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Implementation and Evaluation of a Predictive Maintenance Course Utilizing Machine Learning

Mr. Jonathan Adam Niemirowski, Louisiana Tech University

Jonathan Niemirowski is an Adjunct Professor in Instrumentation and Control Systems Engineering Technology at Louisiana Tech University. He received a Bachelor of Science in Nanosystems Engineering in 2015, a Master of Science in Molecular Science and Nanotechnology in 2018, and is working on a PhD in Engineering Education, all at Louisiana Tech University. Mr. Niemirowski teaches Computer Aided Engineering (ENGT 250), Engineering Problem Solving (ENGR 120, 121, 122), and various electives in machine learning for engineering students (ENGR 489). His doctoral research is on incorporating machine learning topics into the engineering curriculum, providing a foundation for engineers to utilize the technology in their work fields, and developing a framework to assist other educators in expanding ML content in their courses.

Ms. Krystal Corbett Cruse, Louisiana Tech University

Dr. Krystal Corbett is the First-Year Engineering Programs Coordinator and Assistant Professor in the Mechanical Engineering Department at Louisiana Tech University. She is also the Co-Director of the Office for Women in Science and Engineering at Louisiana Tech.

Dr. David Hall, Louisiana Tech University

David Hall develops and promotes project-based engineering for engineering and engineering technology programs. He believes that projects build intuition and confidence which are important for the successful application of fundamentals and the successful development of technology solutions.

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Jonathan Niemirowski, David Hall, Krystal Cruse
Louisiana Tech University

Abstract

This paper explores a course designed to instruct students on project-based machine learning in predictive maintenance. A class of nine students was instructed to predict the remaining useful life of simulated turbofan units using various analysis techniques and machine learning models. Student performance was evaluated with a self-efficacy survey conducted on the first and last day of the course. Participants began with low self-efficacy in knowledge and skill domains, but high attitudes regarding ML. By the end of the course, knowledge and skills saw a significant increase in score, with attitudes remaining constant. This course provides insight into the gains in ML knowledge and skills for non-CS students, as well as a pedagogical example that engineering and engineering technology instructors can employ to incorporate ML content into their courses. Data is presented to show that engineering students can develop practical ML skills for engineering applications.

Keywords

Machine Learning, Education, Predictive Maintenance.

Introduction

The past decade has seen the introduction of the fourth industrial revolution, characterized by an explosive connection of devices, information, and automated processes [1]. Machine learning (ML) stands at the forefront of Industry 4.0, thanks in part to advances in processing and data transfer/storage speeds [2]. Huyen [3] summarized the growth of ML tools, showing an exponential increase from 2012 onwards (Figure 1). As end-user tools continue to lower the technical barrier for entry, more and more fields will find use in ML [2], [4]–[6]. Software such as Edge Impulse equips its users with simplified visual interfaces for data processing, model creation, and training, with minimal computer science knowledge required for model creation. Engineering is a primary field for utilizing ML technologies in applications such as computer vision, predictive maintenance, and control systems. The rapid development of ML necessitates equally rapid developments in ML education.

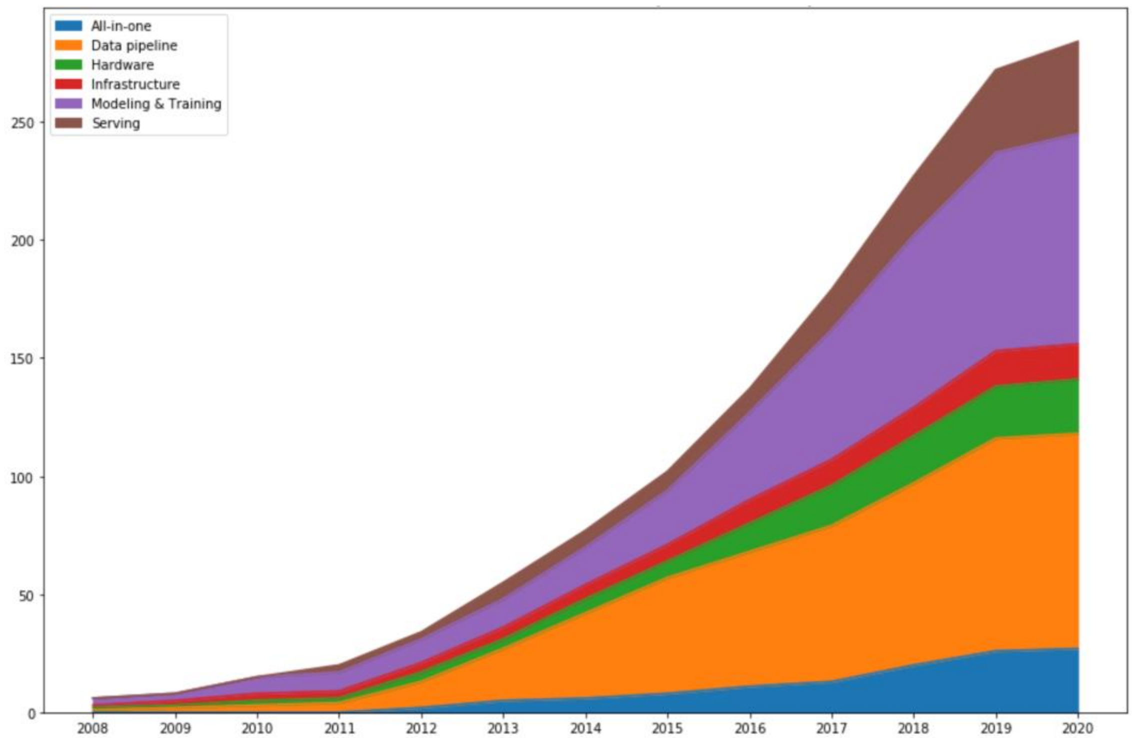

Figure 1. Number of ML / AI Tools (Cumulative) [3].

Coverage of ML in educational settings has lagged the growth of ML in industrial and research settings. Recognizing the profound impact that ML / AI tools will have on engineering and society, engineering faculty are beginning to implement ML content for non-computer science majors. Sulmont [7] noted three preconceptions that non-CS majors carried into courses with ML content. First, students do not understand the importance of learning ML to prepare them for their careers. Second, many students are exposed to ML through popular media channels; these sensationalized accounts of ML need to be addressed. Finally, most students believe that their math and programming skills are insufficient to implement ML. However, Sulmont notes that the perception of lacking skills tends to be a greater barrier than the lack of skills themselves.

Lao [8] explored methods to provide ML education to end-users, recognizing that ML tools are increasing accessibility to the technology. Lao noted three audiences of ML education: high-end technical users, general adults seeking to implement ML in their work, and K-12 students. Technical ML courses assume an existing background in computer science with a high barrier of entry, requiring CS competence, statistics, calculus, and linear algebra. General adult courses are far more accessible but do not provide sufficient depth for implementation. Instead, many of these courses focus on providing a context for conversations with others who will implement ML. Finally, K-12 courses provide smaller activities and projects that develop skills related to model implementation but are simple and abstract enough to bypass math and programming requirements. Lao created a framework that identified learning outcomes to develop the knowledge, skills, and attitudes necessary to foster ML self-efficacy within these three audiences, as shown in Table 1.

Table 1. Lao's Learning Outcomes Adapted from [8]

Knowledge	Skills	Attitudes
General ML Knowledge	ML Problem Scoping	Interest
Knowledge of ML Methods	ML Project Planning	Identity and Community
Bias in ML Systems	Creating ML Artifacts	Self-Efficacy
Societal Implications of ML	Analysis of ML Design Intentions and Results	Persistence
	ML Advocacy	
	Independent Out-of-Class Learning	

While limited research has been performed on ML education, the field's propagation is still lacking in the face of rapid technological progress. While engineers need to develop knowledge and skills for the responsible application of ML [9], there is a particular lack of literature on course offerings and what content should be taught to engineering students.

Though resources exist for introducing non-CS majors to ML, these tools and programs are often only fleeting glimpses into the field. These benchmark applications offer students opportunities to implement ML models in curated sandboxes and prepared datasets, such as MNIST [10], [11]. This content is excellent for teaching theoretical frameworks for ML but fails to instruct on how to implement the frameworks. Students are often not required to perform data analysis or processing to implement their models. While these curated sandboxes streamline the content to allow students to focus on model design, they lack the context and challenges of ML implementation in industrial settings where small, noisy, and incomplete data sets must be processed to identify underlying patterns and determine whether ML methods are applicable.

Further gaps appear in the engineering community's general perception of machine learning. A common outlook is that ML is a "silver bullet" and a flawless, one-size-fits-all solution to any problem, given sufficient model complexity [12]. Students should develop an awareness for the scope and limitations of ML, not simply the tools required to apply them [13]. Likewise, ML is seen as a difficult topic to learn and understand, one that cannot be attempted without years of education in computer science and mathematics. In short, most engineering faculty and students do not know where to begin when implementing or teaching ML in practical applications. This paper introduces a course that attempts to fill some of these gaps for our engineering students.

Course content

In spring of 2022 the author taught a course at Louisiana Tech University titled "Machine Learning in Predictive Maintenance." The purpose of this course was to introduce engineering students to machine learning concepts centered on a real-world application of the technology. Nine students completed the course, five from Mechanical Engineering and four from Instrumentation and Control Systems Engineering Technology.

The selected problem was a dataset of simulated turbofan operation derived from NASA's C-MAPSS simulation software [14]. This dataset was chosen to challenge students with a real-world implementation of ML focusing primarily on data processing and model selection. The dataset contains four sub-datasets, each with an increasing variety of fault modes and operating conditions (Table 2) for increasing problem complexity. Each sub-dataset contained a collection of engine units with a variable number of time steps, simulated to run until failure at the final time step. The data was organized as 26-column csv files containing the following variables:

- Column 1 – unit number
- Column 2 – time, in cycles
- Columns 3-5 – operational settings 1-3
- Columns 6-26 – sensor measurements 1-21

The unit number and cycle time allowed for calculation of Remaining Useful Life (RUL), the number of time steps before failure. The operational settings identified one of six possible operational modes, depending on the sub-dataset. The sensor measurements were unlabeled, and were intended to be evaluated to predict RUL. These 21 sensor variables include a significant amount of noise, which introduces a challenge to address in data processing.

Table 2. NASA C-MAPSS Sub-Dataset Contents

Sub Dataset	**FD001**	**FD002**	**FD003**	**FD004**
Training Units	100	260	100	249
Testing Units	100	259	100	248
Simulation Conditions	1	6	1	6
Fault Modes	1	1	2	2

Students used Python and selected Python libraries to process the data (pandas [15]), train and evaluate predictive models (scikit-learn [16] and TensorFlow [17]) and visualize the results (Matplotlib [18]). The outline of topics and content is modified from a series of articles published by Peters on Towards Data Science [19]. His topics provide a broad selection of models and tools to apply, including several intentional "dead end" methods that help compare and contrast what may work or fail with specific datasets.

The course spanned nine weeks, during which the students met twice a week for two hours. Content was delivered via PowerPoint and example code notebooks which provided the first step for the assignments. Each week began with an online, 20-minute quiz delivered through Moodle. Quizzes were typically three to five multiple choice and/or short answer questions based on material from the prior week. These quizzes were used to ensure that students were able to explain and discuss the concepts and theory as the course progressed. In addition, students were polled on how well they understood the topics from the prior week through a five-point Likert scale and open-ended prompt.

Each week also included an assignment that was due a week later. These assignments included a series of coding tasks and short written problems. As the course progressed, the assignments paralleled the expected scope and format of the final course project. Assignments were uploaded as written documents to Moodle, as well as Jupyter notebooks managed through Google Collab, a cloud-based Python environment. Each student was provided with a folder shared with the instructor to store and upload their assignments. This allowed for quick evaluation of the assignment as well as remote access to assist students with coding problems. As the course progressed, the assignments included brief reports of their data analysis and model performance; this was to ensure that students could justify their decision making through the projects.

The first 3 weeks established a foundation of Python programming skills. Content covered introductory Python concepts for object-oriented programming. Assignments required students to write a series of functions to complete various tasks, primarily concerning list and NumPy array manipulation [20]. Machine learning content was also introduced to embed ML terminology and to provide a general understanding of machine learning concepts.

In Week 4 the NASA dataset was introduced and students were instructed to transfer the data into a pandas DataFrame and build a simple linear regression model to predict remaining useful life (RUL). Students used graphing tools through matplotlib to visualize and identify significant data features within the sensor values for each unit. They then selected sensor data with significant features to build their model. In-class discussion focused on the performance and limitations of a linear model and what assumptions can or cannot be made of the data. The sensor data suggests a non-linear and more complex relationship to the RUL, thus necessitating a more nuanced model to accurately predict failure (Figure 2).

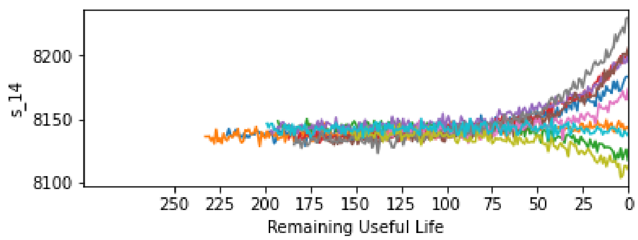

Figure 2. Sample Sensor Data from FD001 Sub-Dataset (From Student Assignment)

Week 5 introduced neural networks as the first example of machine learning models. The content focused on network and hyperparameter design: selecting activation functions, constructing validation sets, and principles of neural network architecture. Tensorflow was used to create and apply models to the NASA dataset. Additional data processing techniques were also covered including standardization, normalization, and time clipping. A critical talking point for this section was the concept of the "No Free Lunch" Theorem: lacking any assumptions about the data or problem, no ML model is inherently more accurate than another. This idea meshes with the interpretability problem where contemporary computer scientists are working to develop tools to analyze ML models and understand their performance and better improve them, instead of designing a sufficiently complex neural network that achieves the required performance metrics.

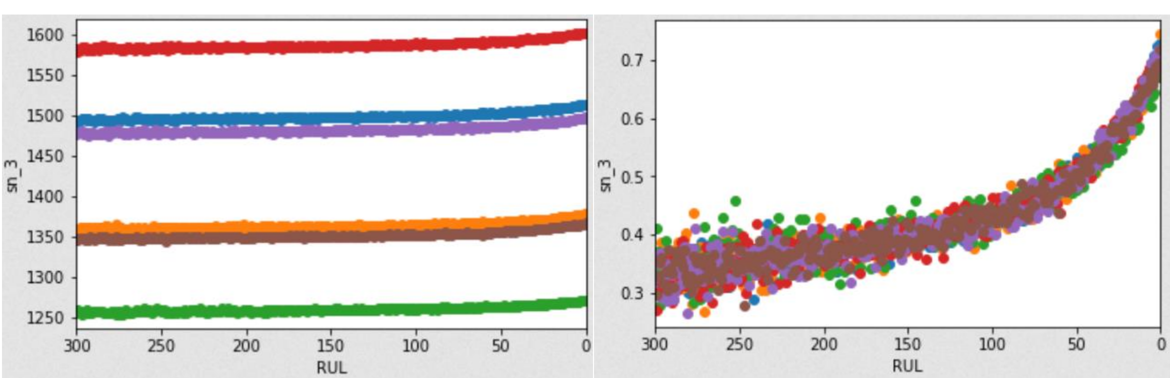

Figure 3. Sample Condition-Based Scaling of Sensor Data (From Student's Final Project)

The second half of the course expanded on tools for regression analysis. Students were taught about additional ML models such as Support Vector Regression, Random Forests, Recurrent Neural Networks (RNN), and eventually Long Short-Term Memory (LSTM) neural networks. Data processing techniques covered included lagged variables, feature generation, and data sequencing for RNN/LSTM models. Tools for finding hyperparameter values and analyzing their performance were discussed, including Akaike Information Criteria and Variance Inflation Factors. Throughout this content, students moved the more complex sub-datasets. This culminated in the final project where students were asked to build, train, and compare three models on the FD004 dataset. This dataset incorporated condition-base scaling to account for the six operational modes within the data (

Figure 3), as each mode could have its own nominal sensor values and failure points. Students were instructed to write a report showing their models' performance: Figure 4 shows one student's visualization of their RNN model, measuring the predicted RUL value to the test data's RUL value for five engine units. The model's performance accounted for 30% of their grade, compared to a baseline linear regression model with no data processing.

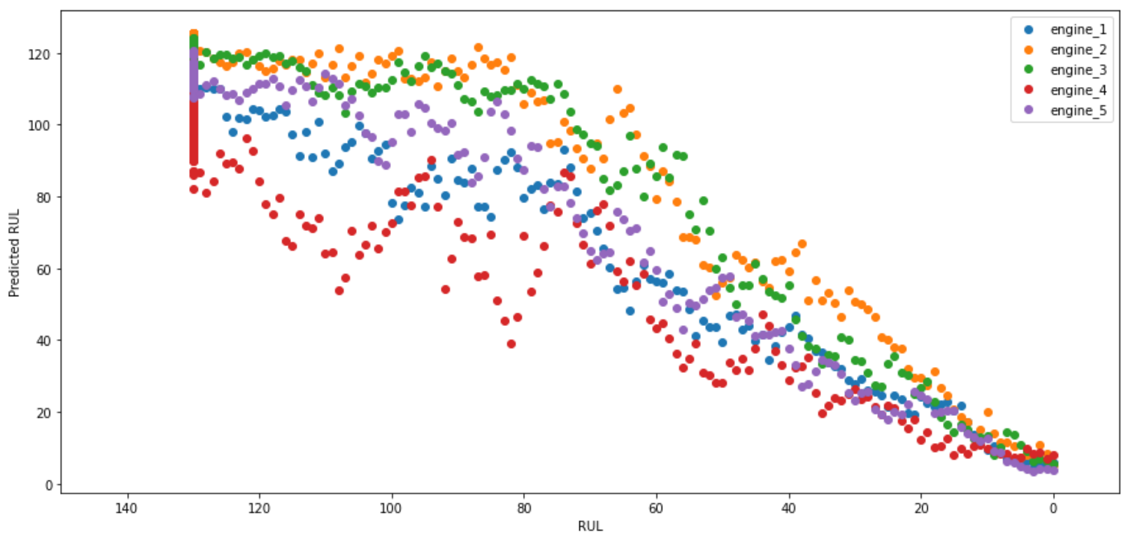

Figure 4. Final Project RNN Model Performance (From Student's Final Project)

Results of pre and post course surveys

A self-efficacy survey was selected as the primary metric for this study, since the primary goal is to increase students' capabilities and attitudes regarding ML. The survey was taken on the first and last day of the course. The design of the survey is a modified form of Wang et al's survey on self-efficacy in data mining and analysis [21]. The selected questions mirrored Lao's framework of ML knowledge, skills, and attitudes, which was one of many lenses incorporated into the course design. Their survey demonstrated sufficient reliability and validation for participant responses. The survey consists of 22 Likert scale questions, 3 list questions, and 6 free response questions, with the post-course survey adding 3 free response questions regarding students' perspectives on the course (see Table 3). Students provided consent to have their course performance and survey results be used for research purposes. Their responses to the pre-course and post-course surveys were anonymized.

Table 3. Survey (O = Open, K = Knowledge, S = Skills, A = Attitudes, L = List, P = Post-Course Open)

O1	In your own words, describe machine learning
O2	In your own words, describe the limitations of machine learning
O3	In your own words, provide specific examples of how machine learning will likely impact your career in the next 10 years
K1	I can describe at least one ML application
K2	I understand the main steps to implement at least one ML application
K3	I understand what distinguishes ML from traditional mathematical approaches
K4	I can compare and contrast at least two ML methods when solving the same problem
K5	I understand how humans can inadvertently program bias into ML applications
K6	I am aware of the positive and negative impacts of ML on society
K7	Overall, I have functional ML knowledge
S1	I can determine when a problem is suitable for ML approaches
S2	I can develop a plan to implement a ML model for at least one application
S3	I know how to identify, collect, and clean data for at least one ML application
S4	I can implement at least one data processing method for ML
S5	I have the programming skills needed to implement at least one ML application
S6	I can analyze the outputs of an ML model
S7	I can evaluate whether or not ML outputs match the design intentions
S8	I can advocate for the use of ML policies, products, and education
S9	I have the ability to continue learning ML outside of this course
S10	Overall, I have functional skills in one or more ML applications
A1	I am motivated to continue developing my ML skills
A2	I feel part of a larger ML community
A3	I feel empowered to use ML
A4	I plan to use ML in my career
A5	Overall, I have the knowledge, skills, and motivation to engage in ML problems
L1	List all examples of ML methods for data analysis that you know
L2	List all examples of traditional methods for data analysis that you know
L3	List all examples of data processing that you know
P1	What was your favorite thing about this course?
P2	What was your least favorite thing about this course?
P3	If you could change something in this course, what would you change?

All nine students responded to both the pre- and post-course surveys. Table 4 provides a concise summary of overall class results showing the average student responses for each question, the average delta between the surveys, and t-test significance for each question. The response score columns are color-coded from 1 to 7. The Delta column is color-coded to highlight positive/negative changes. The t-test column is color-coded to highlight questions with low significance ($p > 0.05$). List responses L1 through L3 were evaluated and counted as correct responses or discarded if irrelevant to the question; examples are provided in the results.

Table 4. Survey Results

Question	Scores (Scaled 1 to 7)		Score Analysis	
	Pre-Course	Post-Course	Pre/Post Change	T-Test
K1	5.8	6.7	0.9	**0.060**
K2	3.9	6.3	2.4	0.000
K3	4.4	6.7	2.3	0.002
K4	2.9	6.3	3.4	0.000
K5	4.3	6.0	1.7	0.030
K6	4.8	5.9	1.1	0.015
K7	3.4	5.9	2.5	0.001
S1	3.9	6.0	2.1	0.000
S2	3.1	5.6	2.5	0.002
S3	3.7	5.7	2.0	0.011
S4	3.1	6.2	3.1	0.000
S5	3.7	6.0	2.3	0.001
S6	3.4	5.8	2.4	0.003
S7	3.6	5.6	2.0	0.006
S8	4.7	6.1	1.4	0.010
S9	4.9	5.6	0.7	**0.085**
S10	3.2	5.8	2.6	0.001
A1	5.8	5.3	-0.5	**0.173**
A2	4.2	4.9	0.7	0.025
A3	4.6	5.2	0.6	**0.085**
A4	5.1	4.8	-0.3	**0.219**
A5	4.9	5.2	0.3	0.040
L1	0.6	4.3	3.7	0.000
L2	0.3	1.2	0.9	0.001
L3	0.1	3.0	2.9	0.001

The two highest scores on the pre-course survey were K1 ("I can describe at least one ML application") and A1 ("I am motivated to continue developing my ML skills"), with 89% and 100% of students agreeing with these statements, respectively. Attitudes were scored relatively high, with only one student slightly disagreeing with A2 ("I feel part of a larger ML community"). Knowledge and skills were rated much lower, with fewer than half the students agreeing with most statements. The list question scores were low: only three students provided examples of machine learning methods (L1), all of whom had prior educational experience with ML. Overall, the t-test scores are acceptable ($P < 0.05$) with a few outliers. K1 ("I can describe at least one ML application"), S9 ("I have the ability to continue learning ML outside of this course"), and most attitude questions suggest an insignificant improvement.

The post-course survey indicated improvements across nearly all categories, with average scores increasing by 1-3 points. The two outliers are A1 ("I am motivated to continue developing my ML skills") and A4 ("I plan to use ML in my career") which show a decrease from the pre-course survey. All students were able to provide at least three examples of machine learning methods for data analysis (L1), and 89% listed at least one example of traditional methods. This is a marked improvement from the pre-course, where only three students provided any example of machine learning, the remainder leaving blank or "don't know" responses. L2 ("examples of traditional methods for data analysis") appeared to have confused some of the students in the pre-course survey; one provided an acceptable response of "linear regression", five left a blank response, and three provided loosely related concepts: "certainty percentage, user feedback, rewards"; "data collection, sorting, census"; and "standard deviation". The post-course survey results for L2 improved, with five students responding with "linear regression". However, some confusion may have remained over what the question asked for with responses including "Bayesian Statistics" and "averaging". L3 ("examples of data processing techniques") had the lowest pre-course score, with one student referring to pandas, a loosely-related response; the remainder were blank (six) or gave inapt responses ("neural networks, excel, R"). Post-course scores for L3 improved vastly, with eight students providing three or more examples ("clipping, lagging, scaling", etc). One student appeared to remain confused at the question, giving examples of machine learning applications.

Figure 5 shows the pre/post course survey scores, sorted by category. The data indicates that student attitudes on ML remained consistent throughout the course. A1 and A4 showed a decrease in average scores between the two surveys. This is a reasonable outcome given the sample population; in a discussion following the pre-course survey, students noted their high self-motivation to take the course, citing that their presence in the class already demonstrates a desire to develop ML knowledge and skills. This reinforces the high initial attitude scores on the pre-course survey. A decrease in pre/post attitude scores may be attributed to an increased awareness of ML technology's scope and limitations.

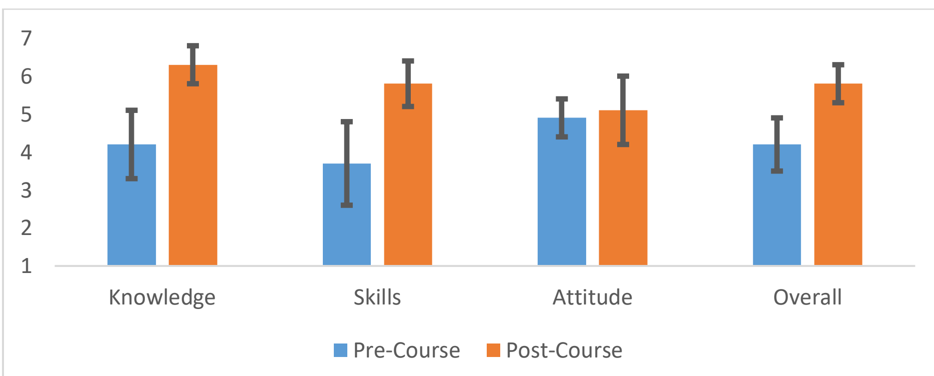

Figure 5. Average Survey Results by Category

The open-ended questions showed an increased vocabulary across all students. Initial definitions of machine learning (O1) and its limitations (O2) were brief ("using neural networks to have a program learn how to predict or classify data") and ambiguous ("process of teaching a machine how to do certain tasks"). Post-course responses were consistently a paragraph with two or three sentences outlining a more complete description of their answer. O3 (examples of ML impact in career) did not see as dramatic a change in tone or vocabulary, only that the examples given were more pointed to in-class examples. Both the pre- and post-course responses showed that all nine students believer ML will greatly impact their career, and that ML will inevitably change the industries in which they are likely to work. These results suggest an overall improvement in students' knowledge of the subject, as well as an increased ability in their attitudes to engage with conversations regarding ML in the industry.

Throughout the course student results and discussions indicated an understanding of the concepts and theory but struggles with implementation. Students self-reported a lack of programming skill in the pre-course discussion; these struggles primarily stemmed from their difficulty in producing working code for the next step of the project.

A brief discussion followed the post-course survey. Compared with the pre-course survey, students provided more accurate and precise wording for describing machine learning and its limitations. When asked about ML's impact on their field and career, they continued to anticipate that ML would bring major changes to their industries.

The students' perspective on their knowledge and skills reinforced the notion that programming remains a challenge to them. This gap was noted to originate from a lack of practice rather than a lack of understanding. Students also mentioned difficulty in understanding how to select an ML algorithm for a specific problem.

When asked how to improve the course, students suggested that the course be flipped; instead of evaluating one dataset over a variety of models, evaluate a single model on a variety of datasets. This flipped approach will be considered in future offerings of the course and will require the acquisition and application of additional datasets beyond the NASA dataset. Students also recommended that the course require a prerequisite of Python programming skills, as they underestimated the level required to complete the course. While such a change would allow for a greater depth of content, it would also set a barrier of entry that would be counter-productive, limiting the ability for "regular" engineering students to access machine learning.

Conclusion

This course provides a perspective on the challenges of teaching machine learning to engineering students. The engineering students that completed this course recognized that ML is important in their field. They demonstrated high motivation to develop ML skills and knowledge to effectively utilize ML technologies. The use of noisy datasets over benchmark data enabled course content on application in real-world settings. Despite skill limitations in coding, the students were able to grasp and apply ML concepts and theory to the selected domain problem. It is believed that current ML tools can be incorporated to help fill this skill gap. The post-course survey and discussion indicated that students can more accurately and confidently provide examples of ML and utilize their skills to complete an ML project.

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