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Machine Learning based Tutor Ward System (MLTWS) for Cognitive Learning style Management

Gautham K1, Julius Fusic S2*, Gurunandhan ADP3, Sugumari T4
[1] System Engineer, Tata Consultancy Services, Chennai, Tamil nadu
[2]Department of Mechatronics Engineering, Thiagarajar College of Engineering, Madurai.
[3] Software Development Engineer, Alfa TKG, Chennai, Tamil nadu
[4]Department of Electronics and Communication Engineering, KLN College of engineering, Madurai.
[1]gauthamkanagaraj1998@gmail.com
[2]sjf@tce.edu
[3]gurunandhanadp@gmail.com
[4]ammusugumari@gmail.com

Abstract: Many educations sector find it difficult to examine a student's performance on each assessment activities and provide feedback based on cognitive, reflective and psychomotor abilities. It is a difficult task for student tutors to individually assess each student's performance in each category (Remember, Understand, Apply, and Analyze) and provide feedback. As a result, a machine learning model is required to help tutors to evaluate the student performance and provide feedback to students and their parents. It serves as an extension of the student portal, allowing access to all information about students, including their assessment scores. A proposed model is to forecast individual student's and the entire class's strengths and weaknesses in single portal. This enables both teachers and students to adjust their teaching and learning methods as needed. This approach paved a way for tutors spent much more time with their slower learners, treated them with more compassion.

S. Julius Fusic
Assistant Professor,
Department of Mechatronics Engineering,
Thiagarajar College of Engineering, Madurai – 625015.
sjf@tce.edu

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1. Introduction

Tutoring ward system is academic assistance provided by a person known as a Tutor who is well-versed in understanding their student affective domain and cognitive skills. A tutor enables students or a group of students succeed academically by giving them instructions or assistance. A successful tutor must improve each student's knowledge and become acquainted with their learning process. One of their most important responsibilities is to evaluate students' performance on each test and provide suggestions that will assist them improve their performance on upcoming tests. The major goal of our research is to automate student feedback based on their performance in each area and to favorable influence on students. This platform could be utilized as an extension of the student portal, allowing access to all information about students, including their assessment scores. Many researchers focused on the improvement in student activities for their career development (Schofield JW et al. 1990). The E-mentoring is a emerging field during pandemic condition for monitoring the students cognitive level as well as their psychological wellness Liat Gafni-Lachter et al. (2021). The extensive evidence on the effectiveness of feedback on learning with the support of five claims about the feedback. The extensive research on the efficacy of feedback reveals that providing feedback to learners is often very effective in promoting learning, but that in a significant proportion of instances, it is ineffective or even deleterious. Ann Poulos et al. (2008). In addition, it has side effects that prevent students from focusing on learning most effectively. Two ways seem particularly germane. First, giving students assignments that the instructor neither grades nor provides individual feedback will offer more of the practice they need to develop expertise Julius fusic et.al (2018). Second, helping students learn how to assess and reflect on their state of learning will allow them to become independent life-long learners. Carles, D. (2006).

Learning styles are significant in educational contexts, according to the authors, because they can assist students and tutors become more self-aware of their strengths and shortcomings as learners lçin, N et al (2018). Over the last years, several approaches have been proposed to automatically detect learning styles, aiming to solve these problems, Nelson B et al. (1993). The authors analyze current trends in the field of automatic detection of learning techniques. The automatic detection of learning styles in data-driven approaches is carried out by AI classification algorithms that take the user model as input and returns the students' learning style preferences as output. They have analyzed and discussed the gaps that need to be addressed Feldman, J et al. (2015).

According to Paul A. Kirschner (2017), claims that one's learning style is not determined by how individuals study. People are divided into various groups, yet objective studies provide little evidence for them. They all tend to fail in the end. One such study provides proof that the fallacy about learning styles should be debunked. Teachers frequently divide students as visual and auditory learners. Despite the absence of actual evidence, it is nonetheless universal practice in education to teach a student's perceived learning style Pashler et al. (2008). Very few research has even used an experimental methodology capable of verifying the validity of learning styles applied to education, concluded after conducting an extensive assessment of the literature. Rogowsky et al. (2015) investigated the extent to which learning style predicts understanding and retention based on the mode of instruction, concentrating primarily on the visual/auditory dichotomy. "The only study found through a rigorous literature search across six distinct databases and the screening of more than 1000 records that were completely compatible with Pashler's criteria. The drawback to the 2015 study, according to Aslaksen and Loras (2019) is that it was done with adult learners. The latest study follows the same design and technique as its predecessor, but it is the first of its type because it is conducted on a school-aged population. The results failed to uncover a significant link between auditory or visual learning style preference and comprehension, which is consistent with previous adult findings. On listening and reading comprehension tests, fifth graders with a visual learning style outperformed those with an auditory learning type. As a result, teachers may be performing a disservice to students by using resources to establish their learning type and then modifying the curriculum to match that learning style, which goes against existing educational principles and practices.

Jan D. Vermunt et al. (2017) devised a theoretical technique for contextualizing higher education learning patterns. The student learning patterns study, which has been published since 2004, has been meticulously discovered and reviewed, and it is a great resource for our research. Jan D. Vermunt et al. (2017) also explains the connections between how students learn and their personal, environmental, and performance factors. This study enlisted individuals from seven various academic backgrounds in order to broaden the data collection. Students' academic subject, prior education, age, and gender were found to have a significant link between learning and personal and environmental variables in this study. Both Machine Learning and Statistics produce substantial regression techniques and algorithms, as described by Uysal I et al. (1999). This overview covers local weighted regression (LWR), rule-based regression (RBR), projection pursuit regression (PPR), instance-based regression (IBR), Multivariate Adaptive Regression Splines (MARS), and recursive partitioning regression algorithms that build regression trees (CART, RETIS and M5).

Smilkov et al. (2019) proposed Tensorflow.js, an open-source hardware-accelerated JavaScript toolkit for training and deploying machine learning models, is used in this article to introduce us to the realm of Machine Learning for the Web. This research also discusses TensorFlow.js' architecture, API, and implementation, as well as some of the most important use cases. Laura Thomson and Luke Welling (2009) instruct us on how to create dynamic, secure Websites and Web apps. Following real-world examples and working sample projects, the book also demonstrates how to integrate and deploy these technologies. It also covers related technologies such as SSL and Full Stack Integration that are required to establish a business Web site. Peter Gasston's (2013) book provides a practical approach to creating modern online apps with HTML, CSS, and JavaScript. This also covers several crucial features of application development, such as multi-device compatibility and integration, which came in handy when it came time to turn this prototype into a fully functional application that tutors may use in any educational institution across the world.

The introduction of Conceive Design Implement Operate (CDIO) framework curriculum-based approach enhance the students creative and analytic skills in engineering courses Fusic, S. Julius et.al (2022). As the curriculum developed the students assessment, monitoring and their tutoring techniques also need to improve. From the study, the innovative approach only made students to focus on courses than conventional approach. In this paper, the Chapter I states the introduction part and related works. Chapter II demonstrate the work contribution approach used to analyses the tutor monitoring system among the engineering mentors. Chapter III details about the experimental case study work to segregate and analyses individual students using machine learning. Chapter IV provides the Tutor ward system model for engineering students. Chapter V stretches the analysis of OBE, CBCS and CDIO curriculum framework results and project-based learning rubrics assessment discussion. Chapter VI states the conclusion and future work to engage the students in different case studies.

2. Work Contribution approach

A tutor should be aware of each student's strengths and shortcomings, as well as their previous performance on assessment examinations. However, when there are a large number of students, it may be difficult for the tutor to remember everyone. Changes in tutors for students may occur for a variety of reasons, and it would be impossible for the new tutor to assess each and every student's performance and learn about them in that situation. As a result, a machine learning model was created and linked to the student site, along with certain enhancements.

The overview of proposed model and its assessment flow diagram is detailed in figure 1. To learn more about how both tutors and students feel, two surveys were done at first, one from tutors and one

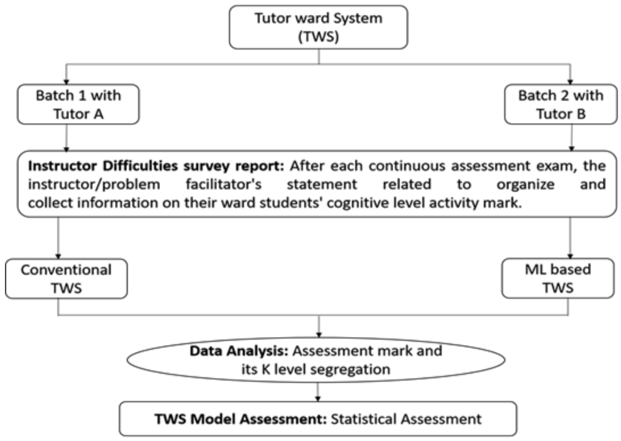


Fig. 1: Overview of proposed workflow.

from students. This survey clearly demonstrates that the majority of students lack the patience to sit with their tutors and examine their performance, and they also had to wait for their tutoring session. They also believe that as the number of students grows, viewing their performance and making advice tailored to their learning style will become more important. Around two-thirds of the tutors believe that automating this work would be useful to them. Students can access their recommendations through their portal at any time and sample feedback collection link is shown in figure 2.

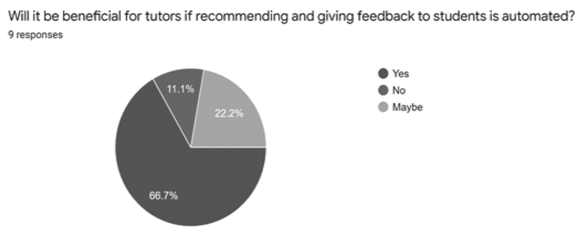


Fig.2: Tutor feedback of conventional Tutor ward System

Paleeri, Sankaranarayanan. (2015), Bloom's Taxonomy is a hierarchical classification of cognitive skills that aids teachers and students in teaching and learning. It divides educational learning outcomes into many categories. Bloom's taxonomy has six levels of cognitive learning in the most recent version (remembering, understanding, applying, analyzing, evaluating, and creating).

Researchers decided to integrate four of these six tiers in our student portal because they were the most relevant. The four k levels are remembering, comprehending, implementing, and analyzing. These levels can help with subject learning outcomes

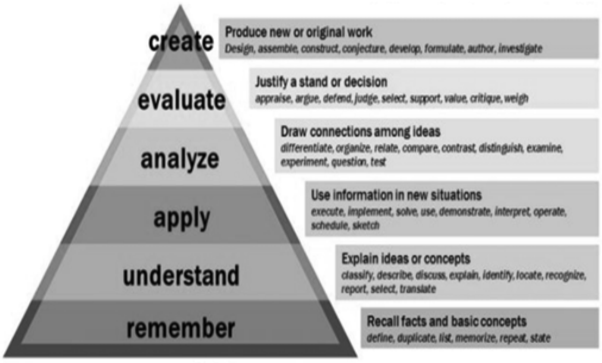


Fig.3 :Cognitive K- levels based on Blooms taxonomy.

growth. The ability to recall or retrieve relevant knowledge from what a student has learned is tested by the remembering skill. The ability to comprehend is measured through one or more modes of explanation. Use skill tests to see how well someone can apply information or a skill in a new setting. The analyses skill assesses a student's ability to break down complex ideas into smaller chunks and relate them to one another.

3. Experimental Case study work

With two tutors in a class of 40 pupils, a case study was conducted to determine the efficiency of our strategy. A total of 20 students have been assigned to each tutor. This was completed over the course of a semester, which included three Continuous Assessment Tests (CAT) and a semester exam. During that semester, students took six classes. The outcomes of how each tutor's students did are assessed by determining the average marks of their 20 students in six disciplines. This study demonstrates the importance of feedback to pupils. It teaches students to critically evaluate their own strengths and limitations, as well as what they may do to better them. They can make modifications in their learning style with timely feedback. It should also be tailored, and tutors should make sure that students receive it.

Case study-1: A tutor who assesses the performance of his 20 students at each level and provides his own critique. The tutor-student relationship is extremely positive throughout this circumstance. The tutor made every attempt to provide each and every student with appropriate comments, although it took a long time. The tutor ward average grades improved substantially. The tutor must more conscious to give negative feedback to certain students which has an indirect impact on a students self-esteem. Feedback must be given in a way that boosts the student's excitement and self-awareness in order for them to score better.

Case study-2: A tutor used the proposed technique to make timely and relevant recommendations to fellow students. The tutor spent proportional time doing things like communicating the prediction to various subject instructors. Based on the instructors comments and feedback the machine learning model was proposed for easy way to assess the students cognitive skills throughout the semester. The findings show how the feedback influenced the students decisions.

4. Proposed model for TWS

A machine learning model prototype is created and linked to a newly built student portal. It contains all of the student's information, including their grades. As a result, there is no need to deal with documentation any longer. Data management and manipulation are

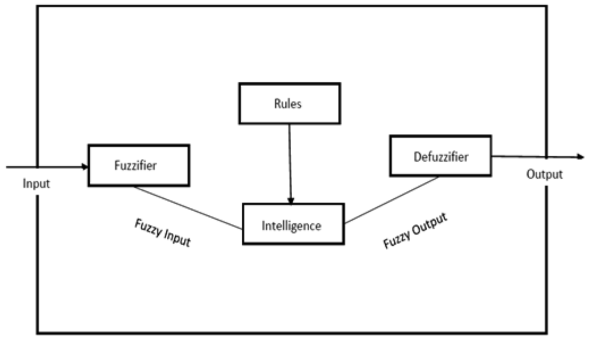


Fig. 4: Fuzzy architecture for cognitive assessment for proposed model

The fuzzy logic implementation contains three processes: fuzzification, fuzzy inference, and defuzzification. Fuzzification operations combine a real input value with stored membership function information used to generate Fuzzy input values. Fuzzy inference matches fuzzified input facts based on Fuzzy rules. Defuzzification combines all Fuzzy outputs to find out the best optimal result. Though Fuzzy Logic is easy to implement, it has a significant drawback for usage in this case since everything has to be explicitly mentioned in Fuzzy, and it does not learn itself from a predefined dataset. So, the Machine learning concept has been chosen and implemented in our framework. On top of Tensorflow.js, ML5 is an open-source toolkit that offers access to machine learning (ML) models and algorithms in the browser. It uses JavaScript, a dynamic scripting language that fosters involvement on the internet, to handle memory management and GPU-accelerated mathematical operations for ML algorithms. The user's browser executes JS code. It makes use of third-party libraries to improve the website's operation. The Machine Learning (ML) model was developed by passing on 200 randomly generated values ranging from 0 to 100, with four rows K1, K2, K3, and K4 denoting remembering, understanding, applying, and analyzing, respectively, and the result is labelled as A, B, C, and D based on the specified conditions. There are an unlimited number of boundary conditions that can be specified; however, because this is a prototype, only five are considered. 15 model files are generated since the inputs would be in any one of these below mentioned 15 combinations.

1 input → 4 Models {K1, K2, K3, K4}

2 inputs → 6 models {K1K2, K1K3, K1K4, K2K3, K2K4, K3K4}

3 Inputs → 4 models {K1K2K3, K1K2K4, K1K3K4, K2K3K4}

4 inputs → 1 models {K1K2K3K4}

Table 1: The proposed ML model sampling

S. No	Condition	Label
1	K1 < 50 AND (K3 < 50 || K4 < 50)	A
2	K1 > 50 && K2< 50	B
3	K1 < 50 && (K3> 50 || K4 > 50	C
4	K3 < 50 || K4< 50) && K1 > 50	D

The regression models are extended using a Multi-Layer Perceptron algorithm as the above-mentioned problem is not linearly-separable and the model is built using two dense layers with activation functions of RELU, and combined with a mean squared error loss function and gradient descent optimizer. They are trained with 200 epochs, batch size of 80, and learning rate of 2. The hyperparameters were fine-tuned by experimenting with various combinations of values, and this set of values produced the best results. In the end, the validation accuracy was 98.46%. For each category, the input data is converted to percentiles. This is done because certain subjects are easier than others, resulting in greater average scores for simpler subjects and lower average scores for tougher subjects, resulting in varying total marks in each category. As a result, all of the scores must be converted into equivalent values. As a result, the percentile is determined. The prediction model is loaded based on the inputs provided by the user in the form of excel. The output will be based on which label each student's score belongs to or closer to and it will be as mentioned below for each label.

A → The student is probably struggling with the subject's basics. Focus on rudimentary concepts must be emphasized.

B → The student has a good grasp of basics, but is struggling with understanding those concepts. Practice is required in areas of content description.

C → The student has a good overall understanding and application skills. He/She is probably struggling with the notion of time management.

D → The student is struggling with applying his ideas to real world problems; however, he/she has a good foundation of all the concepts in the subject. In backend program, a dynamic web page is created with PHP framework which is an open-source server-side popular scripting language. It is embedded with HTML and used in conjunction with a MySQL database which is an open-source Relational Database Management System that uses Structured Query Language. Any kind of web page from small form to a large corporate portal can be created with a combination of PHP and MySQL. All the data is stored in the database. The Database contains students' information, their K level scores and Machine Learning output for enrolled subjects.

Fig. 5: Proposed Model Backend structure

The Storage and Retrieval can be done based on the user's authentication.

HyperText Markup Language (HTML) is used to build the basic skeleton to the website and it is also enhanced by Cascading Style Sheet (CSS) which helps to style the website so it appears in the way the user intended to be seen by adding colors, fonts etc.,

Jquery is a lightweight JavaScript library that makes it much easier to use JS on the website. The Front End and Back End interact through Asynchronous JavaScript and XML (AJAX) which is a technique for creating faster and interactive web applications with HTML, CSS and JavaScript. It reads data from a web server after the page is loaded and sends data to a web server in the background.

JavaScript Object Notation (JSON) is a file for storing and exchanging data. This is used to exchange data between a browser and a server. Any JavaScript object can be converted to JSON and sent to the server and any JSON received from the server can be converted nto JavaScript objects.

The figure 7 details about the steps to follow in the students portal developed in the front end proposed model. Scores of the students are downloaded from the student portal in excel file format and it is parsed into JSON using XLSX library which is used for

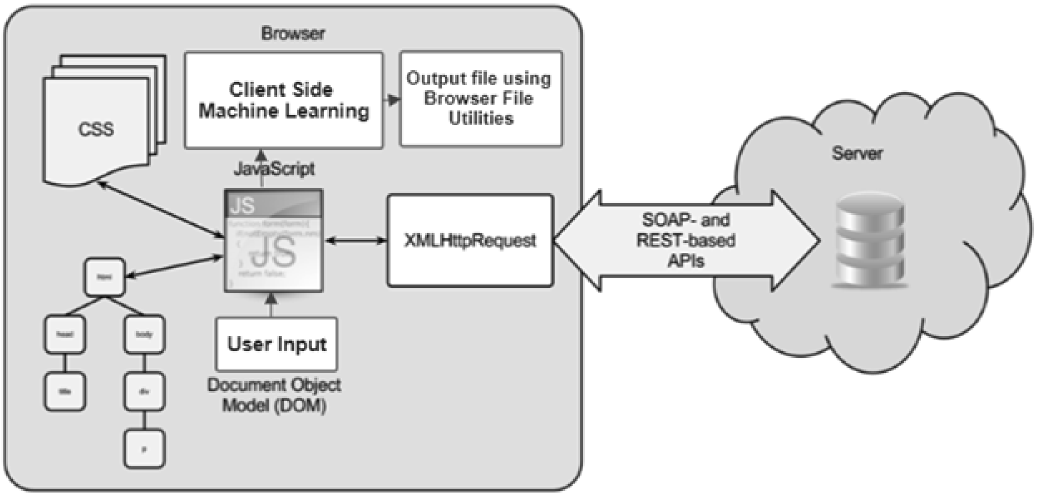


Fig. 6: Proposed model Front end structure

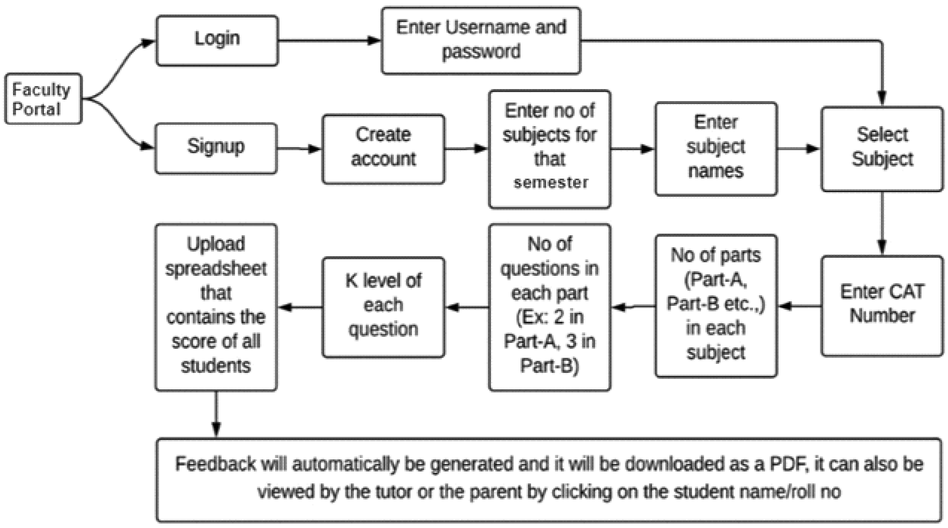


Fig. 7: Proposed model Pipeline diagram at faculty member portal end

reading and writing in spreadsheets and required input alone is segregated. The Developed Model is then imported and the user's input is fed to the appropriate model and results are generated. The Generated output is written to a pdf file using JSPDF which is an open-source library for generating PDF documents using JavaScript.

5. Results and Statistical Analysis

When the model was used in conjunction with a standard mentoring methodology and a student-tutor interaction mode, the results showed that student performance improved significantly. The data utilized to arrive at the results consists of the performance of two separately studied groups of students prior to and after model implementation throughout the course of two examinations, which is then statistically analyzed using Minitab Software to arrive at the following results:

The proposed work comprised of two group of TWS system samples T Test to interpret and provide a clarification that the difference between the two sample sets (ie. Results of students from 2 CAT tests in this case) is due to the actual difference in the population level and not due to some random error in the analysis.

$$t = {}^{(x_1 - x_2)}/_{S}$$

X1 (Set 1) is the mean of our first set – Results of students before employing our tutoring model

X2 (Set 2) is the mean of our second set – Results of students after employing our tutoring model which facilitates the tutors to understand the areas of improvements for individual student.

S – Noise value, X1 – X2 – Signal

Table 3: Interpreting the key results of T Test

Descriptive Statistics					Estimation for difference	
Sample	**N**	**Mean**	**Std. Dev**	**SE Mean**	**SD error Difference**	**95% CI for difference**
Set-1	60	28.02	8.96	1.2	-10.38	(13.28, -7.49)
Set-2	60	38.40	6.89	0.89		

Table 4: Hypothesis Classification of T Test

Null Hypothesis		$*_4: \mu_5 - \mu_6 = 0$
Alternate Hypothesis		$*_5: \mu_5 - \mu_6 \neq 0$
T-Value	**DF**	**P-Value**
-7.12	110	0.0001

In this interpretation, the estimate of the difference in the sample set means for the student's results is -20.38. The t test methodology for group student comparisons based on confidence interval was suggested by Fusic et al in 2022. The 95 percent confidence interval (ci) for this difference is the same out of 100 percent in the propose work includes, Intermediate values from -13.28 to -7.49 were employed in the calculations, with a t value of 9.4567 and a standard error of difference of -10.38. as shown in the Table 3.

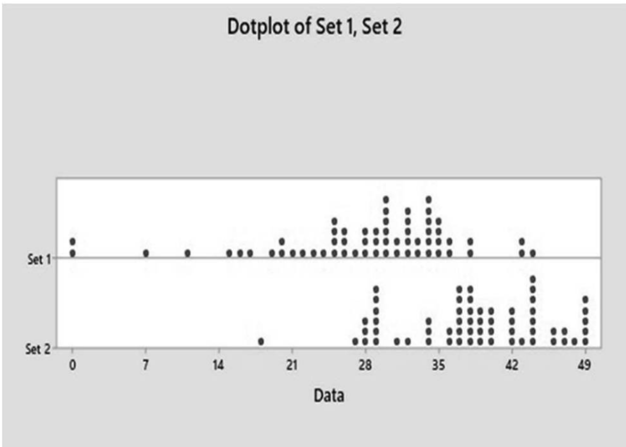


Fig. 8: Dot plot graph for Batch A and B

In the table 4 result, the null hypothesis states that the difference in the mean rating between two results is 0. Because the p-value is 0.000, which is less than the advice level of 0.05, the decision is to reject the null hypothesis and conclude that the results from two CAT tests are different and the dataset is valid for our analysis. For a visual depiction, we plotted the two sets using dot plot, individual value plot, and boxplot.

Dot plot is used to determine the peak and the spread of the data. It can be inferred from the above figure (figure number), the bins are crowded in between the 20 to 35 in the set 1 (pre model data).

However, the set 2 (post model data) shows that majority of the bins are above 30 which reinforces the fact that student's performance has exhibited a significant progress post the ML model

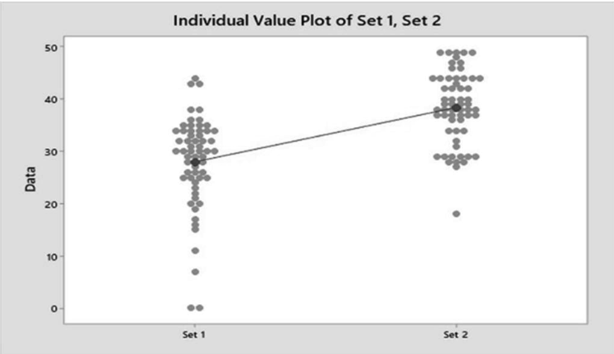


Fig. 9: Individual value plot for Batch A and B

implementation as it helps the tutors narrow down the areas which a tutee has to concentrate more so that the tutors can guide/help them accordingly. It can be inferred that the mean of the set 2 is greater than the set 1, and the whole data for set 2 which comprises the student group's mark post the proposed model implementation is skewed towards the maximum possible value which helps us visualize the student performance and reiterates the effectiveness of the

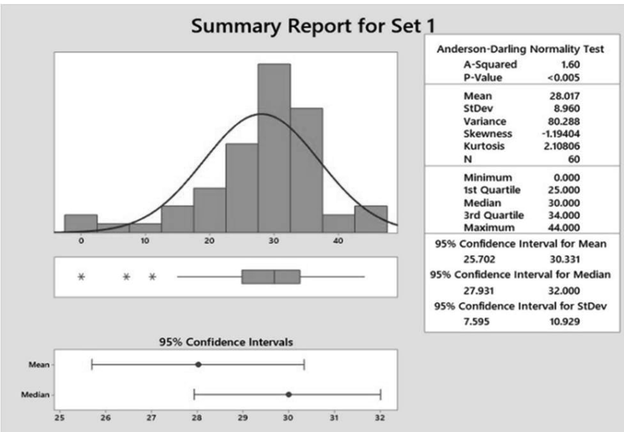


Fig. 10 : Normality test report plot for Batch A

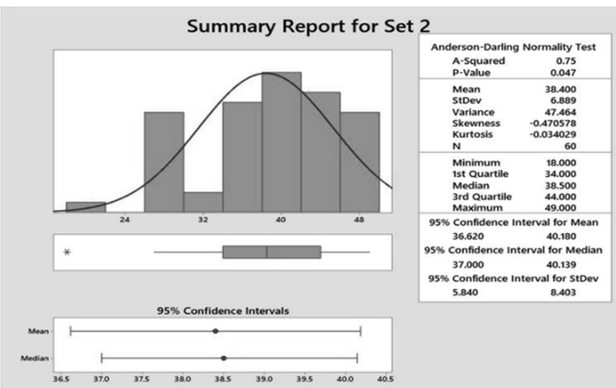


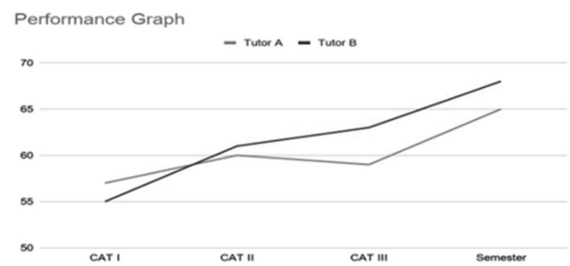
Fig. 11 : Normality test report plot for Batch B

Machine Learning based Tutor Ward System. The p-value is a probability that measures the evidence against the null hypothesis. A smaller p-value provides stronger evidence against the null hypothesis. The p-value is less than or equal to the significance level (0.05). So, the decision is to reject the null hypothesis and conclude that your data do not follow a normal distribution. Kurtosis indicates how the tails of a distribution differ from the normal distribution. Set 1 has a positive kurtosis value that indicates the distribution has heavier tails than the normal distribution from which we can infer that we are most likely to randomly pick a sample with smaller values.

For set 2 also, the p-value is less than or equal to the significance level (0.05). So, the decision is to reject the null hypothesis and conclude that your data do not follow a normal distribution. Set 2 has a negative kurtosis value that indicates the distribution has lighter tails than the normal distribution which is a key indicator of the fact that if we pick a random sample from the distribution, we are not likely to obtain a sample made of smaller values since the overall marks of the student group increased after the administration of the proposed model.

Feedback from students

After using the model of a semester, we surveyed to know about its effectiveness. Approximately 75% of the students have found this useful and they want to continue getting recommendations after each test. The figure 12 graph shows that the performances of student's tutor B who used proposed model of feedback and recommendations has outperformed students of Tutor A.



Tutor	CAT I	CAT II	CAT III	Semester
Tutor A	57	60	59	65
Tutor B	55	61	63	68

Fig. 12: Performance graph for Team A and Team B

6. Conclusion

After each cognitive test, a machine learning model was constructed to provide relevant recommendations to the students. The tutor must identify the student's level of learning based on their performance and take particular efforts to encourage the students to do better in future courses. In addition, the model gives all data on each student's knowledge level in order to compare and maintain the NBA and NAAC aggradation data recording portal. All of these processes are linked to the student site, which allows for parent's visibility. A case study was conducted in the proposed work to determine the effectiveness of the tutor ward model with ease. With minor modifications, this model can be utilized for various training objectives such as campus placements, class committee, skill- rack program and so on. Our future works include adding extracurricular activities, increasing k levels and YouTube videos recommendation. Adding extracurricular activities, raising k levels, and recommending Active learning session activities as co-curricular are among our upcoming way of developing the proposed model.

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