EPiC Series in Built Environment
Volume 6, 2025, Pages 332–341
Proceedings of Associated Schools of Construction 61st Annual International Conference

Enhancing Student Engagement and Skills in Building Structures Course through AI/ML Integration

Busra Yucel[1], Salman Azhar[1], and Amna Salman[1]
[1]Auburn University

Recently, artificial intelligence (AI) and machine learning (ML) have emerged as crucial elements in teaching pedagogy, offering significant improvements in learning, enhancing student skills, promoting collaborative education, and increasing accessibility in both teaching and research environments. This study assessed the effectiveness of an ML image-classification model for evaluating concrete workability in a Building Structures course. Sixty-two (62) students developed and tested the ML model to predict the adequacy of the water/cement ratio using slump test results from various concrete mixtures, including low, adequate, and high-water content. A paired t-test with a 95% confidence interval was conducted to compare pre-and post-assignment survey results. The findings indicate that integrating AI/ML tools into construction education increases students' familiarity with these technologies, positively influencing their perceptions of AI/ML's role in formal construction management education and improving their ability to apply AI/ML in coursework. Additionally, this experience fosters critical thinking about AI/ML applications and enables students to propose model improvements. This study contributes to construction education by demonstrating that AI/ML-based assignments enhance students' understanding of emerging technologies and provide educators with evidence-based strategies to improve construction management programs for future professionals.

Keywords: Artificial Intelligence, Machine Learning, Image Classification, Slump Test, Construction Education

Introduction

Artificial intelligence (AI) and Machine learning (ML) tools have become widely accessible to educators and students for various applications. Technology plays a vital role in education, enhancing personalized learning, hands-on experiences, presentations, information sharing, and more (Bacos, 2019; Shah et al., 2021). As students are expected to keep pace with advancements in their fields (Genc & Tatoglu, 2024), it is essential to introduce them to current technologies and solutions during their coursework. This is particularly important in the construction industry, where the adoption of new technologies is rapidly increasing each year. Incorporating innovative technology applications into the construction education curriculum could significantly enhance students' career prospects. Since the launch of ChatGPT in 2022, the use of artificial intelligence (AI) tools in education has allowed educators to offer students more personalized and hands-on learning opportunities. The current literature shows that integrating AI-based learning activities into education can help students solve complex problems and utilize large language models (LLMs) such as ChatGPT as learning support systems (Rahman & Watanobe, 2023; Hosseini et al., 2023; Grassini, 2023).

In addition to LLM chatbots, a variety of web-based, open-source machine learning tools can support students in their learning processes. Some websites (e.g. Teachable Machine by Google etc.) offer image and sound classification without requiring any coding experience. Since the use of images and media enhances understanding across various disciplines (Petterson, 2020), incorporating image-based machine learning tools could improve the effectiveness of the learning experience through ML-based activities. Integrating these tools into fields like construction, which often involves complex scenarios that cannot be fully captured in classroom settings, enables students to learn from both text and image-based information (Grassini, 2023).

The broad aim of this study is to evaluate the impact of integrating AI/ML tools into construction education by measuring their influence on student engagement, learning, and participation. The underlying research objectives are as follows:

1. To measure how the incorporation of AI/ML tools, including image-based classification models, influences students' familiarity with emerging AI/ML tools.
2. To assess the effect of AI/ML-based activities on students' ability to apply AI/ML techniques to construction concepts within a Building Structures course.
3. To explore students' perceptions of the role of AI/ML tools in enhancing their learning experiences and their applicability in the construction industry.

To achieve these objectives, the following sections outline the development of this research's hypotheses and present the findings of the experimental analysis.

Research Background and Hypotheses Development

Innovations in technology have created new areas of expertise and workforce demands that did not exist before, significantly impacting our way of living and working (Southworth et al., 2023). Kuleto et al. (2021) showed that AI and ML are critical concepts that enhance learning, student skills, collaborative learning, and accessible research environments. Similarly, Tedre et al. (2021) highlighted the benefits of teaching ML and suggested that "data-driven and rule-driven approaches both need to be taught, and ML does not make teaching rule-based programming obsolete. Yet, ignoring ML in computing education leaves a gap that is widening by the day." As a result, several universities have recently begun integrating AI into their curricula. However, most programs that include AI are within the electrical and computer engineering departments. Moreover, existing research in construction and civil engineering literature generally indicates positive student feedback on the integration of AI/ML into the curriculum (Chiang, 2021; Tapeh & Naser, 2023). Research is needed to explore the integration of AI and ML in educational curricula beyond electrical and computer engineering, particularly in fields like construction, where technological advancements are reshaping workforce demands. Despite positive student feedback on AI/ML integration, there is a critical gap in understanding its long-term impacts on learning outcomes and skill development in these areas.

Therefore, based on the current literature, we aim to test the following alternate hypotheses by comparing pre-and post-experience survey results:

- H1: Including AI/ML activities in the curriculum increases students' familiarity with AI/ML-based tools (aligned with Objective 1).
- H2: Integrating AI/ML activities into formal construction management education enhances their perceived applicability in the field (aligned with Objective 2).
- H3: Incorporating AI/ML activities into assignments improves students' ability to apply these techniques (aligned with Objective 2).
- H4: Using AI/ML as part of coursework increases students' interest in the subject (aligned with Objective 3).
- H5: Exposure to AI/ML tools during the course enhances students' perception of their usefulness in the construction industry (aligned with Objective 3).

Research Design and Methodology

To test our hypotheses, we developed an assignment in which students perform image classification for the Building Structures class. To assess the impact of the AI/ML-based assignment on students learning, we prepared pre- and post-assignment surveys. Figure 1 illustrates the research flow of the study, which is explained in more detail in the following sections.

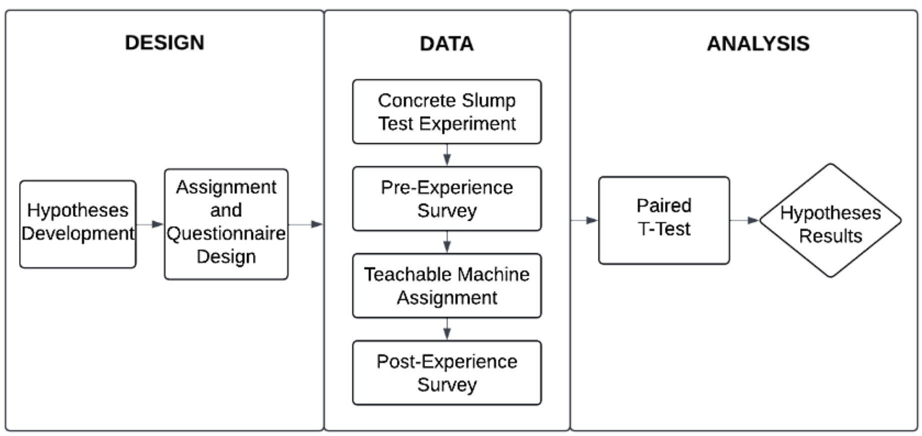


Figure 1. Research methodology flow

Assignment Design and Data Collection

In this research, we developed an assignment for the Building Structures II course, which is taken by third-year construction management students. The course was offered to two sections, and 62 students from the Building Science program at Auburn University completed the survey. This course covers the material properties and design of steel, timber, and concrete structures. The assignment was introduced after a lab class where concrete mixing and slump tests were demonstrated. The students were asked to photograph the slump test results. Before the assignment, students completed a pre-experience survey regarding their familiarity with AI/ML tools and their perceptions of AI/ML applications in the construction industry. We chose an image classification tool as our AI/ML solution due to its suitability for measuring concrete slumps. For simplicity, reliability, and free accessibility, we preferred the Teachable Machine (Google, 2024) platform over other platforms, such as Microsoft Lobe (Microsoft Azure, 2024). The assignment description included a brief tutorial on the Google Teachable Machine website, which allows users to develop image classification models without any coding experience. Students received a set of images depicting various slump test results for concrete mixtures, categorized as “low”, “adequate”, and “high” water content. They were tasked with creating three classes for each category using the provided images and training the image classification model. Finally, they tested the model using the pictures they took during the lab. Figure 2 illustrates an example of one of the student submissions. This assignment was intended for introductory purposes and did not aim to produce a fully reliable slump test classification model.

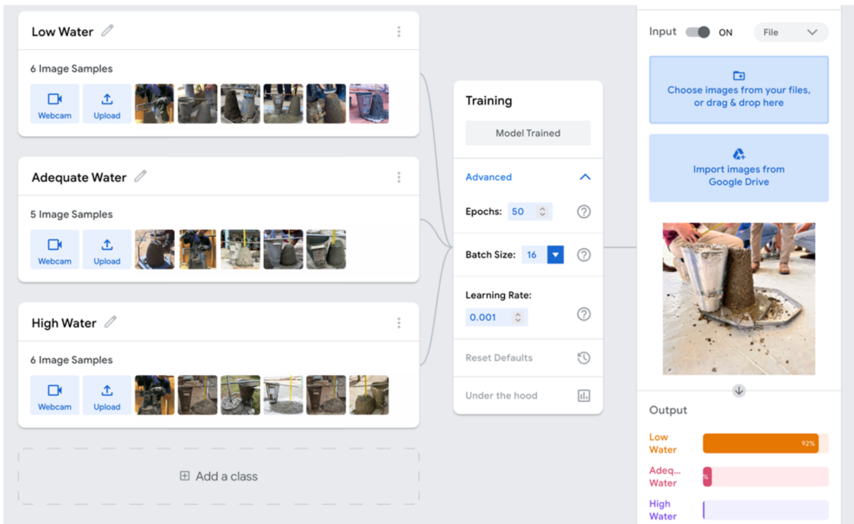


Figure 2. Machine learning (ML) model development to evaluate concrete workability

Students developed the image classification model using 5-6 publicly available online images for each category. The quality and diversity of the images used for training a classification model are critical to the accuracy of the model’s results. However, we aimed to introduce construction students to a machine learning tool to assess their experiences and perceptions regarding the use of machine learning in construction education and industry, rather than to develop a highly accurate assessment tool. This limitation was explained to the students, and they were asked to discuss the accuracy of the classification results.

Paired t-Test

We conducted a paired t-test to evaluate the change in student responses before and after the assignment, as well as to test our study hypotheses. We compared pre- and post-assignment survey results at a 95% confidence level. Additionally, we included Cohen’s d (effect size) and the power of the t-test results. Effect size measures the magnitude of the difference or relationship in a study, independent of sample size, while power is the probability that a test will correctly reject a false null hypothesis. As Kim (2015) states, the independent t-test is used when the two groups being compared are independent of each other, while the paired t-test is used when the two groups are related or dependent on each other. Therefore, we used a paired t-test for this research.

Results and Discussion

Table 1 shows the mean values and standard deviations of student responses for the pre-and post-assignment surveys. We used a 5-point Likert scale to measure the survey responses, where a low value indicates less familiarity or total disagreement, while a score of 5 represents high familiarity or strong agreement. Overall, a change is observed in the mean values, except for question 5.

Table 1. Survey questions

		Mean (N=62)	**Sd (N=62)**
Pre-assignment Questions	How would you rate your familiarity with AI/ML tools? (e.g., image/sound recognition, not large language models like ChatGPT)	2.9193	0.9632
	In your opinion, could Machine Learning tools be used as a part of formal construction management education?	3.9838	0.7353
	How confident are you in your ability to apply AI/ML concepts in your assignments?	3.5322	0.8040
	Are you interested in learning how to use AI/ML tools as a part of your coursework?	3.9193	0.8356
	How do you perceive the usefulness of AI/ML concepts in the construction industry?	4.2580	0.7228
Post-assignment Questions	How would you rate your familiarity with AI/ML tools after completing the assignment?	3.9508	0.8451
	In your opinion, could AI/ML tools be used as a part of formal construction management education?	4.2786	0.8968
	How confident are you now in your ability to classify images into categories after this assignment?	4.2950	0.8030
	I am more interested in learning how to use AI/ML tools as a part of my coursework after this assignment.	4.1147	0.8386
	How do you perceive the usefulness of AI/ML in the construction industry after completing the assignment?	4.2295	0.9200

Table 2 presents the results of the hypothesis testing.

Table 2. Paired t-test results

	t-statistics	**p-value**	**Significance**	**Effect size**	**Power**
Familiarity with AI/ML-based tools (H1)	-6.740	0.0000*	<0.05	0.8630	1.0000
AI/ML tools in construction management education (H2)	-2.204	0.0314*	<0.05	0.2822	0.5828
Ability to apply AI/ML in assignments (H3)	-5.122	0.0000*	<0.05	0.6556	0.9990
Interest in using AI/ML as a part of coursework (H4)	-1.457	0.1501	>0.05	0.1866	0.2999
The usefulness of ML in the construction industry (H5)	0.116	0.9080	>0.05	0.0149	0.0515

As shown in the table, a significant and positive change is observed in students' familiarity with AI/ML-based tools ($t = -6.740$, $p = 0.00$*), their opinions on AI/ML tools in construction management education ($t = -2.204$, $p = 0.03$*), and their ability to apply AI/ML in assignments ($t = -5.122$, $p = 0.00$*). Therefore, we accept the following hypotheses:

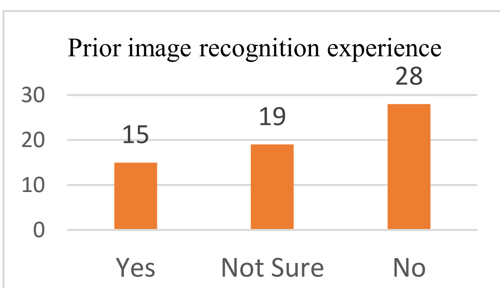
- H1: Including AI/ML activities in the curriculum increases students' familiarity with AI/ML-based tools.
- H2: Integrating AI/ML activities into formal construction management education enhances their perceived applicability in the field.
- H3: Incorporating AI/ML activities into assignments improves students' ability to apply these techniques.

Additionally, effect size results show that the observed difference was highly meaningful for students' familiarity with AI/ML-based tools (H1) and ability to apply AI/ML in assignments (H3).

On the other hand, the results showed that no significant difference was observed in "the interest in using AI/ML as a part of coursework" and "the perceived usefulness of AI/ML in the construction industry" after the AI/ML-based assignment experience. Therefore, we reject the following hypotheses:

- H4: Using AI/ML as part of coursework increases students' interest in the subject.
- H5: Exposure to AI/ML tools during the course enhances students' perception of their usefulness in the construction industry.

The pre-assignment mean value indicated that most students were already interested in using AI/ML as part of their coursework (mean = 3.92). As shown in Table 1, this value increased slightly to 4.11 after the assignment. However, this increase was not significant enough to support our hypotheses. A similar insignificant change was observed in question 5, which measured student perceptions of the usefulness of AI/ML in the construction industry, with a drop of 0.028 in the mean value for this question. This result may suggest that students are interested in learning and applying emerging technologies, regardless of their prior familiarity with the technology. As shown in Figure 3, 45.16% of the students had no prior experience with an image recognition tool. After the assignment, more than 70% of the students reported their understanding of the steps involved in training an ML image classification model as "very good" or "somewhat good".



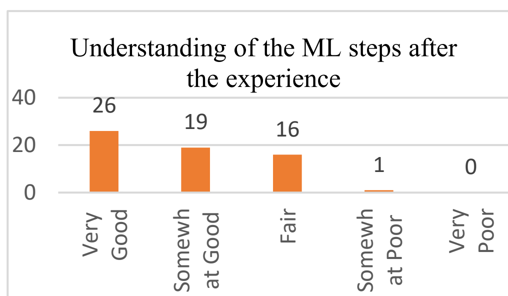


Figure 3. Pre- and post-test image recognition understanding

Model Accuracy Results

Students were asked to assess the model's accuracy using the images they captured during the slump test experiment in the lab. The results show that the model's accuracy on average exceeds 80% for predicting "low" and "high" water content, while it is somewhat lower—approximately 59%—for the "adequate" water range. This is understandable, as "adequate" water content results in a slump of 3-6 inches, which does not display a very distinct pattern.

Overall, students reported satisfaction with the assignment and the model results: "I*n this assignment, I learned a lot about concrete and machine learning. I found that it is relatively easy to use the machine learning tool we were given. Also, it was nice to see the actual visuals of how concrete reacts with water and how to make it*." Another student commented on the 100% accuracy of their model results, stating: "*My group was a Low Water model group, and every picture I submitted got about 100% accuracy for Low Water. It made me realize that AI is not as scary as I thought and that it is fairly accurate. I do find it strange how accurately it reads real-life photographs. I don't know where it could improve because my model was 100% accurate. I think it might have to do with the quality of the images that were taken*." Figure 4 shows some examples of accurate image classification results.

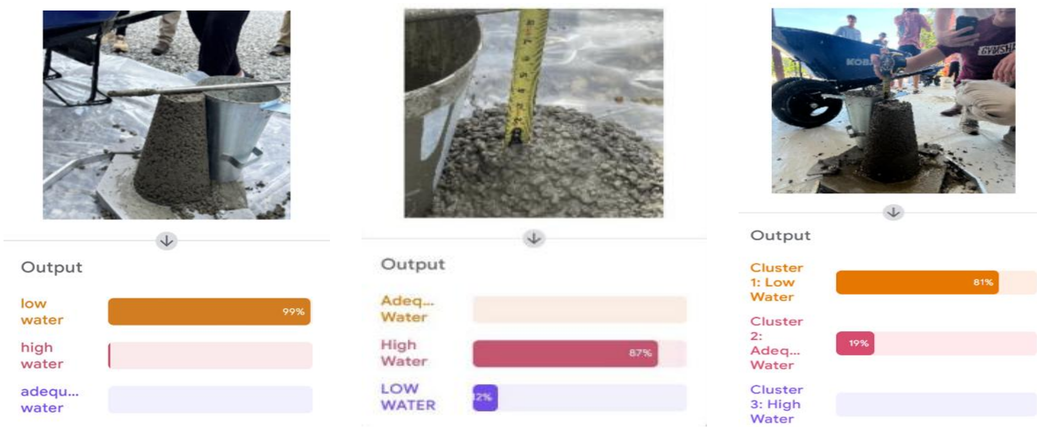


Figure 4. Accurate image classification results

On the other hand, some students noted that the angle, diversity, and inclusion of the measuring tape in the images influence classification accuracy and suggested ways to improve the model: "*The accuracy of the models was not the best; however, there could be improvements with the angles of the pictures and the background color as well. We could have performed the test with a darker background for the pictures so the AI could see the concrete more clearly*." Figure 5 illustrates the change in accuracy depending on the angle of the image.

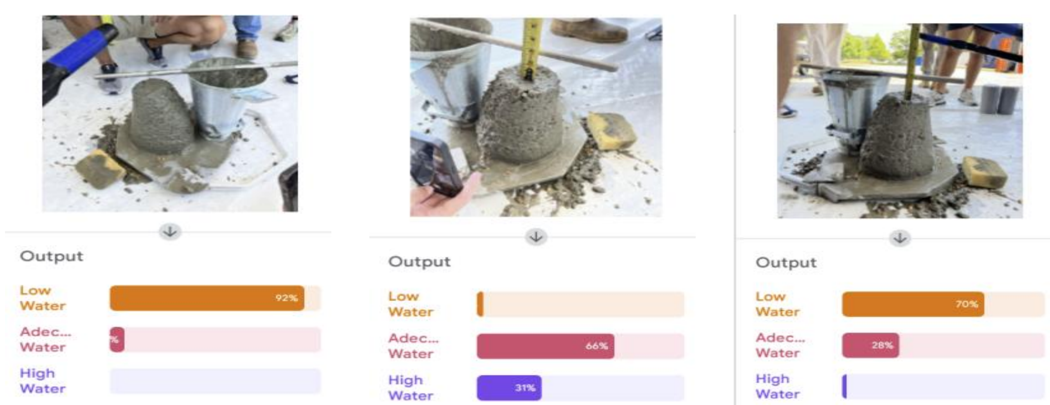


Figure 5. The effect of picture angle on the classification

Similarly, another student stated, "*The evaluation of the machine learning model designed to classify water levels in images shows that it correctly classified 3 out of 4 sample images, yielding almost perfect accuracy. The model performed well in predicting low water levels with high confidence, as demonstrated in the predictions for Images 1, 2, and 4. To improve the model, we should use a wider variety of training images, especially for adequate water and high-water conditions. Additionally, using regularization techniques can help the model generalize better and avoid overfitting*."

Conclusions and Recommendations

As AI and ML technologies are increasingly adopted across various industries, incorporating AI/ML-based tools and activities into construction education can help students become familiar with recent technological trends and meet the needs of an industry that is rapidly embracing new technologies. To this end, we designed an AI/ML-based image classification assignment to detect water content adequacy for different concrete slump levels. We compared pre- and post-assignment survey results using a paired t-test with a 95% confidence level. The results indicated that including AI/ML tools in construction education increases students' familiarity with these tools, improves their perceptions of integrating AI/ML into formal construction management education, and enhances their ability to apply AI/ML in their assignments. Additionally, the experience encouraged students to think critically about AI/ML applications and allowed them to suggest improvements to the ML model. For example, they recommended training the model with more diverse images from different angles, backgrounds, and qualities.

This research contributes to the construction education literature by statistically demonstrating that incorporating AI/ML-based assignments into the curriculum helps students improve their understanding of applying emerging technologies. It also provides practical contributions by offering educators evidence-based methods to enhance construction management programs, ensuring that future professionals are better equipped to leverage AI and ML in their careers. Furthermore, the findings offer insights for industry stakeholders on the value of integrating such technologies into educational practices, thereby aligning academic training with industry needs and expectations.

This research has several limitations. First, while we demonstrated a positive impact of AI/ML tools on students' familiarity and perceptions, the sample size was relatively small, which may limit the generalizability of the findings. Additionally, the accuracy of the model was influenced by factors such as image quality and the diversity of training data, suggesting that further research should explore the impact of these variables on model performance. Future studies could also investigate the long-term effects of incorporating AI/ML tools in construction education, including how these experiences translate to real-world applications in the industry.

Moreover, expanding the scope of research to include different educational contexts and a broader range of AI/ML applications could provide valuable insights. Finally, incorporating qualitative methods, such as interviews or focus groups, could enrich the understanding of student experiences and perceptions related to AI/ML in construction education.

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Appendix A

Assignment: Classifying Water Amount in Concrete with Image Recognition

Pre-Assignment Survey: Please use the following link to complete this survey.

In this assignment, you will examine water quantity in the concrete mix using artificial intelligence and image recognition techniques. You will create three clusters based on different water/cement ratios using the provided images for each case. Follow the steps below to complete the assignment.

Step 1: Open Google Teachable Machine, https://teachablemachine.withgoogle.com/train

Step 2: Click on Image Project → standard image project.

Step 3: Upload corresponding images to each cluster: You will be given a set of images representing different water/cement ratios. Organize these images into three clusters:

Cluster 1: Low water
- Description: The mixture appears too dry and needs additional water.
- Action: Upload images that show a dry, crumbly mixture.

Cluster 2: Adequate water
- Description: The mixture has the right consistency, neither too dry nor too wet.
- Action: Upload images that show a well-formed, stable mixture.

Cluster 3: High water
- Description: The mixture appears too wet and is overly fluid.
- Action: Upload images that show a runny, overly fluid mixture.

Step 4: Train the Model: Click on the "train model" button to train the model based on the images uploaded to each cluster.

Step 5: Save Your Model to Your Google Drive: Once the model is trained, save it to your Google Drive for future use and reference. Ensure that the model file is properly named and organized.

Step 6: Upload the Images You Took in the field lab (Take 3-5 photos of the concrete slump from different angles): You may take images of all slump tests conducted in the field lab. Upload these images to the system where the AI/ML model will analyze them.

Step 7: Evaluate the results after the model processes the field lab photos:
- Take a screenshot of each prediction.
- Accuracy Check: Verify if the model's classification results are accurate. Show results.
- Evaluation: Assess the performance of the model. Discuss any discrepancies or inaccuracies and consider potential improvements.

Deliverables:
1. A report discussing the accuracy and evaluation of the model, including any observations and recommendations for improvement.
2. Submit the post-assignment survey using this link.