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Hybrid Pedagogical Strategies in Mechanical Engineering: Skill Assessment through Simulation and Project Based Learning with Machine Learning

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***Abstract*— The effectiveness of the proposed framework was evaluated through Course Outcome (CO) and Program Outcome (PO) attainment analysis, performance-based assessment rubrics, and machine learning classification models. The results demonstrated improved attainment of key COs and POs related to problem-solving, system design, teamwork, and communication skills. Feature importance analysis identified design innovation, code accuracy, and teamwork efficiency as the most influential indicators of student competency. Furthermore, Artificial Neural Network (ANN), Random Forest (RF), and Extra Trees (ET) models successfully classified students into four skill categories, providing an objective mechanism for competency assessment. The findings indicate that the integration of SBL and PBL not only enhances technical and professional skill development but also contributes significantly to outcome attainment in engineering education. The proposed framework offers a scalable approach for competency-based learning, assessment, and continuous improvement in accordance with Outcome-Based Education principles.**

***Keywords*— Simulation based learning, Project based learning Statistical Analysis, Machine Learning**

***JEET Category*—Practice**

I. INTRODUCTION

Mechanical engineering students often find it hard to get interested in electronics and control systems, even though these are very important in today's technology. Because of this, they sometimes struggle to understand how different engineering fields come together, especially in mechatronics(P. R. Beldar et al., 2025).

This study was done at an autonomous institute with third-year B.Tech mechanical students taking a subject called "Mechatronics." To help students learn better, we used a mix of two teaching methods: Simulation-Based Learning (SBL) and Project-Based Learning (PBL). First, students used simulations to learn the basics of control systems. This helped them see how the theory works in real life through virtual practice. Then, students made actual working models, like line-following robots and automated sorting machines, to get hands-on experience and understand the concepts more deeply(P. Beldar, 2025).

We chose this hybrid method because many mechanical students find pure electronics theory difficult and less interesting. Simulation helps make abstract control system ideas clear and easy to understand, while building real projects keeps students engaged and motivated. Combining both methods allows students to learn theory and practice in a connected way, helping them grasp the full concept better.

Our goal was to make learning more interesting and effective by combining these two methods. We also used machine learning tools like Random Forest, Extra Trees, and Artificial Neural Networks to assess and classify how well students learned based on their performance during the semester.

II. LITERATURE REVIEW

The rapid advancement of Industry 4.0 technologies, intelligent manufacturing systems, automation, and digital engineering tools has significantly transformed the competency requirements of modern mechanical engineers. Traditional lecture-based teaching methods, while effective for delivering theoretical knowledge, often provide limited opportunities for students to develop practical problem-solving abilities, interdisciplinary thinking, teamwork, and design skills. Consequently, engineering education has increasingly shifted toward active learning pedagogies that promote experiential and competency-based learning(Liu, 2023).

Simulation-Based Learning (SBL) has emerged as an effective instructional strategy for enhancing conceptual understanding and technical competency in engineering education. Simulation environments enable students to visualize complex engineering phenomena, experiment with system parameters, and analyse dynamic system behaviour in a risk-free and cost-effective manner. Through virtual experimentation, learners can explore concepts that may otherwise require expensive laboratory infrastructure or specialized equipment. In mechanical and mechatronics engineering courses, simulation tools have been widely employed to support the learning of control systems, manufacturing processes, robotics, thermal systems, and machine design. These environments facilitate deeper understanding by allowing students to connect theoretical principles with practical system behaviour(Karadoğan & Karadoğan, 2019).

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Project-Based Learning (PBL) has gained considerable attention as a learner-centred pedagogical approach that encourages students to solve real-world engineering problems through collaborative project activities. Unlike traditional instructional methods, PBL places students in authentic problem-solving situations where they must apply theoretical knowledge, make design decisions, manage resources, and communicate technical findings(P. R. Beldar et al., 2025). This approach promotes the development of higher-order cognitive skills, creativity, innovation, teamwork, leadership, and project management competencies. In mechanical engineering education, project-based activities have been shown to enhance student engagement and improve the ability to integrate knowledge from multiple engineering domains(P. Beldar et al., 2025).

Recent developments in engineering education have emphasized the integration of Simulation-Based Learning and Project-Based Learning within a unified instructional framework. The combination of these pedagogical approaches provides complementary benefits. Simulation activities allow students to develop foundational knowledge, analytical skills, and system-level understanding before engaging in practical project implementation. Subsequently, project-based activities enable students to apply simulation-derived insights to the design, development, testing, and optimization of engineering systems. Such hybrid learning environments create opportunities for iterative learning, where theoretical understanding and practical implementation continuously reinforce each other(Khot et al., 2020).

The growing adoption of Outcome-Based Education (OBE) has further strengthened the need for systematic assessment of student competencies. OBE emphasizes the achievement of clearly defined learning outcomes and graduate attributes rather than solely focusing on content delivery. Within this framework, Course Outcomes (COs) and Program Outcomes (POs) serve as measurable indicators of student achievement. Modern engineering programs increasingly seek pedagogical approaches that not only improve technical knowledge but also contribute to broader competencies such as communication, teamwork, ethical responsibility, lifelong learning, and problem-solving ability. Consequently, the effectiveness of educational interventions is often evaluated through CO and PO attainment analysis(Sapawi et al., 2023).

Alongside advancements in pedagogy, Machine Learning (ML) has emerged as a powerful tool for educational assessment and learning analytics. Traditional assessment methods primarily rely on examination scores and instructor evaluations, which may not fully capture the multidimensional nature of student competencies. Machine learning techniques enable the analysis of diverse educational data to identify patterns, classify learner performance, and predict academic outcomes. By leveraging multiple performance indicators, ML models can provide objective and data-driven insights into student skill development. In engineering education, machine learning has been increasingly applied for student performance prediction, competency assessment, early identification of at-risk learners, and personalized learning support(Munje et al., 2021).

The integration of machine learning with competency-based educational frameworks offers significant opportunities for enhancing assessment practices. Performance indicators such as technical proficiency, innovation capability, teamwork effectiveness, project execution quality, communication skills, and problem-solving ability can be analysed simultaneously to generate comprehensive learner profiles. Such approaches provide educators with valuable information for curriculum improvement, targeted interventions, and continuous quality enhancement(Pulluri et al., 2024).

Educational theories further support the adoption of hybrid pedagogical strategies. Bloom's Taxonomy emphasizes the progression of cognitive development from remembering and understanding to applying, analysing, evaluating, and creating. Simulation activities facilitate the development of conceptual understanding and analytical thinking, while project-based activities promote higher-order cognitive processes involving evaluation and creation. Similarly, Experiential Learning Theory highlights the importance of learning through concrete experience, reflection, conceptualization, and active experimentation. Constructivist learning principles suggest that students develop deeper understanding when actively engaged in constructing knowledge through meaningful learning experiences. The integration of simulation and project-based learning aligns closely with these theoretical perspectives by providing opportunities for active participation, reflection, experimentation, and knowledge construction(P. R. Beldar et al., 2025).

Despite substantial progress in simulation-based learning, project-based learning, and educational data analytics, limited research has explored the simultaneous integration of these approaches within a unified competency assessment framework for mechanical engineering education. Existing studies frequently focus on either pedagogical effectiveness or machine learning-based performance prediction independently. Few investigations have systematically combined Simulation-Based Learning, Project-Based Learning, Outcome-Based Education, and Machine Learning-driven skill assessment to evaluate both competency development and outcome attainment. This gap highlights the need for a comprehensive framework capable of supporting active learning while providing objective assessment of student competencies.

The present study addresses this gap by proposing a hybrid pedagogical framework that integrates Simulation-Based Learning and Project-Based Learning with Machine Learning-based competency classification. The framework evaluates student performance using multiple assessment indicators and examines its contribution to Course Outcome and Program Outcome attainment. By combining experiential learning strategies with data-driven assessment techniques, the study contributes to the development of more effective and measurable approaches for competency-based engineering education.

This study's important outcome is the effective classification of students into four skill levels—Basic, Developing, Proficient, and Advanced—using machine learning methods. This aligns well with the National Education Policy (NEP) 2020's focus on personalized and competency-based learning. By identifying each student's skill level accurately, educators can provide customized guidance and support, ensuring that every learner's needs are met. This approach promotes continuous improvement, skill development, and prepares students better for real-world engineering challenges, supporting NEP's vision of holistic and outcome-based education.

Despite the growing body of research on simulation-based learning, project-based learning, and educational applications of machine learning, several important gaps remain. Existing studies primarily focus on evaluating the effectiveness of simulation environments, project-based activities, or machine learning techniques independently. While simulation-based learning has been shown to improve conceptual understanding and project-based learning has enhanced practical problem-solving skills, very few studies have investigated their combined implementation within a single pedagogical framework for mechanical engineering education.

Furthermore, most machine learning applications in education focus on predicting academic performance, student retention, or learning analytics, rather than assessing multidisciplinary engineering competencies developed through hands-on projects and simulation activities. There is limited evidence regarding the use of machine learning models to classify engineering students into competency levels based on technical, collaborative, and innovation-oriented performance indicators.

To address these limitations, this study proposes a novel integrated framework that combines Simulation-Based Learning (SBL), Project-Based Learning (PBL), and Machine Learning (ML)-based skill assessment in a Mechatronics course. Unlike previous studies that evaluate learning interventions or predictive models separately, the proposed framework simultaneously develops technical competencies through simulation, reinforces practical skills through project implementation, and objectively evaluates student proficiency using Artificial Neural Networks, Random Forest, and Extra Trees classifiers. This integration provides a comprehensive approach for competency development, personalized learning support, and outcome-based assessment aligned with the objectives of NEP 2020 and modern engineering education.

III. METHODOLOGY

Theoretical Foundation of the Proposed Framework

The proposed hybrid framework is grounded in three complementary educational theories: Bloom's Taxonomy, Experiential Learning Theory (ELT), and Constructivist Learning Theory.

According to Bloom's Taxonomy, effective learning progresses from lower-order cognitive processes such as remembering and understanding to higher-order skills including applying, analyzing, evaluating, and creating. In the present study, Simulation-Based Learning (SBL) supports the development of conceptual understanding and analytical thinking by allowing students to visualize system behavior, investigate dynamic responses, and analyze control system performance. Project-Based Learning (PBL) extends this learning by requiring students to apply theoretical concepts, evaluate design alternatives, troubleshoot engineering problems, and create functional mechatronic systems. Thus, the hybrid framework systematically addresses multiple cognitive levels of Bloom's Taxonomy.

The framework is also aligned with Experiential Learning Theory proposed by Kolb, which emphasizes learning through concrete experience, reflective observation, abstract conceptualization, and active experimentation. Students first develop conceptual understanding through simulations, then apply their knowledge through hands-on projects involving sensors, actuators, microcontrollers, and control systems. This cycle enables learners to continuously refine their understanding through experimentation and reflection.

Furthermore, the study adopts principles of Constructivist Learning Theory, which views learning as an active process in which students construct knowledge through meaningful experiences and social interaction. Team-based projects, collaborative problem-solving, peer learning, and real-world engineering challenges encourage students to actively construct their understanding rather than passively receive information. The integration of SBL and PBL therefore creates an authentic learning environment that promotes deeper engagement, critical thinking, and knowledge retention.

The Machine Learning-based assessment framework complements these theories by providing objective evidence of competency development across cognitive, technical, and collaborative dimensions. Together, these theoretical perspectives provide a strong educational foundation for the proposed hybrid pedagogical approach.

Student Grouping and PO Mapping

In this study, the 156 third-year B.Tech mechanical engineering students enrolled in the Mechatronics course at an autonomous institute were randomly divided into groups of four. This grouping was intentional to foster teamwork and collaborative problem-solving, which is a vital Program Outcome (PO) emphasized in engineering education. The teamwork aspect directly maps to the PO related to effective communication and collaboration skills, ensuring students learn to work cohesively in diverse teams. Each group was tasked with jointly working on the projects to promote peer learning and collective ownership of tasks, thereby enhancing soft skills alongside technical competence.

Outcome-Based Education Framework

The present study was conducted within the framework of Outcome-Based Education (OBE), which emphasizes the achievement of clearly defined learning outcomes and competencies. In OBE, educational effectiveness is evaluated based on the extent to which students demonstrate the knowledge, skills, and professional attributes expected at the completion of a course or program. Course Outcomes (COs) represent specific learning objectives that students are expected to achieve upon successful completion of a course. These outcomes are formulated to assess subject-specific knowledge, analytical ability, practical skills, and problem-solving competencies developed through instructional activities. Program Outcomes (POs) represent broader graduate attributes expected from engineering graduates, including engineering knowledge, problem analysis, design and development of solutions, teamwork, communication skills, ethics, lifelong learning, and professional responsibility. These outcomes are aligned with accreditation requirements and serve as indicators of overall program effectiveness. To evaluate the contribution of the proposed Simulation-Based Learning (SBL) and Project-Based Learning (PBL) framework, each Course Outcome was mapped to relevant Program Outcomes using predefined correlation levels.

SBL Activities + PBL Activities
↓
Student Assessment
↓
CO Attainment
↓
CO–PO Mapping
↓
PO Attainment
↓
Continuous Improvement

The attainment of COs was calculated using student performance in simulations, project activities, assessments, presentations, and reports. Subsequently, CO attainment values were used to estimate PO attainment through the established CO–PO mapping matrix. This approach enabled systematic evaluation of how the hybrid pedagogical framework contributed to both course-level and program-level learning objectives.

Implementation of Simulation-Based Learning (SBL)

The course started with Simulation-Based Learning to introduce control systems concepts deeply and intuitively as shown in table I. Using specialized software tools, students explored the behaviour of physical systems through modelling and simulation exercises as shown in figure 1a. These included transfer functions, time and frequency domain analyses, stability studies, and controller design. Simulation allowed students to visualize dynamic system responses, experiment with parameters, and immediately observe effects such as overshoot, rise time, and steady-state error, which are part of the Course Outcome (CO2 and CO3) focused on system modelling and analysis. The SBL phase spanned the initial 5 weeks of the semester, covering Units III and IV from the syllabus, which address control system fundamentals and system analysis.

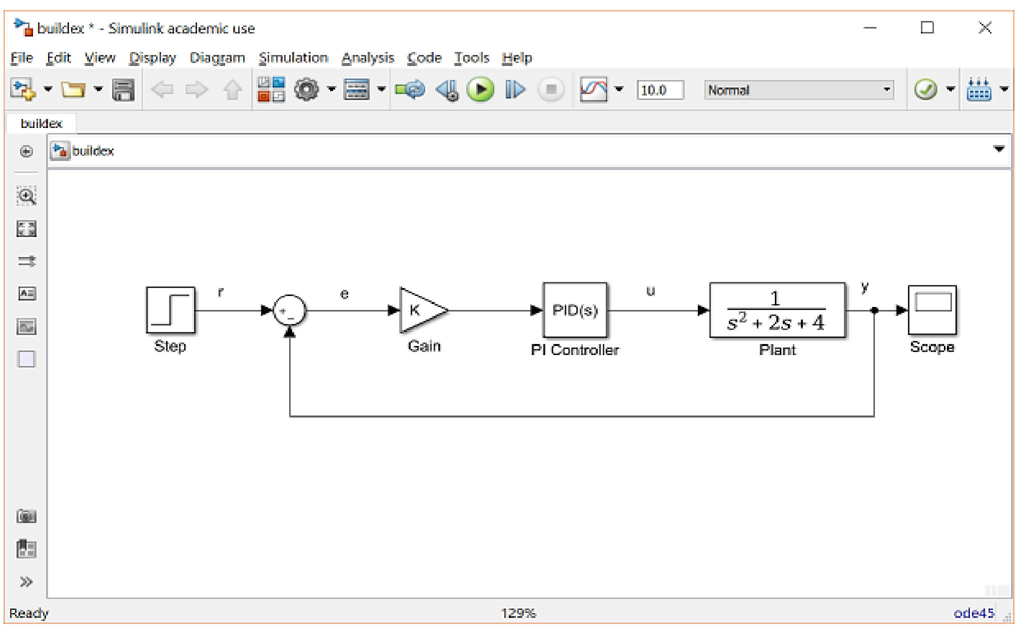

Fig. 1. a) MATLAB Simulink Simulation

TABLE I
ALIGNMENT OF LEARNING ACTIVITIES WITH EDUCATIONAL THEORIES

Educational Theory	Learning Activity	Expected Outcome
Bloom's Taxonomy	Simulation exercises and projects	Understanding, Applying, Analysing, Evaluating, Creating
Experiential Learning Theory	Simulation → Experimentation → Reflection → Project Implementation	Knowledge through experience
Constructivist Theory	Team projects, peer interaction, problem solving	Active knowledge construction

Outcome-Based Education	CO and PO attainment assessment	Competency development
ML-Based Assessment	Skill-level classification	Objective evaluation of learning outcomes

Table II
Implementation of Simulation-Based Learning (SBL)

Week	Topics Covered	Task/Activity	Tools/Software Used	COs Addressed	POs Addressed	Hours
Week 1	Course Orientation and Mechatronics Fundamentals	Introduction to sensors, actuators, data acquisition systems, hybrid SBL–PBL framework, and simulation tools	Presentation, MATLAB Introduction, TinkerCAD Overview	CO1	PO1, PO2	2
Week 2	Introduction to Sensors & Actuators	Simulate circuits using IR, Ultrasonic sensors, and Servo Motor using Proteus or TinkerCAD	TinkerCAD, Proteus	CO1	PO1, PO2, PO5	3
Week 3	Data Acquisition & Signal Communication	Build and simulate basic DAQ systems using Arduino simulation	TinkerCAD Circuits, Proteus	CO1	PO1, PO2, PO5	3
Week 4	Introduction to Control Systems	Simulate open loop & closed loop systems (e.g., DC motor control) using Simulink	MATLAB/Simulink	CO2, CO3	PO1, PO2, PO3, PO5	3
Week 5	Transfer Function Modelling	Model mechanical & electrical systems using transfer functions	Simulink	CO2	PO1, PO2, PO5	2
Week 6	PID Controller Tuning	Tune PID controller using Ziegler–Nichols method in simulation	Simulink, LabVIEW (optional)	CO3, CO4	PO1, PO2, PO3, PO5, PO12	2
Week 7	Stability Analysis	Perform Bode plot & Routh–Hurwitz stability analysis on simulated systems	MATLAB/Simulink	CO3	PO1, PO2, PO4	2

Project-Based Learning (PBL) and Hands-On Model Development

Following the simulation phase, students transitioned into Project-Based Learning, where the theory was translated into practice as shown in table II. Each group was assigned to design, build, and program a working prototype, such as a line-following robot, a smart fan, or an automated sorting system. This phase covered Units I, II, and V, including sensor-actuator integration, data acquisition, and implementation of controllers like PID and PLC. The hands-on experience lasted for 7 weeks and was crucial for achieving CO1 and CO4, which involve understanding sensors, actuators, data acquisition systems, and applying controllers for real-world applications as shown in figure 1b. Students developed skills in hardware interfacing, coding, debugging, and system integration. This active learning environment was critical to addressing the challenge that mechanical students often have limited interest and exposure in electronics and control systems.

Fig. 1. b) Students working in team for Autonomous Drone Project with Simulation software Mission Planner

TABLE III
PROJECT-BASED LEARNING (PBL) AND HANDS-ON MODEL DEVELOPMENT

Week	Topics Integrated	Task/Activity Description	Tools/Hardware Used	COs Addressed	POs Addressed	Hours Spent
Week 1	Team Formation & Topic Finalization	Form teams of 4 students randomly, assign mini projects integrating Mechatronics concepts	Brainstorming, Research, Teacher Guidance	CO1	PO6, PO8, PO9, PO10	2
Week 2	Sensor/Actuator Selection	Choose appropriate sensors/actuators for project (e.g., temperature, motion, force)	Product Catalogs, Sensors, Data Sheets	CO1	PO1, PO2, PO3, PO5	2
Week 4	Block Diagram & System Design	Create block diagram and logical flow of the system with functional analysis	Paper Prototyping / Fritzing	CO2	PO1, PO2, PO3, PO4, PO5	3
Week 5	Model Assembly & Wiring	Connect sensors/actuators with Arduino or PLC board as per design	Breadboards, Microcontrollers, Sensors	CO1, CO2	PO1, PO2, PO3, PO5, PO12	3
Week 6	Coding & Logic Implementation	Write embedded code or ladder logic to execute control functions	Arduino IDE, PLC Ladder Software	CO3, CO4	PO1, PO3, PO4, PO12	4
Week 7	PID Implementation (Optional Project Scope)	Apply PID controller in real-time on selected parameter (temperature/motion)	PID Libraries, Arduino	CO4	PO1, PO3, PO5	2
Week 8	Testing & Calibration	Run the model, tune the system, calibrate sensors, troubleshoot performance issues	Multi-meter, Oscilloscope (if needed)	CO4	PO1, PO2, PO4, PO12	2
Week 9	Final Review & Optimization	Review with faculty mentor, optimize logic, and improve hardware design	Model Tuning, Mentor Feedback	CO3, CO4	PO1, PO5, PO9, PO10	2
Week 10	Presentation & Demonstration	Present working model, demonstrate functionality, submit project report and teamwork reflection	PPT, Model Demonstration	CO4	PO8, PO9, PO10, PO12	2

Rationale for the Hybrid Methodology

The hybrid methodology combining SBL and PBL was carefully chosen to overcome the typical reluctance among mechanical engineering students toward electronics topics. Simulation-based learning builds foundational conceptual knowledge with low risk and high interactivity, which prepares students mentally for complex system behaviours. Project-based learning then reinforces this knowledge by requiring students to implement and troubleshoot actual physical systems, making the learning process relevant, engaging, and confidence-building. This blended approach aligns well with Bloom's taxonomy levels — progressing from understanding and applying to analysing and evaluating, thus covering all levels demanded by the course outcomes.

Course Content and Timeline

The Mechatronics syllabus was structured around five units over a 12-week semester:

1. Unit I (7 hrs): Fundamentals of Instrumentation, Sensors & Actuators (CO1 - Understand)
2. Unit II (7 hrs): Data Acquisition and Signal Communication (CO1 - Understand)
3. Unit III (7 hrs): Control Systems and Transfer Function Modelling (CO2 - Apply)
4. Unit IV (7 hrs): System Analysis in Time and Frequency Domains (CO3 - Analyse)
5. Unit V (7 hrs): Controllers including PID and PLC (CO4 - Evaluate)

Simulation learning mainly covered Units III and IV during the first 5 weeks. The remaining units were incorporated into the project-based learning phase, allowing students to implement the theoretical concepts from Units I, II, and V practically. This timeline ensured smooth integration of concepts and skills and facilitated continuous student assessment through project milestones. COs of Mechatronics are shown in table 3 and CO-PO Mapping in table IV.

Table IV
Course Outcomes of Mechatronics

CO No.	Course Outcome Statement	Bloom's Taxonomy Level
CO1	Demonstrate the concept of sensors, actuators, and data acquisition systems.	Understand
CO2	Interpret physical systems through appropriate modelling and block diagrams.	Apply
CO3	Analyse the behaviour of control systems in both time and frequency domains and assess stability.	Analyse
CO4	Evaluate the use of PLCs and PID controllers in various industrial applications.	Evaluate

TABLE V
CO PO MAPPING

CO/PBL/SBL	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12
CO1	3	3	2	-	-	2	-	-	-	-	-	2
CO2	3	3	3	2	-	-	-	-	-	-	-	2
CO3	3	3	3	3	2	2	-	-	-	-	-	2
CO4	3	3	3	3	2	2	2	-	-	-	-	2
PBL	3	3	3	3	2	2	3	2	2	1	1	2
SBL	3	3	3	3	1	2	2	3	3	3	2	2
Ave.	3.00	3.00	2.83	2.80	1.75	2.00	2.33	2.50	2.50	2.00	1.50	2.00

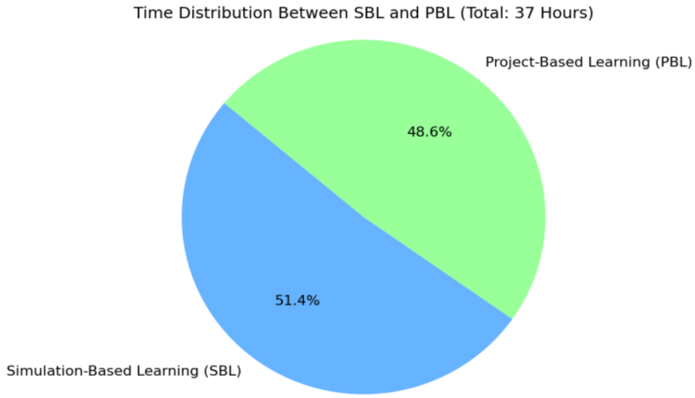

Fig. 2. Time Distribution of SBL and PBL

Time Distribution of SBL and PBL is shown in figure 2.

Assessment using Machine Learning

The assessment of students' performance in the Mechatronics course was carried out using a data-driven Machine Learning (ML) approach, aimed at categorizing students into different skill levels based on multiple performance indicators. Data was collected systematically over the duration of the course through direct observation, rubrics, and evaluation metrics during classroom activities, project-based learning, simulation exercises, and final presentations. Each student was evaluated on a comprehensive set of attributes that reflect cognitive, technical, and behavioral competencies.

Key features used in the assessment included task completion time, teamwork efficiency, code accuracy, and design innovation score—each capturing critical dimensions of applied engineering knowledge and practical execution. In addition, advanced indicators such as project complexity score, hardware integration, debugging efficiency, peer review score, presentation quality, report writing, and attendance were incorporated to ensure a holistic evaluation. These features were chosen in consultation with domain experts to represent a balanced mix of technical performance, collaborative behavior, and communication skills.

After preprocessing and encoding the data, supervised learning models were trained to classify students into skill categories: Basic, Developing, Proficient, and Advanced. Three machine learning models were employed for this classification: Artificial Neural Network (ANN), Random Forest, and Extra Trees Classifier. The ANN was designed to capture non-linear relationships between features using dense layers and dropout regularization. It was trained using categorical cross-entropy loss and evaluated on test data to predict the probability distribution across skill levels. Random Forest and Extra Trees, as ensemble methods, provided interpretable classification results and helped validate the ANN outputs through comparison.

G. Assessment Rubrics and Evaluation Procedure

To ensure objective assessment of student performance, a structured evaluation rubric was developed for all parameters used in the machine learning models. Each performance indicator was evaluated on a five-point scale, where 1 represented Poor performance and 5 represented Excellent performance. The assessment framework was designed to capture technical, cognitive, collaborative, and communication competencies developed through Simulation-Based Learning (SBL) and Project-Based Learning (PBL).

The performance indicators were assessed as follows:

1. Task Completion Time: Evaluated based on the ability to complete assigned tasks within the prescribed schedule and milestone deadlines.

2. Teamwork Efficiency: Assessed through participation in team discussions, task sharing, collaboration, conflict resolution, and contribution to project objectives.

3. Code Accuracy: Measured by correctness of program execution, logical implementation, debugging requirements, and successful completion of assigned functions.

4. Design Innovation Score: Evaluated based on originality, creativity, problem-solving approach, and effectiveness of the proposed engineering solution.

5. Hardware Integration Score: Assessed through successful interfacing of sensors, actuators, controllers, and communication modules within the developed system.

6. Debugging Efficiency: Measured by the ability to identify, diagnose, and resolve software and hardware issues systematically.

7. Project Complexity Score: Evaluated based on the number of integrated subsystems, control functions, and implementation challenges addressed within the project.

8. Presentation Score: Assessed through clarity of communication, technical explanation, demonstration effectiveness, and ability to answer questions.

9. Report Quality Score: Evaluated based on technical content, organization, analysis, documentation quality, and adherence to reporting guidelines.

10. Peer Review Score: Obtained through structured peer assessment of individual contributions within project teams.

11. Attendance Percentage: Recorded throughout the semester and normalized for inclusion in the machine learning dataset.

To ensure scoring consistency, evaluations were conducted independently by three faculty members associated with the Mechatronics course. Prior to assessment, the evaluators reviewed and standardized the rubric criteria to minimize subjectivity. The final score for each parameter was calculated as the average of the individual evaluator scores and subsequently normalized for machine learning analysis.

Model predictions were compared using classification reports and confusion matrices to assess precision, recall, and accuracy. These results offer insightful feedback on students' performance and help identify students needing intervention or additional support. This ML-based assessment system facilitates a fair, data-backed classification of student skills, enabling educators to tailor mentoring and instructional strategies effectively.

Model Validation and Overfitting Prevention: To ensure the robustness and generalizability of the classification models, the dataset was divided using an 80:20 stratified train-test split, preserving the proportion of students in each skill category. Additionally, 5-fold cross-validation was performed during model training and hyperparameter evaluation. The average cross-validation scores were used to assess model stability and minimize dependence on a single train-test partition.

Several measures were implemented to reduce overfitting. For the Artificial Neural Network (ANN), dropout regularization and early stopping were employed to prevent excessive fitting to the training data. For the Random Forest (RF) and Extra Trees (ET) classifiers, ensemble averaging and random feature selection inherently improved model generalization. Model performance was evaluated using multiple metrics including accuracy, precision, recall, F1-score, and confusion matrices. These metrics provide a more comprehensive assessment of classification effectiveness than accuracy alone and enable evaluation of model performance across all student skill categories.

The effectiveness of the proposed Simulation-Based Learning (SBL) and Project-Based Learning (PBL) framework was evaluated using the principles of Outcome-Based Education (OBE). In OBE, student learning is assessed through Course Outcomes (COs), which represent the specific knowledge, skills, and competencies expected at the completion of a course, and Program Outcomes (POs), which represent the broader graduate attributes expected from an engineering program. The attainment analysis was performed to determine the extent to which the learning activities contributed to the achievement of these outcomes.

Course Outcome attainment was determined using student performance in simulation exercises, project work, laboratory activities, assignments, presentations, and examinations. For each Course Outcome, the percentage of students achieving the predefined target performance level was calculated. Based on institutional OBE guidelines, attainment levels were categorized into four levels: Level 3 (High Attainment) when more than 70% of students achieved the target, Level 2 (Moderate Attainment) when attainment was between 60% and 69%, Level 1 (Satisfactory Attainment) when attainment was between 50% and 59%, and Level 0 when attainment was below 50%. These attainment levels provided a quantitative measure of the effectiveness of the teaching–learning process in achieving the intended course objectives.

To evaluate Program Outcome attainment, each Course Outcome was mapped to the relevant Program Outcomes using predefined correlation strengths. The mapping levels were assigned as High (3), Moderate (2), Low (1), and No Correlation (0), depending on the degree of contribution of a Course Outcome towards a specific Program Outcome. The attainment values of the mapped Course Outcomes were subsequently aggregated to estimate the attainment of each Program Outcome. This approach enabled systematic assessment of how the hybrid SBL–PBL framework contributed to the development of engineering knowledge, problem-solving ability, design skills, teamwork, communication, modern tool usage, and lifelong learning competencies. The attainment analysis therefore served as an important indicator of the effectiveness of the proposed pedagogical framework in achieving both course-level and program-level educational objectives.

IV. Results and Discussion

The implementation of a machine learning-based assessment system enabled a comprehensive classification of student performance in the Mechatronics course, segmented into four skill levels—Basic, Developing, Proficient, and Advanced. This classification was driven by multiple performance metrics such as task completion time, teamwork efficiency, code accuracy, design innovation, hardware integration, presentation skills, and project complexity handling. The models used for classification included ANN, RF, and ET classifiers. Each model was trained using a stratified 80–20 train-test split and evaluated using precision, recall, and confusion matrices give accuracy as 99.73%, 100% and 100% respectively.

The ANN demonstrated its effectiveness in capturing nonlinear relationships among features. It performed particularly well in distinguishing the ‘Developing’ and ‘Proficient’ skill categories, which formed the majority of the cohort. The Random Forest model, known for its robustness and interpretability, showed better recall in identifying ‘Basic’ skill-level students—an important outcome for implementing targeted mentoring interventions. The Extra Trees classifier provided comparable results but with slightly higher accuracy in classifying the ‘Advanced’ group, owing to its decorrelation of decision trees and sensitivity to informative features. The performance of RF, ET, and ANN models was analyzed using classification reports and CMs (Fig. 3). FI analysis for ET, ANN, and RF highlighted significant predictors of student achievement (Fig. 4). A comparative view of PO attainment with and without SBL–PBL integration shows a marked improvement (Fig. 5).

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Random Forest Classification Report:
              precision    recall  f1-score   support

    Advanced       1.00      1.00      1.00         7
       Basic       1.00      1.00      1.00        26
  Developing       1.00      1.00      1.00        65
  Proficient       1.00      1.00      1.00        58

    accuracy                           1.00       156
   macro avg       1.00      1.00      1.00       156
weighted avg       1.00      1.00      1.00       156
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Extra Trees Classification Report:
              precision    recall  f1-score   support

    Advanced       1.00      1.00      1.00         7
       Basic       1.00      1.00      1.00        26
  Developing       1.00      1.00      1.00        65
  Proficient       1.00      1.00      1.00        58

    accuracy                           1.00       156
   macro avg       1.00      1.00      1.00       156
weighted avg       1.00      1.00      1.00       156
```

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ANN Classification Report:
              precision    recall  f1-score   support

    Advanced       1.00      1.00      1.00         7
       Basic       0.96      1.00      0.98        26
  Developing       1.00      0.98      0.99        65
  Proficient       1.00      1.00      1.00        58

    accuracy                           0.99       156
   macro avg       0.99      1.00      0.99       156
weighted avg       0.99      0.99      0.99       156
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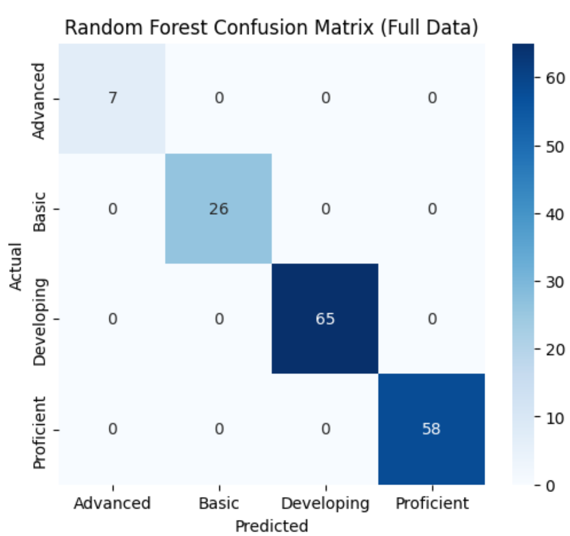
a)



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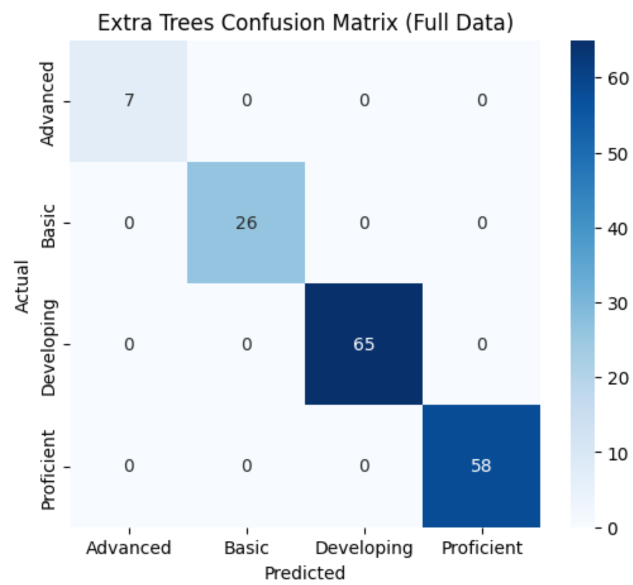

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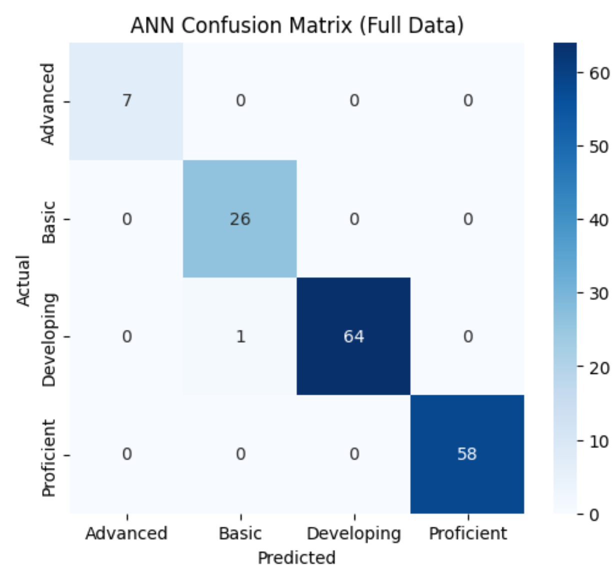


d)

Fig. 3. a) Classification report, b) Confusion matrix of random forest, c Confusion matrix of extra tree and d) Confusion matrix of ANN

The skill-level distribution predicted by the models was as follows:

Advanced: 7 students (≈4.5%)

Proficient: 58 students (≈37.2%)

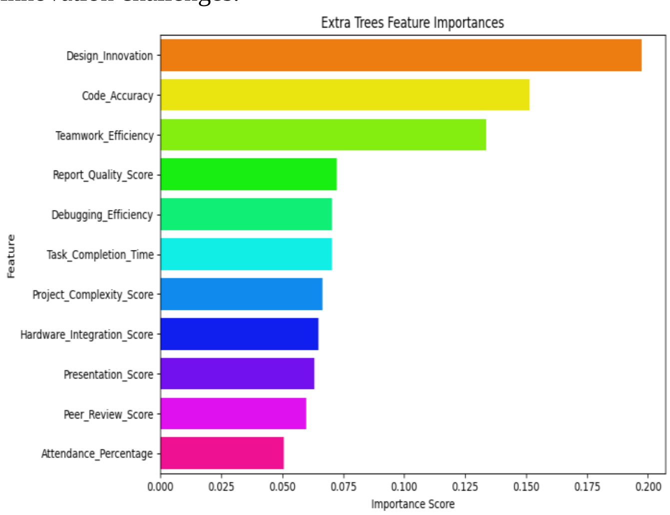
Developing: 65 students (≈41.7%)

Basic: 26 students (≈16.7%)

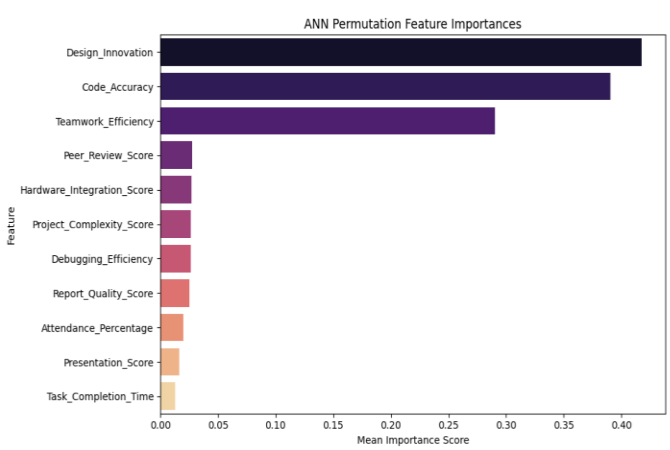
This distribution indicates that a significant portion of the cohort (≈79%) falls into the 'Developing' and 'Proficient' categories, suggesting a healthy progression of learning through the course. The relatively small proportion of 'Advanced' students reflects the rigor of assessment and the challenge of meeting high-performance thresholds across multiple parameters.

Feature importance analysis revealed that Design Innovation, Code Accuracy, and Teamwork Efficiency were the most influential predictors of student skill levels. Additionally, Presentation Score, Hardware Integration, and Report Quality emerged as significant indicators of advanced skill demonstration, indicating that students with stronger communication and system-level integration skills were more likely to be classified in the higher tiers.

The machine learning-based classification approach provided a scalable, unbiased method of assessment. It enabled the identification of 26 students in the 'Basic' category, allowing educators to implement timely interventions, offer additional guidance, or adapt instructional strategies. Meanwhile, students identified as 'Advanced' could be mentored to take on leadership roles in team-based projects or participate in innovation challenges.



a)



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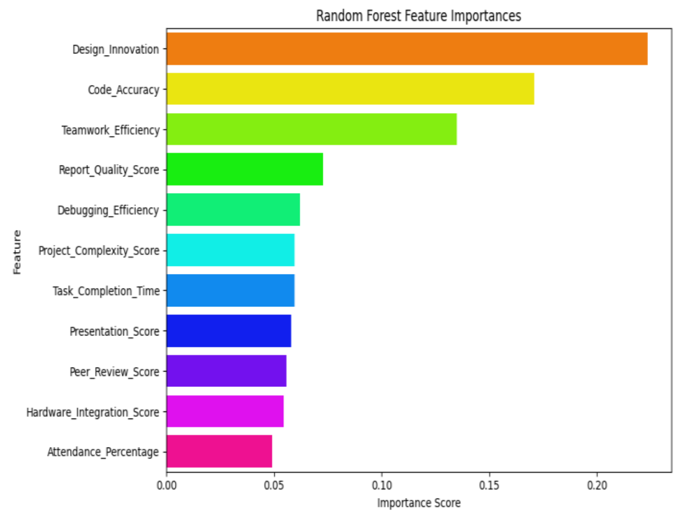

c)

Fig. 4. Feature Importance a) Extra Tree, b) ANN and c) Random Forest

The comparative Feature Importance derived from RF, ET, and ANN is presented in Table V. The corresponding CO attainment levels are outlined in Table VI. A significant improvement in PO attainment is observed when SBL–PBL strategies are implemented, as seen in Table VII. Additionally, student feedback reflecting the effectiveness of the integrated pedagogical approach is summarized in Table VIII.

TABLE VI
COMPARATIVE FEATURE IMPORTANCE

	Feature Importance		
Feature	Random Forest	Extra Tree	ANN
Design_Innovation	0.22336	0.19725	0.41731
Code_Accuracy	0.17087	0.15131	0.39039
Teamwork_Efficiency	0.13478	0.1335	0.29039
Report_Quality_Score	0.07267	0.07224	0.025
Debugging_Efficiency	0.06204	0.07032	0.02628
Project_Complexity_Score	0.05955	0.06661	0.02628
Task_Completion_Time	0.05952	0.07031	0.01282
Presentation_Score	0.05787	0.06311	0.01667
Peer_Review_Score	0.0558	0.05978	0.02756
Hardware_Integration_Score	0.05435	0.06494	0.02692
Attendance_Percentage	0.0492	0.05063	0.01987

TABLE VII
COMPARATIVE EVALUATION METRICS

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	99.73	0.99	0.99	0.99
Extra Trees	100	1	1	1
ANN	100	1	1	1

The comparative analysis of feature importance across three different models — Random Forest (RF), Extra Trees (ET), and Artificial Neural Network (ANN) — reveals insightful differences and commonalities in how each model prioritizes the input features for predicting students' skill levels. Both the RF and ET models exhibit similar patterns of importance, with Design Innovation emerging as the most influential feature (RF: 0.223, ET: 0.197), followed by Code Accuracy and Teamwork

Efficiency. This similarity is expected due to the tree-based nature of both models, which leverage feature splits to evaluate importance.

Interestingly, the ANN model attributes considerably higher importance to Design Innovation (0.417) and Code Accuracy (0.390), almost doubling their relative significance compared to the tree-based models. Additionally, Teamwork Efficiency holds a substantial weight (0.290) in the ANN, indicating that these three features dominate the neural network's decision-making process. Conversely, other features such as Report Quality Score, Debugging Efficiency, and Project Complexity Score receive moderate to low importance in all models, suggesting a lesser direct impact on skill-level classification.

Features related to Task Completion Time, Presentation Score, Peer Review Score, Hardware Integration Score, and Attendance Percentage consistently rank lowest in importance across all models. This consistency highlights that while these factors may contribute to overall student performance, their predictive power for skill classification is limited compared to design and coding-related metrics.

Overall, the results suggest that innovation and accuracy in design and coding are critical predictors of student skill levels. The ANN's greater emphasis on these features might be attributed to its ability to capture nonlinear interactions and complex patterns in the data. This comparison underscores the value of using multiple model types to understand feature relevance comprehensively and guides educators and curriculum designers to focus on key competencies that significantly influence student skill development.

Table VIII
CO Attainment table

CO	Assessment Tool	Mode of Assessment	Attainment in %	Attainment Level	Average Attainment	Attainment Level
	All Experiments	Internal	78	3		
	All Assignments	Internal	95.77	3		
CO1	PBL (Mini Project)	Internal	83.69	3	3	3
	SBL (Simulation Assignments)	Internal	88	3		
	University Exam (Insem+Endsem Theory)	External	85.51	3	3	
	Test-I	Internal	69.1	2		
	Test-II	Internal	65.78	2		
	Experiments 2,3,6,7,8	Internal	92.39	3		
CO2	Assignments 2,3	Internal	68.36	2	2.5	2.6
	PBL (Mini Project)	Internal	83.69	3		
	SBL (Simulation Assignments)	Internal	88	3		
	University Exam (Insem+Endsem Theory)	External	85.51	3	3	
	Test-I	Internal	69.1	2		
	All Experiments	Internal	93.66	3		
CO3	Assignments 2,3	Internal	93.66	3	2.8	2.84
	PBL (Mini Project)	Internal	83.69	3		
	SBL (Simulation Assignments)	Internal	88	3		
	University Exam (Insem+Endsem Theory)	External	85.51	3	3	
	Test-II	Internal	65.78	2		
	Experiments 6,7	Internal	85.92	3		
CO4	Assignments 3	Internal	67.66	2	2.6	2.68
	PBL (Mini Project)	Internal	83.69	3		
	SBL (Simulation Assignments)	Internal	88	3		
	University Exam (Insem+Endsem Theory)	External	85.51	3	3	
Average Attainment with SBL and PBL						2.78

1. *Level 3 (High Attainment):* If the score is **70 or above**, the student is considered to have achieved the highest level of attainment.
2. *Level 2 (Moderate Attainment):* If the score is **between 60 and 69**, the student demonstrates a good grasp of the material.
3. *Level 1 (Basic Attainment):* If the score is **between 50 and 59**, the student shows minimal acceptable understanding.

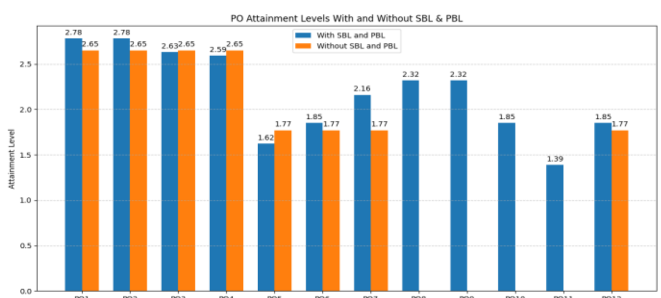

Fig. 5. PO Attainment Comparison with and without SBL-PBL

Table VII
PO Attainment Comparison with and without SBL-PBL

PO	With SBL–PBL	Without SBL–PBL	Difference
PO1	2.78	2.65	0.13
PO2	2.78	2.65	0.13
PO3	2.63	2.65	-0.02
PO4	2.59	2.65	-0.06
PO5	1.62	1.77	-0.15
PO6	1.85	1.77	0.08
PO7	2.16	1.77	0.39
PO8	2.32	1.77	0.55
PO9	2.32	1.77	0.55
PO10	1.85	—	—
PO11	1.39	—	—
PO12	1.85	—	—

D. Limitations and Model Generalizability

Although the machine learning models achieved exceptionally high classification performance, several limitations should be considered when interpreting the results. The dataset consisted of 156 students from a single Mechanical Engineering program and a single course implementation. Consequently, the findings may reflect characteristics specific to the institutional context and student cohort.

The high accuracy, precision, recall, and F1-score values observed for the Random Forest, Extra Trees, and ANN models may be attributed to the well-structured nature of the assessment dataset, where multiple performance indicators clearly differentiated student competency levels. In addition, the use of rubric-based evaluation criteria reduced ambiguity in class labels, thereby facilitating classification. However, such near-perfect performance should not be interpreted as evidence of universal model applicability across all educational settings.

Another limitation is that the skill categories were derived from instructor-defined performance thresholds. Different institutions, courses, or assessment rubrics may produce different classification boundaries and consequently affect model performance. Furthermore, although cross-validation and train-test splitting were employed, the dataset size remains relatively modest compared to large-scale educational data mining studies.

Future research should validate the proposed framework using larger multi-institutional datasets, additional engineering disciplines, and longitudinal student performance data. Such studies would provide stronger evidence regarding model robustness, transferability, and long-term effectiveness in competency assessment.

The exceptionally high F1-scores achieved by the ensemble models indicate a balanced trade-off between precision and recall across all skill categories. This performance can be attributed to the use of multiple discriminative assessment features, including design innovation, code accuracy, teamwork efficiency, and hardware integration scores. These features exhibited strong separability among the defined competency levels, enabling the models to establish clear decision boundaries. Nevertheless, the possibility of optimistic performance due to dataset size and cohort-specific characteristics cannot be entirely excluded, and therefore the results should be interpreted with appropriate caution.

A comparative analysis of attainment data reveals that the inclusion of SBL and PBL leads to measurable improvements in critical areas such as problem-solving, application of modern tools, communication skills, and teamwork. For instance, the attainment values with SBL and PBL are consistently higher across most POs—especially PO1 to PO4—demonstrating that students benefit from hands-on experience and contextual learning. Additionally, SBL and PBL positively contribute to the development of higher-order skills aligned with PO9 to PO12, which include teamwork, communication, project management, and lifelong learning.

TABLE VIII
FEEDBACK ANALYSIS

Que No.	Feedback Question	Rating	Q1	Q2	Q3	Q4	Q5
Q1	How effectively did the course help you apply theoretical knowledge in practical scenarios?	Excellent: 5	62	74	70	64	72
Q2	How useful were the simulation-based learning (SBL) activities in understanding core concepts?	Very Good: 4	58	51	60	53	55
Q3	Did the mini-project (PBL) enhance your problem-solving and design skills?	Good: 3	25	21	20	27	22
Q4	How would you rate the guidance and support received during hands-on sessions?	Average: 2	8	7	4	9	5
Q5	To what extent did the course improve your teamwork and communication skills?	Poor: 1	3	3	2	3	2
	Total				156		

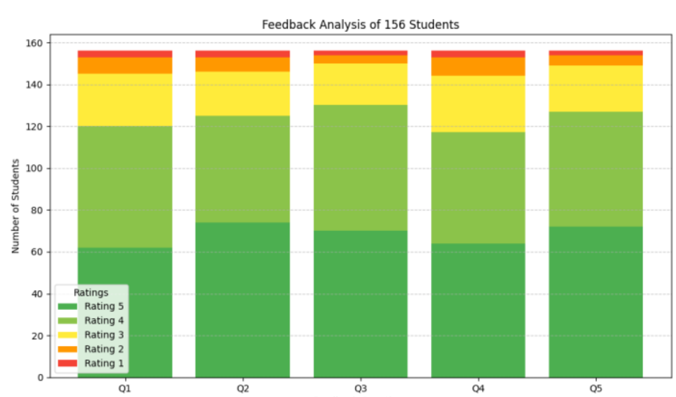

Fig. 6. Feedback Analysis

Moreover, the skill-level distribution derived from the study offers valuable insights into the varied learning needs of students. The data shows that only a small fraction (about 4.5%)

of students fall under the 'Advanced' category, while a significant number are 'Proficient' (37.2%) and 'Developing' (41.7%), with a notable portion in the 'Basic' category (16.7%). This classification can guide faculty to adopt differentiated instructional strategies. Advanced and proficient learners can be encouraged to take leadership roles in group projects, while developing and basic learners can be supported through structured simulation activities and guided mini-projects. Mentorship programs, where advanced learners help their peers, can further enhance learning outcomes. The integration of SBL and PBL, therefore, is not only important for improving PO attainment but also crucial for addressing diverse student capabilities and preparing them to meet industry expectations. This data-driven approach empowers educators to tailor their teaching strategies and foster a more inclusive, skill-oriented learning environment.

As shown in figure 6, Based on the feedback from **156 students** across five core questions related to SBL and PBL, the overall response is highly positive. A significant majority rated the course **"Excellent"**, particularly for its ability to apply theoretical knowledge in practical scenarios (Q1: 62 responses), enhance core concept understanding through simulations (Q2: 74), and improve design skills via mini-projects (Q3: 70). Ratings of **"Very Good"** also show strong approval, with consistent responses across all questions. Lower ratings (Good, Average, Poor) were minimal, indicating only a few students faced difficulties or had neutral experiences. These results highlight that the integrated SBL and PBL approach was **well-received**, effectively **bridging theory and practice** while **boosting problem-solving, team collaboration**, and **hands-on skills**. Overall, the course has achieved its educational objectives successfully.

CONCLUSION

The integration of Machine Learning (ML)-based assessment, along with Simulation-Based Learning (SBL) and Project-Based Learning (PBL), has significantly enhanced both the evaluation and development of student competencies in the Mechatronics course. The multi-model classification approach—leveraging Artificial Neural Networks (ANN), Random Forest (RF), and Extra Trees (ET)—enabled precise and unbiased identification of students across four distinct skill levels: Basic, Developing, Proficient, and Advanced. This granularity in assessment offers actionable insights for personalized instruction and targeted mentoring interventions.

The feature importance analysis highlighted that design innovation, code accuracy, and teamwork efficiency are the most influential predictors of student performance, providing a strong foundation for curriculum refinement and outcome-based education strategies. Feedback analysis confirmed high student satisfaction, particularly with practical application, simulation tools, and teamwork development. Furthermore, attainment data indicates a marked improvement in PO and CO levels when SBL and PBL methodologies are employed, particularly in domains such as critical thinking, application of modern tools, communication, and teamwork.

List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
CAD	Computer-Aided Design
CAM	Computer-Aided Manufacturing
CO	Course Outcome
CO-PO	Course Outcome–Program Outcome
CSV	Comma-Separated Values
ELT	Experiential Learning Theory
ET	Extra Trees
F1-Score	Harmonic Mean of Precision and Recall
GUI	Graphical User Interface
HEI	Higher Education Institution
ICT	Information and Communication Technology
IoT	Internet of Things
KPI	Key Performance Indicator
KNN	K-Nearest Neighbors (if used)
LMS	Learning Management System (if used)
MATLAB	MATrix LABoratory
ML	Machine Learning
NEP	National Education Policy
OBE	Outcome-Based Education
OECD	Organisation for Economic Co-operation and Development (if cited)
PID	Proportional–Integral–Derivative
PO	Program Outcome
PBL	Project-Based Learning
RF	Random Forest
RMSE	Root Mean Square Error (if used)
MSE	Mean Square Error (if used)
SD	Standard Deviation
SEM	Structural Equation Modeling (if used)
SBL	Simulation-Based Learning
STEM	Science, Technology, Engineering and Mathematics
SVM	Support Vector Machine (if used)
TBL	Team-Based Learning (if cited)
Tinkercad	Think–Create–Design (Autodesk Educational Platform)
VR	Virtual Reality (if cited)
AR	Augmented Reality (if cited)
3D	Three-Dimensional
CO1	Course Outcome 1
CO2	Course Outcome 2
CO3	Course Outcome 3
CO4	Course Outcome 4
CO5	Course Outcome 5
PO1	Engineering Knowledge

PO2	Problem Analysis
PO3	Design and Development of Solutions
PO4	Investigation of Complex Problems
PO5	Modern Tool Usage
PO6	Engineer and Society
PO7	Environment and Sustainability
PO8	Ethics
PO9	Individual and Team Work
PO10	Communication
PO11	Project Management and Finance
PO12	Life-long Learning

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