the quality of assessments [21]. Unlike this, one study sheds light on how we can make the most out of SSL, which becomes essential when we confront challenges such as the insufficiency of labeled data in the context of educational data, showing that it could possibly be beneficial to the performance of grading systems by using both types of data viz., labeled, and unlabeled in a very effective way [12]. Other researchers made attempts to uncover different uses of ensemble methods in educational settings. Thus, a particular study suggested the possibility of applying randomized forest algorithms first through the use of historical data to predict learners' accomplishments, and secondly, to generate educational patterns.

The researcher, through the study of student performance prediction, saw that the application could extend support to the learning patterns and in cases where the students would require additional help [13]. Ultimately, it was also noticed that the use of randomized forest to grade such types of questions is another interesting direction of research, where it was found that the algorithm itself had a very high accuracy in evaluating the written answers [14]. Additionally, the examination revealed the impact of using various machine learning models in combination with one another, of course, on the integrity and equity of the grading results, the conclusion being that only hybrid models, through the highest level of performance, could successfully surpass the single-method methods even in complicated tests [15].

Artificial intelligence's role in educational assessment is the subject of investigation in the aspect of justice and bias. A particular study analyzed different AI rating strategies that are fair, providing evidence for the difficulty of addressing the issue of algorithms not being prejudiced on specific demographic groups or certain learning styles [16]. Another summary of certain research suggested a fairer approach that can be implemented on AI grading systems. This approach engaged the use of a new set of checks and balances that aligned with the system goals, therefore minimizing the bias of algorithms and consequently making the system a better one for all [17]. Another study also emphasized the potential of mobile learning platforms for students and suggests that institutions should make use of such platforms [18, 22]. With regard to the feedback for the learners, a published article delved into the ways through which AI-powered automated grading of student work could give instant feedback of practical benefit to the students, allowing them to improve their performance via self-evaluation and continuous learning. [23] A similar piece of research proved the practicability of AI-based personalized learning systems in terms of student engagement and academic success. Automation of evaluation and grading might be an important part of personalized learning where the response is individual, and the students are encouraged to grow at their own pace [19–20].

3 PROPOSED SYSTEM

The AI-powered assessment system integrated with mobile technology is equipped with an ordered chain of processing steps to automate exams and grading systematically. The passage commenced with the collection of data, the preparation of student responses from various question formats, such as multiple-choice and open-ended questions. Next, these responses are preprocessed i.e., normalized, tokenized, and feature extraction is done to ensure that the data is the same and noise is eliminated. After the purged data, the SSL model is implemented, in which some labeled, and some not labeled data are used at the same time to improve the model of training. This strategy not only allows for continuous system learning and the making of the grading criteria finer without making use of very many tagged datasets but also ensures student satisfaction. The halo point in the classification model, which is the RF algorithm, an algorithm recognized by the robustness of its method and the ability to solve complex pattern organization, is introduced for the evaluation of the learner's work. The purpose of this model is to predict grading patterns and thus be able to deliver very accurate and reliable predictions for the assessment; this is in line with Figure 1. The very initial step taken in that direction is error-correcting and bias-reduction techniques. For instance, the error detection of algorithms and the bias correction process are two of the tools that can help in achieving this. The processing involves checks and ensembles of learning exercises, and reviews of work twice to reduce possible errors and ensure that the results are impartial. The third part of the system is subsequent of automatic feedback, which provides students with interpretations of their performance and areas for improvement. Moreover, the system includes the performance analysis module, which goes a long way in teachers' ability to monitor their students' progression for an extended period and conceptually change their instruction depending on their scenario.

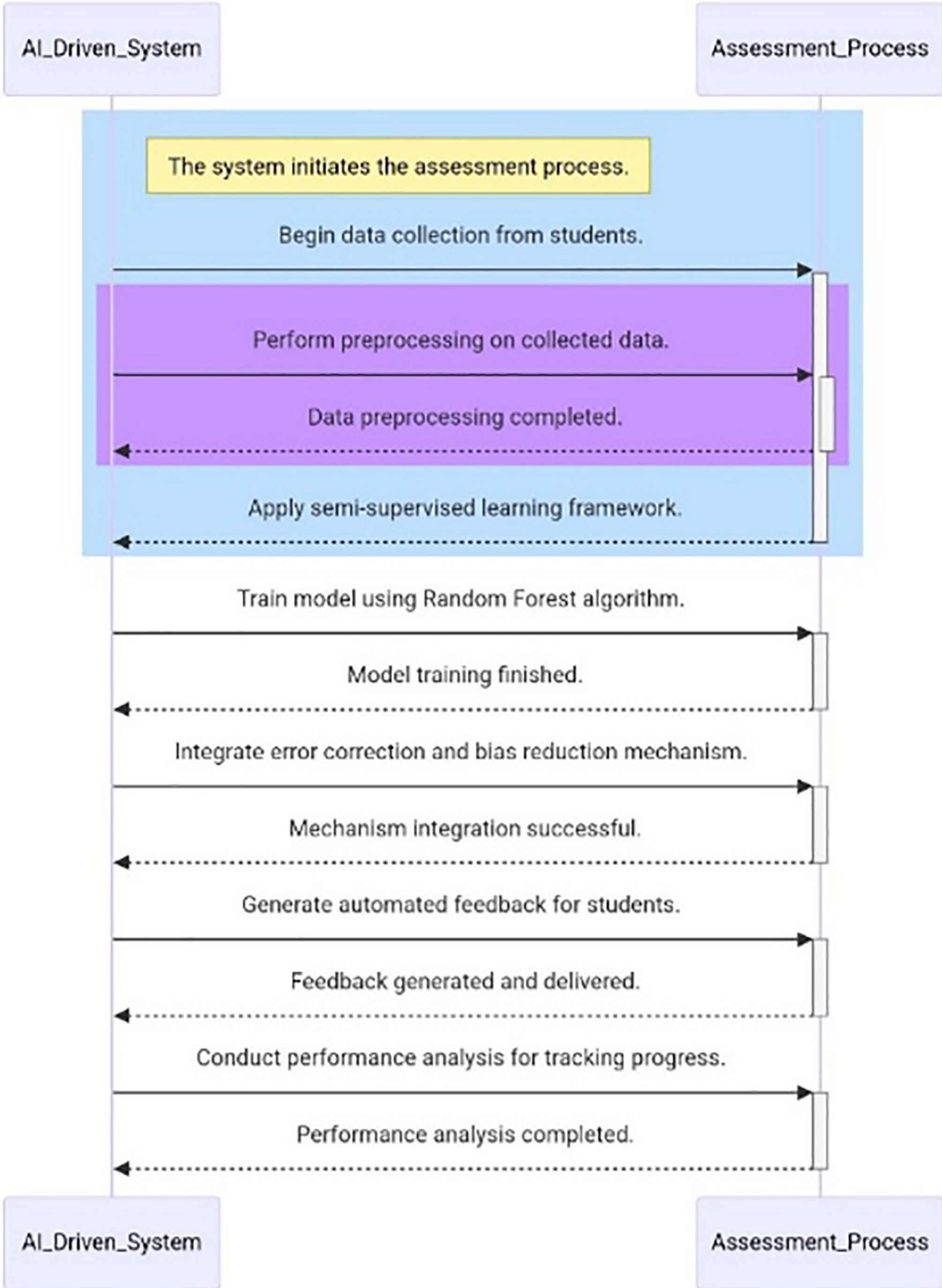

Fig. 1. Internal processing steps of proposed system

An intelligent system that can be driven by AI is proposed is in fact, a step-by-step arrangement that may serve the purpose of grading and evaluation instantly. The system is kicked off with the first phase of data collection, where student responses from several assessment tests are captured and depicted as feature vectors. Each response is converted into a numerical representation, the formula given in (1):

$$D = \{d_1, d_2, \ldots, d_n\} \tag{1}$$

Using di as a specific feature of the response. The next stage, namely preprocessing, is responsible for removing noise and making the data. The stage of data standardization in the next stage is the preprocessing step of the project, which includes smoothing the data by removing noise and making the data shown in (2)

$$D' = D - \mu D/\sigma D. \tag{2}$$

Where μD is the mean of the dataset and σD is the standard deviation, hence the uniform scale will be achieved across various inputs. The process through (3) the system employs the SSL approach, which is a rich source of human experience that is essential in machine learning. In this method, labeled (Ls) and unlabeled (Us) data sets are both used to train the model in such a way that the weight changes adaptively (3):

$$Ws = |Ls||Ls| + |Us|. \tag{3}$$

This equation also guarantees that one is effectively making use of the labeling data to learn the underlying knowledge pattern of the new data. The used form of the system is through the method of RF. This method is a set of individual decision trees' ensemble. The classification method involves the RF algorithm, which is an ensemble of many decision trees. Each tree is represented by T1, T2, Tk and it votes the final predicted grade (Gp) through a majority voting mechanism in (4):

$$Gp = \mathrm{argmax}_g \Sigma j = 1kI(Tj(D) = g). \tag{4}$$

Where I is an indicator function to assign the grade g of the predicted votes. The Gini impurity function that measures the ease of separating each class of (5) is used to construct each tree:

$$Gini(D) = 1 - \Sigma ipi^2, (i = 1 \text{ to } C). \tag{5}$$

Where the variable C to be count of classes, pi = Proportion of examples in class i within dataset D. In order to split the dataset into subsets that are as pure (homogeneous) as possible, one can each split to maximize information gain (6):

$$Gain(F, A) = Entropy(F) - \Sigma v \in A|Fv||F|Entropy(Fv). \tag{6}$$

Where A is the attribute set, F is the data, and Fv is a subset of F for attribute value v. In order to improve grading fairness and overcome the bias, a weighted loss function is merged into the system in (7):

$$Lb = \Sigma iwi\cdot(yi - y\^{}i)^2(i = 1 \text{ to } N). \tag{7}$$

Where wi is a weight advocating the removal of possible biases, yi is the true grade, and y^i is predicted grade. The confidence level of the model in each of its classifications is checked by calculating a confidence Sconf in (8):

$$Sconf = 1k\Sigma j = 1kP(Tj(D) = Gp). \tag{8}$$

Where is the probability of each tree's prediction. The error correction mechanism in the system is set for the evaluation of the incorrect responses via the gradient of the loss function with respect to model parameters in (9):

$$\partial Lb/\partial\theta = \Sigma i2wi(yi - y\^{}i)^*(\partial y\^{}i/\partial\theta). (i = 1 \text{ to } N) \tag{9}$$

Where θ is the model parameters subject to optimization. A similarity-based evaluation is conducted by the cosine similarities function, providing that student responses are compared with historical patterns in the grading process (10):

$$\mathrm{Sim}(D1, D2) = (D1 \cdot D2) / (\|D1\|\|D2\|). \tag{10}$$

Where D1 and D2 are two response vectors. A feedback score (Fb) is derived through the combined contribution of the similarity and model confidence in (11):

$$Fb = \alpha \mathrm{Sim}(D, H) + (1 - \alpha)\mathrm{Sconf}. \tag{11}$$

Where H is the historical data, and α is a parameter for balancing. Also, the system operates on performance analysis for a trend check using a linear regression model for the progress of a particular student over time in (12):

$$Gt = \gamma 0 + \gamma 1t + \in t. \tag{12}$$

Where Gt is the grade predicted at time t, γ0 and γ1 are regression coefficients, and ∈t is the error term. If the grading outcomes are coherent, the standard deviation metric is used in (13):

$$\sigma g = \surd(1 / N)\Sigma i(Gi - G^{-})2.(i = 1 \text{ to } N) \tag{13}$$

Where Gi stands for the grades of individual students, and G^{-} stands for the average grade. Decision thresholds of the system are updated in (14):

$$Tnew = Told + \eta \cdot \partial Lb \partial T. \tag{14}$$

Where T is the decision threshold, and η is the learning rate controlling the update step. The concept used in the work is the use of SSL for adaptable grading, RF for robust classification, a method to eliminate the bias in the dataset for the fairness of the system, and the generation of feedback automatically for improving the learning outcomes. The solution presented in this paper is the incorporation of a method based on mathematics, multiple learning algorithms as well as automatic decision-making for this system to be scalable.

4 RESULTS AND DISCUSSION

The outcomes of the suggested AI-driven evaluation system give evidence of the system's efficiency in grading in an automatic way while at the same time ensuring that the process is fair and adaptive. The uninterruptedly was defined as that one of the machine learning methods that allows the system to utilize both unlabeled and labeled data, which enables to increase the classification accuracy and at the same time to eliminate the dependence on manually annotated datasets. The RF classifier that was used definitely increased the reliability of predictions by forming the ensemble of various decision trees, thus creating consistent and reliable results for scoring. "The bias correction mechanism is responsible for reducing disparities between the grading operating in different assessment situations and for maintaining an unbiased grading process irrelevant to the obstacles." The fact that the confidence scoring and feedback generation modules are included results in a vaster understanding of the evaluation process, where students get useful information about their performance. In addition, the system's ability to reconcile itself by tweaking changes in the thresholds with the help of adaptive learning techniques empowers it to stand against different assessment patterns. The analysis of the pattern of the system's performance shows that the model not only continues to score consistently over time, but also shows a minimal variance from the expected results. It follows from the debate that the co-occurrence of the similarity-based assessment along with the historical data of students can sharpen the teachers' grading scale thus the students' responses are appraised in a complex context but not by themselves. Moreover, the error correction mechanism is very successful in the identification and overcoming of these wrongly classified pieces of evidence that students produce, as well as in the automation, it also hacks the process of creating new and better automated responses at the same time.

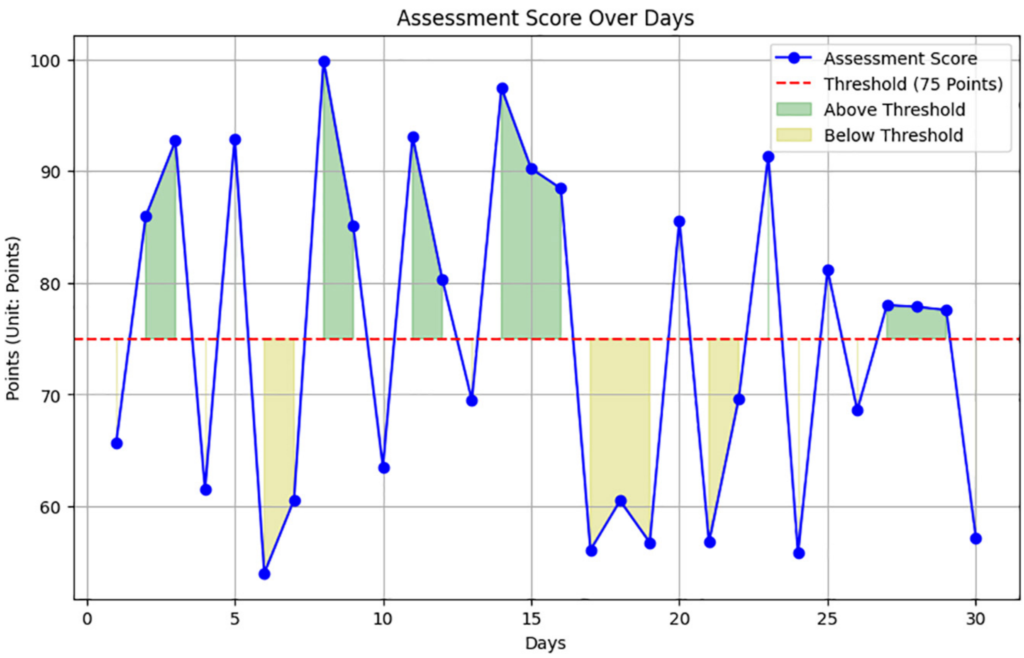

Fig. 2. Assessment score analysis over days

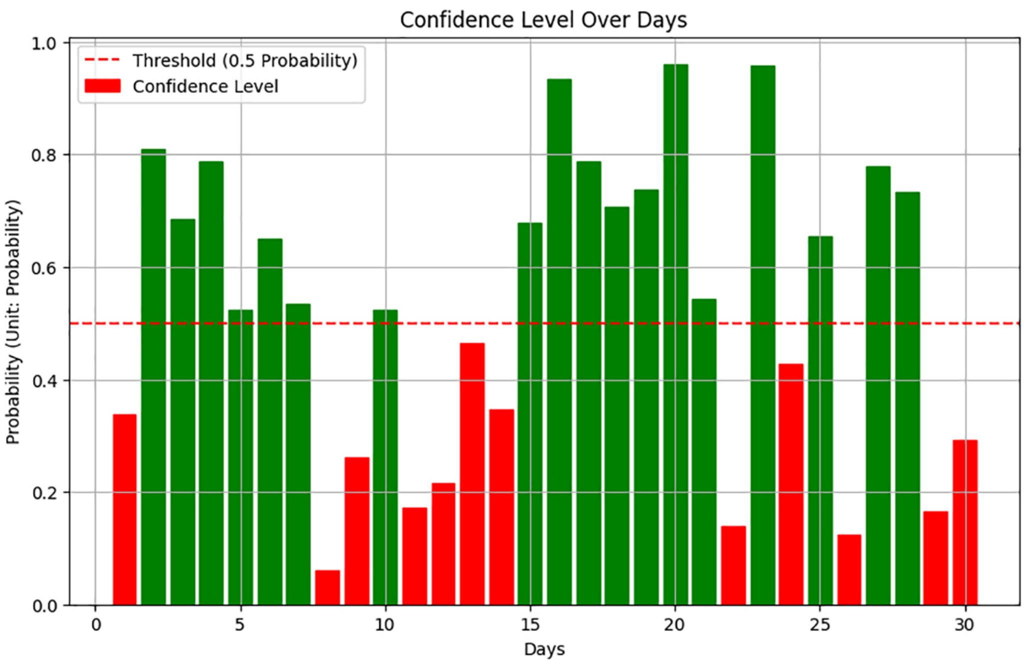

Fig. 3. Confidence level analysis proposed system

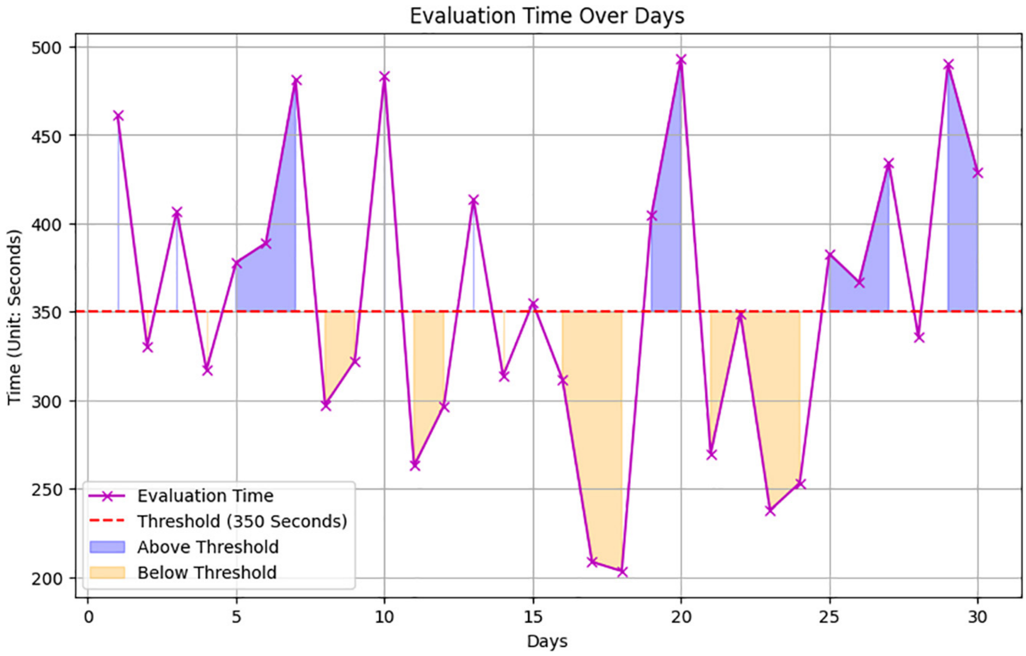

Fig. 4. Evaluation time span analysis of proposed system

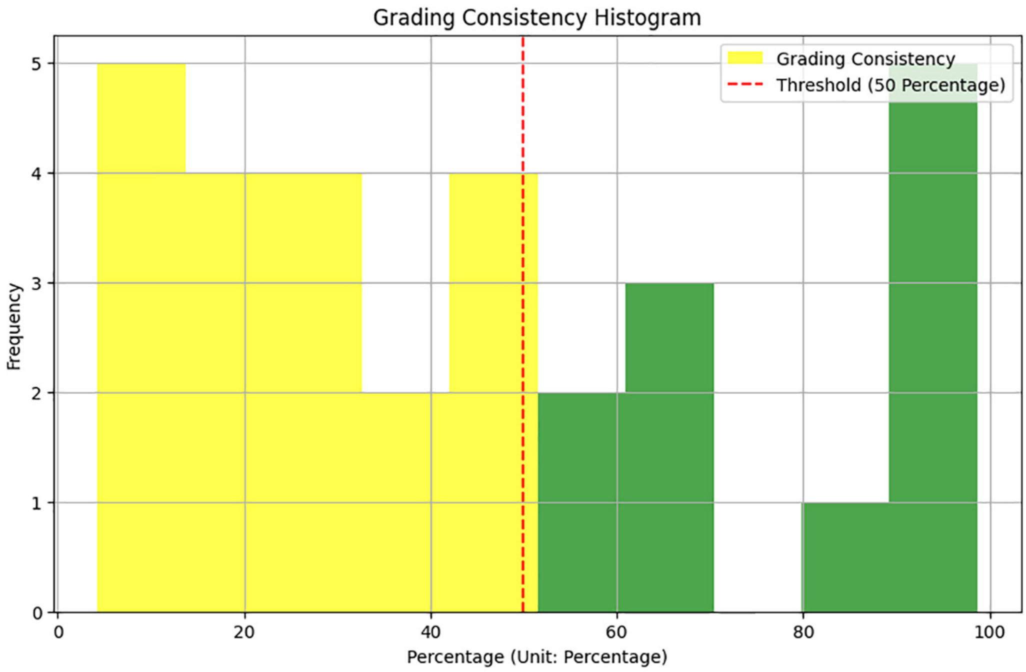

Fig. 5. Grading system analysis by proposed system

The variation of the assessment score (in points) is presented in Figure 2 over the course of 30 days, with 75 clearly marked as the threshold value. The readings give the number of 16 out of 30 days (53.3%) when the assessment score was higher than 75, indicating a good validation process. However, in the 14 days (46.7%) when the score was below the threshold, there were uncovered instances of poor service without improvement. The fact that there is a significant effect when the scores are below 75 reveals that the data may not have been stored well, and it is necessary to continue refining the model in order to be correctly done by the artificial intelligence.

As shown in, Figure 3 is the distribution of the confidence level (in probability) that sets the threshold value at 0.5. Just pointing at the graph, it is seen that on the 18 (60%) days the confidence level was over the edge thus we have a predictive model we can rely upon. However, in the 12 (40%) days during which the confidence level went down and was thus below 0.5 an indication of the model being probably not the best in grading emerged, and maybe we should do the latter. The sinking of the level of confidence below such a threshold may implicitly note the existence of high uncertainties in the generated results that can only be removed through an update of the sets of weights for more trustful results.

The distribution of the different days (seconds) taken for the evaluation in a single day was depicted in Figure 4, where the threshold was chosen as 350 seconds. The result shows that, on the one hand, for the 19 days the evaluation time was higher than the threshold (63.3%) and the system seemed to be less efficient in automated grading. And, on the other hand, for the 11 days (36.7%) when the evaluation time was lower than the threshold, the efficiency of the processing part was evident. In the case of going above the threshold, we can say that there may be the presence of computational cracks while making sure that the time is well balanced for the optimization of the process is necessary in order to not only get it done fast but also to do it right.

In the representation of the Grading Consistency (in percentage) as a bar plot in the histogram in Figure 5, with the efficiency criterion at 50% as the lower bound of the green area. From the examination of the data, it is clear that 22 (73.3%) of the time the grading consistency was above 50%, thus guaranteeing the accuracy of the assessment. In contrast, only on 8 (26.7%) days was the grading consistency below the threshold value, resulting in unbalanced AI-based evaluations. When the level of grading consistency falls below 50%, there is a risk of bias introduction which can, in turn, influence that this is one of the factors likely to necessitate the reworking of the data in order to obtain fairer student outcomes.

5 CONCLUSION

In conclusion, AI-powered evaluation model integrated with mobile technology shows a lot of advantages in the assessment of students' performance, with the important parameters being investigated within 30 days. The Assessment Score did not go below the mark on 53.3% of the days, the results meaning that the whole evaluation was adequate, but the 46.7% of days which were less than the threshold show the need for checking to nullify potential grade variations. The same was around the Confidence Level, whose value was greater than the threshold in 60% of cases, which showed good predictions, but 40% of cases below the threshold identified the areas in which the model's decision-making confidence needed to be boosted. As said about the efficiency, the Evaluation Time was more than the threshold in 63.3% of the events. This indicated that there could be possible delays in the process of doing the evaluation, while the opposite is true for 36.7% of the cases – the goal of the threshold is achieved, evaluations being made quickly. It is equally important to make a useful AI grading algorithm that meets the requirement of both accuracy and efficiency. Analogy to this, the consistency in the Grading, the one, which was kept above the 50% of the times was 73.3% of the cases about equitability, while 26.7% of the cases under the threshold expose the potential errors that could lead to a course of a bias in the assessment and should be revised to remove the trend. Thus, the proposed model when integrated into a mobile platform enables real-time student engagement and benefit the students in enhancing their performance. Also, the student assessment data provided by the mobile applications for the RF model made the model more robust and is beneficial in tracking student performance and analyzing their progress.

6 REFERENCES

[1] A. J. Mahamuni and S. S. Tonpe, "Enhancing educational assessment with artificial intelligence: Challenges and opportunities," in *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, vol. 1, 2024, pp. 1–5. https://doi.org/10.1109/ICKECS61492.2024.10616620

[2] P. Yathurshan, K. Aishwarya, R. M. D. G. Gimhani, K. Janani, M. S. Suriyaa Kumari, and M. N. H. P. Ravi Supunya Swarnakantha, "Student learning and assessment support system," Published in *International Research Journal of Innovations in Engineering and Technology – IRJIET*, vol. 7, no. 10, pp. 123–130, 2023. https://doi.org/10.47001/IRJIET/2023.710016

[3] M. D. Adewale, A. Azeta, A. Abayomi-Alli, and A. Sambo-Magaji, "Empirical investigation of multilayered framework for predicting academic performance in open and distance learning," *Electronics*, vol. 13, no. 14, p. 2808, 2024. https://doi.org/10.3390/electronics13142808

[4] B. Hu and Y. Wu, "Unlocking causal relationships in commercial banking risk management: An examination of explainable AI integration with multi-factor risk models," *Journal of Financial Risk Management*, vol. 12, no. 3, pp. 262–274, 2023. https://doi.org/10.4236/jfrm.2023.123014

[5] X. Xi, "Advancing language assessment with AI and ML–leaning into AI is inevitable, but can theory keep up?" *Language Assessment Quarterly*, vol. 20, nos. 4–5, pp. 357–376, 2023. https://doi.org/10.1080/15434303.2023.2291488

[6] M. Lettieri, "Embracing empathy: How AI technologies enhance the pedagogy of kindness in education," in *Redefining Education with Pandemic Pedagogies*, IGI Global Scientific Publishing, Teresa Lobalsamo and Dellannia Segret, Eds., 2025, pp. 167–186. https://doi.org/10.4018/979-8-3693-3695-3.ch006

[7] J. B. Diekuu, M. S. Mekala, U. S. Abonie, J. Isaacs, and E. Elyan, "Predicting student next-term performance in degree programs using AI-based approach: A case study from Ghana," *Cogent Education*, vol. 12, no. 1, p. 2481000, 2025. https://doi.org/10.1080/2331186X.2025.2481000

[8] I. Goel *et al.*, "Role of AI in empowering and redefining the oncology care landscape: Perspective from a developing nation," *Frontiers in Digital Health*, vol. 7, p. 1550407, 2025. https://doi.org/10.3389/fdgth.2025.1550407

[9] Z. H. Ma, W. Y. Hwang, and T. K. Shih, "Effects of a peer tutor recommender system (PTRS) with machine learning and automated assessment on vocational high school students' computer application operating skills," *Journal of Computers in Education*, vol. 7, no. 3, pp. 435–462, 2020. https://doi.org/10.1007/s40692-020-00162-9

[10] M. Kawka, A. Dawidziuk, L. R. Jiao, and T. M. Gall, "Artificial intelligence in the detection, characterisation and prediction of hepatocellular carcinoma: A narrative review," *Translational Gastroenterology and Hepatology*, vol. 7, p. 41, 2022. https://doi.org/10.21037/tgh-20-242

[11] A. O. Ajlouni, A. H. Ibrahim, and M. Hendawi, "Predicting preservice teachers' intentions to integrate AI-based mobile applications in special education: Examining the role of technology self-efficacy and attitudes," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 7, pp. 22–43, 2025. https://doi.org/10.3991/ijim.v19i07.53177

[12] A. Mehrabi, J. W. Morphew, B. N. Araabi, N. Memarian, and H. Memarian, "AI-enhanced decision-making for course modality preferences in higher engineering education during the post-COVID-19 era," *Information*, vol. 15, no. 10, p. 590, 2024. https://doi.org/10.3390/info15100590

[13] S. Yuan, "Personalized college English learning experience assisted by artificial intelligence: An algorithm-driven adaptive learning approach," *International Journal of High Speed Electronics and Systems*, p. 2540157, 2024. https://doi.org/10.1142/S0129156425401573

[14] V. Nikolovski, D. Trajanov, and I. Chorbev, "Advancing AI in higher education: A comparative study of large language model-based agents for exam question generation, improvement, and evaluation," *Algorithms*, vol. 18, no. 3, p. 144, 2025. https://doi.org/10.3390/a18030144

[15] I. S. Galdames, "From anatomy to algorithm: Scope of AI-assisted diagnostic competencies in health sciences education," *International Journal of Medical and Surgical Sciences (IJMSS)*, vol. 11, no. 3, pp. 1–24, 2024. https://doi.org/10.32457/ijmss.v11i3.2818

[16] S. C. Necula, D. Fotache, and E. Rieder, "Assessing the impact of artificial intelligence tools on employee productivity: Insights from a comprehensive survey analysis," *Electronics*, vol. 13, no. 18, p. 3758, 2024. https://doi.org/10.3390/electronics13183758

[17] R. Abe, "Utilizing predictive insights for future planning: Redefining choices with advanced data solutions," *International Journal of Computer Applications Technology and Research*, vol. 14, no. 2, pp. 53–65, 2025. https://doi.org/10.7753/IJCATR1402.1004

[18] B. H. Hayadi and T. Hariguna, "Predictive analytics in mobile education: Evaluating logistic regression, random forest, and gradient boosting for course completion forecasting," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 19, no. 5, pp. 210–232, 2025. https://doi.org/10.3991/ijim.v19i05.52381

[19] P. S. Chaudhary, M. R. Khurana, and M. Ayalasomayajula, "Real-world applications of data analytics, big data, and machine learning," in *Data Analytics and Machine Learning*, Studies in Big Data, P. Singh, A. R. Mishra, and P. Garg, Eds., vol. 145, 2024, pp. 237–263. https://doi.org/10.1007/978-981-97-0448-4_12

[20] W. Rojas-Carabali *et al.*, "Managing a patient with uveitis in the era of artificial intelligence: Current approaches, emerging trends, and future perspectives," *Asia-Pacific Journal of Ophthalmology*, vol. 13, no. 4, p. 100082, 2024. https://doi.org/10.1016/j.apjo.2024.100082

[21] Y. Mezquita, J. Parra, R. Alonso-Rincón, and J. Prieto, "Data-driven academic performance evaluation: A smart platform approach," in *Progress in Artificial Intelligence, EPIA 2024,* in Lecture Notes in Computer Science, M. F. Santos, J. Machado, P. Novais, P. Cortez, and P. M. Moreira, Eds., vol. 14967, 2024, pp. 105–114. https://doi.org/10.1007/978-3-031-73497-7_9

[22] M. T. Alshurideh, S. A. Salloum, B. Al Kurdi, A. Abdel Monem, and K. Shaalan, "Understanding the quality determinants that influence the intention to use the mobile learning platforms: A practical study," *International Journal of Interactive Mobile Technologies*, vol. 13, no. 11, pp. 157–183, 2019. https://doi.org/10.3991/ijim.v13i11.10300

[23] Y. Hew, D. Kutuk, T. Duzcu, Y. Ergun, and M. Basar, "Artificial intelligence in IVF laboratories: Elevating outcomes through precision and efficiency," *Biology*, vol. 13, no. 12, p. 988, 2024. https://doi.org/10.3390/biology13120988

7 AUTHORS

Dr. Sukhmeet Kaur is a Research Fellow in the INTI International University, Nilai, Malaysia (E-mail: sukhmeetkaur9686@gmail.com).

Dr. Divya Goel is an Assistant Professor Senior Grade at the Jaypee Business School, Jaypee Institute of Information Technology, Noida, Uttar Pradesh, India (E-mail: divya.goel@mail.jiit.ac.in, divyagoel.jmi@gmail.com).

Dr. Sharmila Devi Ramachandaran is a Senior Lecturer at the Faculty of Business and Communication, INTI International University, Nilai, Malaysia (E-mail: sharmila.devi@newinti.edu.my).

Dr. Saloni Devi is a Senior Assistant Professor in The Business School, University of Jammu, Jammu, India (E-mail: salonidevi@jammuuniversity.ac.in).

Dr. Babita Yadav is an Assistant Professor at the Department of Business Management, Doctor Harisingh Gour Central University, Sagar, Madhya Pradesh, India (E-mail: byadav@dhsgsu.edu.in).

Dr. Anita Goyal is an Associate Professor and the Head at the Department of Computer Applications, Rayat Bahra University, Chandigarh (E-mail: anita.goyal@rayatbahrauniversity.edu.in).