



## Integration of Problem-Based Learning (PBL) in Machine Learning Course to Enhance the Problem-solving Skills of Undergraduate Engineering Students in India

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### ABSTRACT

#### BACKGROUND & CONTEXT

Machine Learning (ML) courses are essential to undergraduate computer science programs due to industry demand for qualified workers. However, teaching and learning an ML course pose challenges for faculty and students due to its technical complexity and interdisciplinary nature. This study focuses on integrating problem-based learning (PBL) into ML courses to provide opportunities for students to engage in problem-solving.

#### PURPOSE OR GOAL

**RQ1:** How does integrating PBL in ML courses enhance students' ability to apply theory to practical applications of real-world problems? **Hypothesis:** Engaging students in a PBL environment enhances their problem-solving skills by helping them to apply machine learning concepts to real-world problems. **Goal:** To evaluate the effectiveness of the PBL approach in fostering deep learning of ML concepts and problem-solving abilities among the students.

#### APPROACH OR METHODOLOGY

A quasi-experimental design is employed to evaluate the impact of PBL integration into an ML course on students' problem-solving skills. The data were collected through a pre-test on ML fundamentals, mathematical foundations, and problem-solving approaches and a post-test on problem-solving scenarios to measure the ML concepts application.

#### OUTCOMES

A significant statistical improvement in post-test scores after the PBL intervention compared to the pre-test scores.

#### CONCLUSIONS

The study proves that PBL significantly enhances student performance in applying theoretical knowledge to real-world ML problems. Thus, incorporating PBL into ML courses improves conceptual understanding and problem-solving, which are crucial for industry readiness.

#### KEYWORDS

Machine learning, Problem-based learning, Experiential Learning.

## Introduction

Machine Learning (ML) has quickly emerged as a key component of contemporary engineering practice and education. Engineers are expected to design and implement intelligent systems as industries across domains embrace artificial intelligence and data-driven decision-making, making machine learning (ML) expertise a highly sought-after skill set (Mosly, 2024). The rise in AI use, particularly in India, has led engineering curricula to place more emphasis on machine learning courses. However, a significant skill gap remains, underscoring the need to enhance machine learning instruction in undergraduate engineering programs to meet contemporary industry demands and develop a workforce proficient in next-generation technologies (Verma et al., 2021).

Undergraduate ML courses are often taught in a traditional lecture-centric manner, emphasizing mathematical derivations and end-of-semester examinations rather than hands-on problem-based activities (Malik & Zhu, 2022). This theory-heavy approach has led to observable gaps in student competencies. As a result, many graduates lack opportunities to practice solving open-ended problems and fail to develop flexible problem-solving skills (Dang et al., 2023).

In this scenario, Problem-Based Learning (PBL) emerges as a promising pedagogical approach to enhance students' problem-solving capabilities in ML education (Kommana et al. 2024). PBL is a student-centered instructional method wherein learners work in teams to tackle real-world, ill-structured problems, thereby driving the learning process (Acharya, 2024). Instead of passively acquiring factual content, students in PBL must select what they need to learn, use interdisciplinary knowledge, and iteratively revise solutions, much like professional engineers facing a new challenge (Kandakatla, Dustker, et al., 2023). It actively engages students and encourages deep conceptual understanding while developing transferable skills such as critical thinking, collaboration, and lifelong learning habits. Despite its potential, PBL has seen limited adoption in Indian higher education, especially engineering education.

Traditional lecture-based teaching remains the norm in many institutions under affiliated universities, partly due to large class sizes, fixed syllabi, and evaluation systems centered on written exams (Baligar et al., 2022). Faculty may be less familiar or comfortable with student-centric methods like PBL, and resource constraints can pose practical challenges (Koppikar et al., 2023b). However, the landscape is now gradually shifting as India's academic leaders and educational policymakers increasingly call for active-learning pedagogies to replace rote learning. The new National Education Policy 2020 explicitly urges a shift toward experiential and inquiry-driven education, emphasizing that students must learn "how to think critically and solve problems" rather than merely absorbing content (Kandakatla et al., 2024).

Given this context, the present study is both relevant and timely. Integrating PBL into an ML course in engineering education could address the identified skill gaps by systematically nurturing problem-solving skills. This study examines the development of problem-solving skills using machine learning (ML) concepts (algorithms and techniques) and aims to answer the following research question.

RQ1: How does the integration of PBL in ML courses impact students' ability to apply theory to practical applications of real-world problems?

Hypothesis: Engaging students in a PBL environment enhances their problem-solving skills by helping them apply machine learning concepts to real-world problems.

## Literature Review

### Machine Learning Education in India

Machine learning (ML) has become a transformative force across engineering and IT disciplines, enabling predictive modeling, optimization, and intelligent automation. ML has enhanced manufacturing processes by predicting material removal rates with over 99%

accuracy in electrochemical machining (Seenivasan et al., 2025). ML is central to cybersecurity in the IT sector, as it detects fraudulent transactions in real-time within India's rapidly growing Unified Payments Interface (UPI) ecosystem (Yasir et al., 2025). The rapid advancement and widespread application of ML have made it a vital component of modern engineering education. Today, ML is increasingly integrated into various sub-disciplines such as computer science education, data science, automation, robotics, healthcare engineering, financial modeling, and smart infrastructure. Consequently, universities worldwide are embedding ML courses into undergraduate and postgraduate engineering programs to equip the necessary skills to meet industry demands (Pan et al., 2020).

Globally and in India, the prevailing pedagogy for teaching ML remains largely conventional and instructor-centered. This approach relies on lecture-based delivery, soiled laboratory sessions for coding practice often disconnected from real-world problem contexts, and summative assessments emphasizing correctness over exploration or creativity.

Research on ML education noted that ML as a discipline demands not just mathematical rigor but also experiential learning, as the field is characterized by constant evolution, uncertainty, and the need for iterative experimentation (Riazifar & Khajehsaeid, 2024).

### **Problem-Based Learning for Machine Learning**

Problem-based learning is a student-centered approach that promotes student engagement through active participation in authentic, real-world problems. Instead of receiving direct instructions through PPT presentations and chalk and talk, investigate open-ended problems, engage in teams, and develop solutions through inquiry and research. Specifically, in engineering contexts, PBL has increased student motivation, promoted interdisciplinary thinking, and improved long-term retention of complex concepts (Hagedorn et al., 2023). Implementation PBL in freshman engineering courses significantly enhanced students' problem-solving, creativity, and teamwork through real-world projects and design thinking strategies (Naik et al., 2024).

PBL changes the paradigm of learning from passive acquisition of knowledge to active participation, in which students work together to solve open-ended, real-world problems. According to research, PBL develops transferable problem-solving skills, enhances critical thinking, and fosters more in-depth conceptual understanding (Hmelo-Silver, 2004).

In computer science education, PBL has been increasingly recognized as an effective strategy for fostering students' mastery of abstract concepts and enhancing their computational thinking skills (Rahayu et al., 2025). Several studies successfully implemented PBL in subfields such as knowledge representation and cellular automata, demonstrating its capacity to deepen students' understanding of computational models (Neto et al., 2024; Wolnik et al., 2025). Despite these promising applications, a notable gap remains in the literature regarding how PBL can be leveraged to teach ML concepts.

Some related research has focused on employing ML models to support PBL environments rather than directly using PBL as a pedagogical method for ML instruction. For example, Natural Language Processing (NLP), Decision Trees and Naïve Bayes classifiers has been utilized to monitor student interactions throughout the problem-solving process, to predict student performance within PBL settings (Pan et al., 2020; Rohmat et al., 2021)

### **Gaps in the Literature**

Despite the global momentum in adopting PBL, limited research has explored its integration within the Indian higher education system. In India, particularly in engineering and computer science disciplines, the lecture-based approach and teacher-centered pedagogies continue to dominate classroom instruction (Agarwal, 2006). Additionally, several systemic factors, such as faculty preparedness and culturally embedded expectations regarding teaching and learning, further complicate the adoption of PBL approaches in the Indian higher education system (Lakra, 2024).

To date, there remains a notable absence of empirical studies specifically investigating the implementation and effectiveness of PBL in teaching ML courses within the Indian academic context. Given the rapid expansion of India's technology sector and growing demand for ML competencies across industries, addressing this pedagogical gap is both timely and strategically significant for Indian higher education. This proposed study aims to address performance gaps related to problem-solving abilities by applying ML algorithms to real-world scenarios and investigating how PBL-based ML instruction can enhance Indian engineering students' ability to apply theoretical knowledge in practice.

## Methodology

### Context

Students enrolled in the ML course should focus on learning and applying ML algorithms to real-world problems. Instead of learning algorithms alone, students work with authentic datasets, create models, refine their answers, and critically assess results for real-world problem scenarios, reflecting professionals' difficulties (Tseng et al., 2024). Obtaining this skill set as an ML engineer is crucial for engineering graduates. PBL can be effective for developing these skill sets among undergraduate engineering students, as it is a teaching and learning approach that uses actual situations to inspire students to acquire knowledge, skills, and attitudes critical to their success as professionals (Ribeiro, 2008).

The site of the study is an autonomous engineering college offering a Bachelor of Technology in Computer Science and Engineering in the south of India. The institution offers a machine learning course to third-year computer science and engineering students, which was often taught in conventional lecture-based teaching techniques. The primary author and the instructor integrated PBL into the ML course and evaluated its impact on the students' performance. The study was conducted in one section of the third-year computer science and engineering machine learning course in which project-based learning was incorporated to enhance students' problem-solving skills.

### PBL Integration into Machine Learning Course

PBL was selectively integrated into three out of five modules, namely supervised learning, neural networks, and probabilistic learning of the ML course, to investigate the impact of problem-solving skills by applying these concepts to solve authentic and real-world problems. These concepts represent foundational and applied aspects of ML that students struggle to connect in traditional lecture-based formats. Students engaged in PBL activities such as collaboratively solving unstructured problem scenarios, which are characterized by a lack of clear definition, solution, and process.

The intervention was split into three phases: 1. Orientation and baseline assessment (week 1), 2. PBL implementation through unstructured problem scenarios aligned with ML topics such as supervised learning and neural networks (weeks 2–9), and 3. Post-intervention assessment and feedback collection (week 10).

**Phase 1:** Orientation and baseline assessment: An orientation on collaborative learning, team roles, and expectations in the PBL environment was shared, and a pre-test was conducted on ML, assessing students on ML fundamentals and problem-solving skills.

**Phase 2:** PBL implementation: students were introduced to PBL and formed heterogeneous teams of 4-5 based on their academic performance. During week 1, students presented unstructured problem scenarios and carried out various phases to implement the chosen problem. The week-wise PBL implementation steps are mentioned in Table 1.

**Table 1: PBL Implementation Phases**

| Week      | Phase                                | Activities & Tasks                                                                                                                                                                                                                                                                                                                                                                          |
|-----------|--------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Week 1    | Problem Identification & Analysis    | <ul style="list-style-type: none"> <li>• Introduction to PBL</li> <li>• Formation of student groups,</li> <li>• Pre-test</li> <li>• Identify &amp; define real-world ML problems (students select a problem from suggested options)</li> <li>• First problem statement submission with initial research questions</li> </ul>                                                                |
| Week 2    | Research & Knowledge Implementation. | <ul style="list-style-type: none"> <li>• Students explore theoretical ML concepts related to the problem identified. Conduct literature reviews &amp; case study analysis</li> <li>• Identify datasets, tools, and algorithms for implementation</li> <li>• Faculty provides guidance sessions and group discussions</li> <li>• Students develop hypotheses and define ML models</li> </ul> |
| Weeks 3-4 | Problem-Solving & Experimentation    | <ul style="list-style-type: none"> <li>• Implement initial prototypes using Python and Scikit-Learn</li> <li>• Conduct experiments and test ML algorithms</li> <li>• Mid-term peer review session &amp; feedback</li> <li>• Optimize model performance based on evaluation metrics (Accuracy, Precision, Recall)</li> </ul>                                                                 |
| Weeks 5-6 | Model Optimization                   | <ul style="list-style-type: none"> <li>• Perform a comparative analysis of different ML approaches. Work on the presentation and documentation of findings</li> <li>• Faculty mentors assist in refining solutions</li> <li>• Final team presentations &amp; model demonstrations</li> </ul>                                                                                                |
| Weeks 7-8 | Presentation, Evaluation, Reflection | <ul style="list-style-type: none"> <li>• Peer &amp; faculty evaluations &amp; discussions</li> <li>• Students document learning outcomes and reflect on challenges</li> <li>• Post-test</li> </ul>                                                                                                                                                                                          |

**Phase 3:** Post-intervention assessment and feedback: A post-test was conducted with equivalent complexity to the baseline test. Peer evaluations assessed intra-group contributions toward collaborative dynamics in solving the chosen problem.

## Research Design

This study employs a quasi-experimental design focusing on a single section of students enrolled in an ML course that uses PBL to deliver selected modules. A quasi-experimental approach is appropriate because the intervention is implemented in an intact, pre-existing classroom setting without random assignment or use of a separate control group. In educational contexts, particularly when operating within the constraints of existing course structures, it is often neither practical nor ethical to split students randomly or to withhold potentially beneficial teaching methods from part of the class. This quasi-experimental design assessed the impact of PBL integration into an ML course by comparing pre- and post-intervention outcomes (problem-solving skills, application of ML concepts) within the same classroom.

The conceptual framework for integrating PBL into an ML course is shown in Figure 1. This framework was derived from existing research (Syed et al., 2024), and a few modifications were made according to this study.

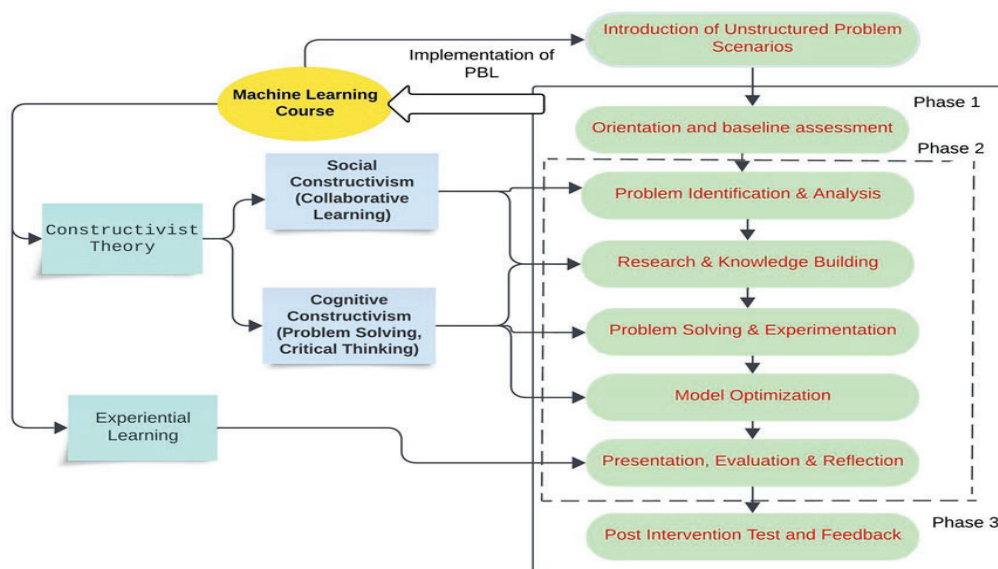


**Figure 1: Conceptual framework of Integration of PBL into ML Course**

### Data Collection and Analysis:

The participants for the study were selected using a purposeful sampling strategy, and an entire section of students who were enrolled in an ML course that integrated PBL as an instructional approach was chosen. A total of 67 third-year undergraduates from the computer science and engineering program were included in the sample. The data collection process was designed to capture changes in students' problem-solving abilities and the application of ML algorithms to solve real-world problems. Pre- and post-intervention assessments and group project evaluations were conducted.

Students took a pre-test designed to assess their baseline knowledge of ML concepts from the chosen module of the ML course. The test included conceptual (multiple-choice questions and short answers) and applied problem-solving tasks. At the end of the intervention, students completed a post-test of equivalent complexity and structure, similar to the pre-test, measuring their understanding and ability to apply ML algorithms after finishing the PBL stages. Students submitted their project implementations on an unstructured problem related to the ML modules chosen for PBL implementation. These projects were presented by the students and evaluated based on algorithm implementation, collaborative learning, and communication skills.

The paired sample t-tests were conducted to determine if there was a statistically significant improvement in scores from pre- to post-intervention tests and from pre- to post-project evaluation scores. In-class problem-solving exercises and algorithm implementation tasks were used as pedagogy to enhance logical, programming, and problem-solving skills for various algorithms, including Find-S, Decision Tree, and Linear Regression. These skills will assist students in solving the problems chosen as part of PBL tasks.

Five different problem statements and datasets that can be solved using the Find-S algorithm were given to each team as an in-class problem-solving exercise. Students can select one problem statement and dataset of their choice to practice and implement the Find-S algorithm,

and they are expected to provide their reflections after completing the task. One out of five task details and dataset table in Table 2 are mentioned below:

**Task: Run the Find-S algorithm on this dataset to determine the most specific consistent hypothesis.**

**Problem Statement 1:** Using the Find-S algorithm, determine the most specific set of weather conditions (e.g., sky, temperature, humidity, wind, and forecast) that consistently lead to a person deciding to go on a picnic. Learn only from positive ("Yes") instances to identify a consistent hypothesis describing favorable picnic weather.

**Table 2: Dataset 1 (Weather for Picnic)**

| Sky   | Temperature | Humidity | Wind   | Forecast | Picnic |
|-------|-------------|----------|--------|----------|--------|
| Sunny | Warm        | Normal   | Weak   | Same     | Yes    |
| Sunny | Warm        | High     | Weak   | Change   | Yes    |
| Rainy | Cold        | High     | Strong | Same     | No     |
| Sunny | Warm        | Normal   | Strong | Change   | Yes    |

#### Reflection Questions:

1. Why did we only consider positive examples?
2. Could this hypothesis perfectly classify future instances?
3. What are the limitations of Find-S?

## Results

The research question of this study focuses on whether integrating PBL into the ML course enhances students' ability to apply ML concepts to real-world problems. To ensure alignment, both the pre- and post-tests were designed not merely to test theoretical knowledge but to evaluate students' practical problem-solving skills using ML algorithms. The tests included applied tasks such as selecting appropriate ML algorithms for solving the identified real-world problem. The assessment of integrating PBL into the ML course is aimed at improving students' ability to transfer theoretical ML concepts to practical applications for solving real-world problems by comparing students' scores before and after the PBL intervention.

To evaluate the impact of the intervention, we conducted a normalization test (Shapiro-Wilk), which revealed that the pre-test, post-test, and PBL scores were all non-normally distributed ( $p < 0.01$ ). Therefore, we applied the Wilcoxon signed-rank test for paired comparisons.

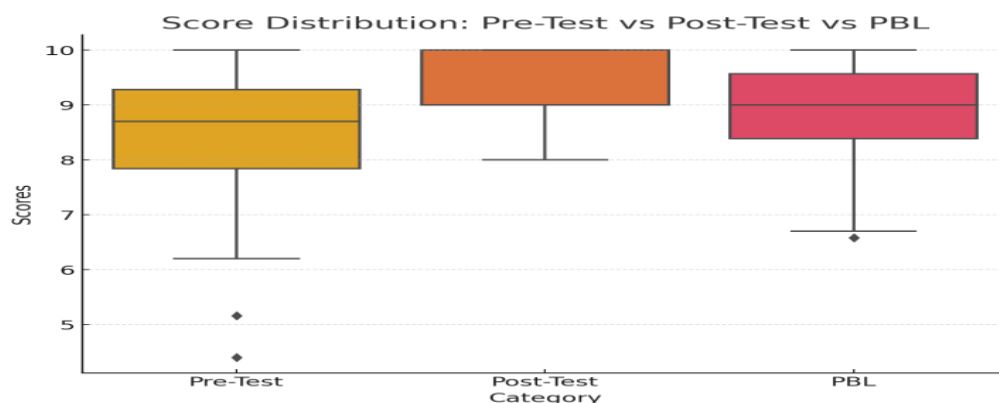


**Figure 2: Pre-Test, Post-Test, and PBL evaluation score distribution**

The results showed highly significant improvements between pre-test and post-test scores ( $W = 182.0$ ,  $p \approx 1.12 \times 10^{-7}$ ), pre-test and PBL evaluation scores ( $W = 182.5$ ,  $p \approx 1.14 \times 10^{-7}$ ), and post-test and PBL evaluation scores ( $W = 181.5$ ,  $p \approx 1.09 \times 10^{-7}$ ). These findings indicate not only statistically significant differences but also a strong and meaningful enhancement in students' performance following the intervention and implementation of PBL. The improvement in the post-test performance represents more than merely memorization of algorithms; it also demonstrates genuine advancement in applying ML algorithms through problem-solving skills. These findings confirm that integrating PBL into the ML course as an intervention significantly strengthened students' problem-solving skills.

The peer review of various evaluation criteria, such as collaboration, problem-solving, algorithm understanding (pre- and post-PBL intervention), and knowledge application, was conducted and is illustrated in Figure 2. The visual pattern highlights the positive impact of PBL, particularly in improving algorithm understanding and practical knowledge application among students, which are essential skills for problem-solving in computer science undergraduate engineering programs.

## Discussion

The results of the study provide robust evidence that the applied intervention, particularly the integration of PBL into an ML learning course, significantly enhances students' performance in problem-solving skills and applying ML algorithms to solve real-world problem scenarios. The increased average post-test and PBL evaluation scores compared to the pre-test scores reveal that integrating PBL into the ML course facilitated more profound engagement and demonstrated a high level of competency in problem-solving skills among the undergraduate students. These findings align with the existing literature, which emphasizes the benefits of active learning approaches, such as PBL, in enhancing problem-solving skills, critical thinking, and a deeper understanding of conceptual knowledge (Hmelo-Silver, 2004). The reduction in score variability, as shown in Figure 2 (boxplot), provides a detailed indication that the PBL bridges a gap among learners with varying initial competencies, leading to more uniform outcomes.

During the PBL phase, the structured use of unstructured problems encourages independent exploration, collaboration, and the development of problem-solving skills (Amashi et al., 2022). These key component skills help in developing higher-order cognitive skills for applying ML algorithms to solve real-world problems. It aligns with constructivist learning shift theories, which emphasize the role of active problem-solving and peer interaction in knowledge construction (Baligar et al., 2021). The observed evaluation criteria, depicted in Figure 3, indicate improvement in group dynamics and task ownership through peer review evaluations. Furthermore, the finding suggests that PBL enhances technical learning and fosters critical soft skills, including teamwork and communication (Baligar et al., 2022).

The feedback from students suggests that their perception of ML is shifting toward viewing it as a practical and engaging field for their career development. In Figure 3, it is observed that the average score of post-PBL understanding of ML algorithms is improved by a scale of 4 points as compared with the pre-PBL understanding of ML algorithms. Feedback from students on problem-solving and knowledge application parameters, as shown in Figure 3, reveals the students' confidence level in applying ML conceptual knowledge to solve identified problems through enhanced problem-solving skills. This finding validates the pedagogical shift toward experiential and problem-centered learning in undergraduate engineering education (Kandakatla et al., 2024). Although the study yields promising results, it has some limitations. This study highlights the effectiveness of PBL in improving students problem-solving skills, as shown through pre- and post-tests that were aligned with course outcomes and reviewed internally by subject experts for validity. External validation, qualitative evidence such as student reflections and thematic analysis was not included. Future work will refine these assessment tools through expert review and statistical analysis and incorporate qualitative

insights through mixed-methods approach to triangulate results and provide a more holistic understanding of students experience with PBL.

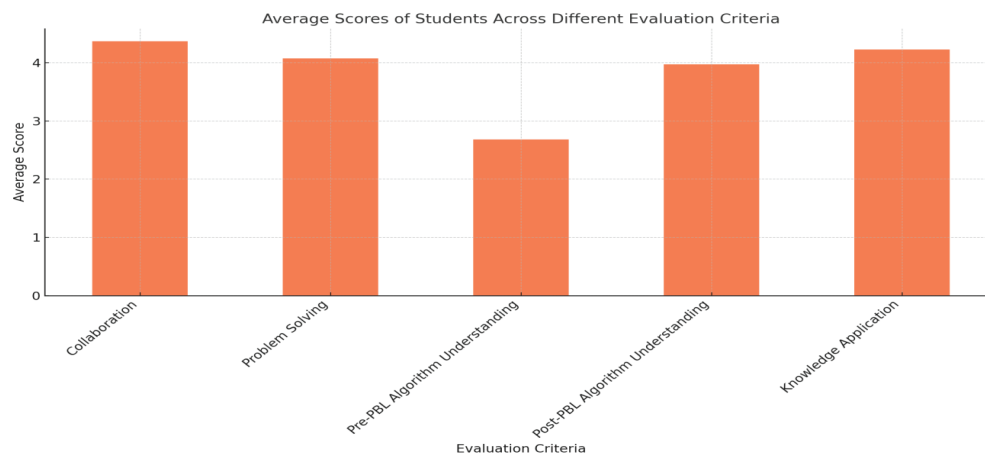


**Figure 3: Average Scores of students across different evaluation criteria**

## Conclusion

This study demonstrates that integrating PBL into the ML course resulted in significant and meaningful improvements in performance. Statistical tests confirmed that the intervention had a positive impact on students' problem-solving abilities in applying ML algorithms, resulting in higher average scores and reduced performance variability among students. These findings support the value of active, student-centered pedagogical approaches (PBL) in technical education, particularly in enhancing problem-solving skills as well as logical and programming skills. Future work should explore long-term effects, knowledge transfer to complex real-world applications, and comparative evaluations across various teaching modalities, despite the positive results. Additionally, gathering and analyzing in-depth qualitative data such as student reflections may enhance our understanding of how these interventions affect student experiences and academic achievement.

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