Module Seven Portfolio Project, Final Research Paper

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Abstract

The United States Army spends billions of dollars per year maintaining the ground combat vehicle fleet. In this case, a ground combat vehicle is defined as a self-propelled piece of equipment that fulfills a role in combat operations like tanks and infantry fighting vehicles. This study examined the potential benefits of an Internet of Things (IoT) sensor-based predictive maintenance model for Army ground combat vehicles. It addressed the research question, ‘How effective are IoT-based predictive maintenance models at forecasting unplanned maintenance events in ground combat vehicles?’

Using a simulated dataset of IoT sensor readings, two-sample t-tests and a binary logistic regression model were developed to analyze relationships between vehicle diagnostics and the likelihood of unplanned maintenance events. The specific vehicle diagnostics analyzed by the study were rotations per minute (rpm), oil pressure, fuel pressure, coolant pressure, oil temperature, and coolant temperature. The results of the statistical tests showed statistically significant relationships between most IoT sensor readings and unplanned maintenance events. Only coolant temperature failed to meet the required confidence level of 0.05.

The results of the study show that IoT sensor data can be used in conjunction with predictive analytics to successfully forecast unplanned maintenance events. While the results were statistically significant, it is important to highlight that the dataset was simulated. Due to security concerns, operational information on military vehicles is not available to the public. With this limitation in mind, the study argues for the slow implementation of a predictive maintenance program. Gradual implementation minimizes initial investment and allows for program modification as actual operational data becomes available.

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Introduction

The United States Department of Defense is responsible for providing the military forces required to deter conflict around the globe and, if required, fight and win the nation's wars (Office of the Secretary of Defense, 2025a). The Department of Defense contains all five branches of the armed forces. These branches include the Army, Marine Corps, Navy, Air Force, and Space Force (Office of the Secretary of Defense, 2025b). Each branch specializes in a warfighting function that enables the military to successfully carry out the mission. The Army is the largest and oldest branch which is responsible for providing the ground forces that engage with and destroy the enemy (Office of the Secretary of Defense, 2025b).

As the largest branch, the Army requires a robust annual operating budget. In fact, the Fiscal Year 2025 budget for the Army is $185.9 billion (Camarillo, 2024). This budget is spread across six major categories. The largest category is operations and maintenance covering $71.4 billion, or 38.41% of the total budget (Camarillo, 2024). This category consists of multiple subcategories such as ground combat vehicles maintenance, aviation maintenance, facility maintenance, and infrastructures investments. Maintenance of ground combat platforms such as tanks and infantry fighting vehicles is responsible for $12.2 billion, or 6.56% of the total budget (Office of the Under Secretary of Defense, 2024). This is a crucial activity that ensures Army personnel have access to reliable equipment. In fact, maintenance posture is a key factor in overall operational readiness.

For modern maintenance programs, real-time IoT sensors allow for the collection of a large amount of operational data (Cinar et al., 2020). IoT sensor data can aid in automated fault detection (Cinar et al., 2020). While IoT sensors have been proven to decrease unplanned maintenance events, the feasibility of using these sensors in ground combat equipment must be researched further. The effectiveness of IoT sensor data at predicting maintenance events must also be analyzed.

Objectives

The first research objective is to assess the effectiveness of a predictive maintenance model for ground combat vehicles based on IoT sensor data. The purpose of this objective is to analyze the overall feasibility of deploying a predictive maintenance model for the Army. Testing the effectiveness of the model as a whole ensures the validity of the predictive maintenance concept. Establishing this validity upfront is a crucial first step in integrating predictive analytics into the Army's maintenance program for ground combat vehicles.

The second research objective is to evaluate how combat vehicle engine diagnostics, such as fuel pressure and coolant temperature, individually impact engine failure rates. This objective allows IoT sensors with the highest impact on mechanical failures to be identified and prioritized for installation. Prioritizing sensors allows the organization to make informed decisions on which sensors to invest in. Since the Army does not currently have IoT sensor infrastructure in place for ground combat vehicles, only highly impactful sensors should be initially installed.

Analyzing the effect of each vehicle diagnostic on unplanned maintenance events will provide the potential to slowly implement the program in a step-by-step process. For example, assume the rpm variable has the highest impact on maintenance event predictability. This sensor should be invested in and installed in the fleet before less effective sensors. Starting the predictive maintenance program with one or two highly impactful sensors minimizes initial investment while maximizing initial effectiveness. Other sensors can be utilized in the future. This slowly enhances the program over time while spreading out investments over a longer period.

Finally, the third research objective is to explore how real-time IoT sensor data can be used to optimize repair parts availability on the battlefield. This objective assesses how the predictive model can be used to trigger automatic inventory actions like issues and replenishments. This objective focuses on understanding how specific sensor readings affect the probability of a maintenance event occurring. For example, the predictive maintenance model can be set to trigger automatic alerts based on vehicle operating conditions. If oil pressure hits a certain threshold, then that could trigger an automatic message to the operator recommending a replacement part be ordered. This communication from the model to the operator creates a buffer between replacing a part and unplanned maintenance events. Ordering parts before failure ensures the repair part supply chain is more responsive.

Overview of Study

This study focuses on improving operational readiness and decreasing unplanned maintenance costs for Army ground combat vehicles by developing an IoT-based predictive maintenance model. Maintenance expenditures are required to keep equipment operational. This is especially true for heavier equipment such as tanks and other tracked vehicles. Near constant use in hostile environments causes increased wear and tear on equipment.

Organizations like the Army that rely on heavy equipment must have robust maintenance budgets that take into account both planned and unplanned maintenance activities. Planned maintenance activities include routine checks and tasks such as annual oil changes. Unplanned maintenance activities include failures of parts that result in equipment being unusable, such as an engine.

While some unplanned maintenance events are inevitable, these events significantly impact the Army's ability to successfully complete the mission. Downtime for ground combat platforms such as tanks and infantry fighting vehicles negatively impact operational effectiveness and, consequently, national security. Traditional maintenance approaches, such as reactive maintenance, have been used with a varying degree of success in the past, but outdated methods similar to this one often suffer from high repair costs (Zhu et al., 2019). Implementing a predictive maintenance program will benefit the Army in numerous ways.

First and foremost, employing a successful predictive maintenance model will reduce downtime and unplanned maintenance costs (Cinar et al., 2020). Minimizing downtime of ground combat vehicles ensures the Army consistently has access to required equipment. This improves operational readiness and ensures the organization has access to the resources required to execute its mission. Furthermore, decreasing unplanned maintenance events will free up funds for other purposes such as facility maintenance and infrastructure investments. Decreasing overall maintenance costs will add more flexibility to the budget.

Next, data collected from IoT sensors can be used to make more informed planned maintenance decisions. For example, assume the analysis shows engines consistently operating at a coolant temperature of 85 or higher tend to fail. These vehicles can be immediately flagged for engine replacement instead of waiting for a failure to happen. This information transforms a potential unplanned maintenance event into a planned event which allows the organization to properly allocate labor and resources in an efficient manner.

Finally, IoT sensor data can be used to manage inventory and allocate repair parts in a battlefield situation. These sensors provide a real-time look at the health of the ground combat fleet. Repair parts can be ordered and distributed based on fleet health measures. Ordering parts before unplanned maintenance events occur provides logisticians and maintainers better flexibility in sourcing material and executing repairs. Sensor data can also be used to order equipment off the front line to ensure recovery operations are not required. Overall, predictive maintenance for ground combat vehicles will decrease costs, increase readiness, and allow for more data-driven decisions to be made on the battlefield.

Research Questions and Hypotheses

The main research question this project focuses on is 'How effective are IoT-based predictive maintenance models at forecasting unplanned maintenance events in ground combat vehicles?' The null hypothesis for this research question is 'There is not a statistically significant relationship between IoT sensor data and unplanned maintenance events in ground combat vehicles.' The alternative hypothesis is 'There is a statistically significant relationship between IoT sensor data and unplanned maintenance events in ground combat vehicles.' In both cases, IoT sensor data refers to vehicle diagnostics such as rpm, fuel pressure, coolant pressure, coolant temperature, oil pressure, and oil temperature. The null and alternative hypotheses are also listed below in Table 1.

Table 1

Null and Alternative Hypotheses

Hypothesis Type	Hypothesis Statement
H_0	There is not a statistically significant relationship between IoT sensor data and unplanned maintenance events in ground combat vehicles.
H_a	There is a statistically significant relationship between IoT sensor data and unplanned maintenance events in ground combat vehicles.

Testing the relationship between vehicle diagnostics provided by IoT sensors and unplanned maintenance events will show whether the sensor data can be used to reliably predict unplanned maintenance events. A statistically significant relationship would show that an investment in IoT technology could improve maintenance outcomes of ground combat vehicles by reducing the number of unplanned maintenance events. Furthermore, statistical significance of specific variables will allow the Army to make informed decisions on which sensors to invest in. For example, assume only the rpm and oil pressure variables are statistically significant predictors for unplanned maintenance events. If this is the case, then only rpm and oil pressure sensors should be installed on vehicles. This will ensure the predictive maintenance model is statistically significant while also preventing the organization from investing in sensors that are not useful.

Literature Review

Organizations that use predictive maintenance experience reduced equipment downtime and improved equipment reliability (Sengupta et al., 2023). The military has used predictive maintenance tools in a limited scope. In fact, the Army and the Navy have used it to improve operational readiness (Davis et al., 2024). However, predictive maintenance has only been used for specific combat platforms like the Army's AH-64 Apache helicopter and the Navy's F/A-18 Super Hornet jet (Government Accountability Office, 2022). Predictive maintenance concepts and tools have prevented aviation accidents, but they have not been applied to other military equipment due to high costs (Government Accountability Office, 2022). While there has been hesitancy to invest in additional predictive maintenance programs, other types of military equipment such as the Army's fleet of ground combat vehicles can greatly benefit from predictive maintenance.

Ground combat vehicles like tanks and other armored vehicles "play a critical role in modern warfare, providing mobility, protection, and firepower on the battlefield" (Narayanan & Padhy, 2023, p. 1). However, maintaining complex machinery like tanks that routinely operate in austere environments poses significant challenges (Narayanan & Padhy, 2023). A predictive maintenance model leveraging IoT sensor data can help confront these challenges. Narayanan and Padhy (2023) show that remaining useful life of critical components in tanks can be predicted with 84.46% accuracy by using a multiple linear regression model and data from 7 different IoT sensors. The sensor data included various vehicle diagnostics such as oil pressure, engine vibration, torque, coolant temperature, and fuel consumption (Narayanan & Padhy, 2023).

While that level of accuracy is impressive, Mykich et al. (2024) describe a predictive maintenance model that attained predictive accuracy of 85.01% through the use of 6 IoT sensors. In this case, various models such as a binary logistic regression, neural network, and support vector model (SVM) were used to predict unplanned maintenance events. Furthermore, the sensors used by Mykich et al. (2024) are more common than the specialized sensors used by Narayanan and Padhy (2023). The sensors used by Mykich et al. (2024) include rpm, fuel pressure, coolant pressure, coolant temperature, oil pressure, and oil temperature. Ground combat vehicles are already equipped with these sensors. Instead of installing completely new sensors, the IoT sensors sync with the already installed ones to communicate the required data to the predictive maintenance tools.

While the binary logistic regression model from Mykich et al. (2024) did not have the highest predictive accuracy, the other more complicated models performed only marginally better. More specifically, the SVM had the highest predictive accuracy at 85.52%, only 0.51% better than the logistic regression model. While deep learning models like SVMs tend to have higher accuracy, they act as 'black boxes' where the results cannot be interpreted (Sharma et al., 2022). Effective predictive maintenance models must have high interpretability to be effective (Sharma et al., 2022). High interpretability allows for the strength of each predictor to be taken into account. This information can then be used to determine which IoT sensors are required to build an effective model. Furthermore, a simpler model allows for easier communication to nontechnical stakeholders. This communication is crucial when changing business processes through the implementation of a new maintenance program.

Clearly, predictive maintenance does have advantages when compared to other methods. However, it requires technological advancements and investments. More specifically, Narayanan and Padhy (2023) explain that predictive maintenance models require access to real-time vehicle diagnostic data like oil pressure and coolant temperature. This type of real-time monitoring is only available through the use of IoT sensors. Installing sensors in a fleet of vehicles requires a significant financial investment, but understanding how specific sensor data affects the likelihood of unplanned maintenance events allows for cost-effective investment decisions to be made. Simple models with high interpretability and common IoT sensors can be used with minimal loss of predictive power. This ensures unplanned maintenance predictions are accurate while also minimizing required investments. While some investment is inevitably required, the gains in operational readiness and resource allocation caused by predictive maintenance justifies it (Davis et al., 2024).

Methodology

A quantitative methodology will be employed to analyze potential relationships between IoT sensor data and unplanned maintenance events. Ideally, quantitative data would be collected directly from IoT sensors installed on ground combat vehicles. However, this data is currently not available to the public. Instead, a simulated open-source dataset based on actual IoT sensor data pulled from vehicles will be used.

The chosen dataset is named Automotive Vehicles Engine Health Dataset (Modi, 2023). Mykich et al. (2024) used this dataset to develop a predictive maintenance model for military vehicles as well. The dataset consists of 7 columns and 19,535 rows. It includes vehicle diagnostics and engine condition. Vehicle diagnostics include rpm, oil pressure, fuel pressure, coolant pressure, oil temperature, and coolant temperature. Oil pressure, fuel pressure, and coolant pressure are measured in bar. Oil temperature and coolant temperature are measured in degrees Celsius.

All variables except engine condition are numeric. More specifically, the rpm variable is an integer. Oil pressure, fuel pressure, coolant pressure, oil temperature, and coolant temperature are decimals. Engine condition is a binary variable. A 1 shows the engine is in good condition and operational. A 0 shows the engine is non-operational and in need of repair. The data dictionary for the selected dataset is found in Table 2 below.

Table 2

Data Dictionary

Column	Data Type	Description
rpm	integer	Rotations per minute
oil_pres	decimal	Oil pressure. Measured in bar
fuel_pres	decimal	Fuel pressure. Measured in bar
coolant_pres	decimal	Coolant pressure. Measured in bar
oil_temp	decimal	Oil temperature. Measured in degrees Celsius
coolant_temp	decimal	Coolant temperature. Measured in degrees Celsius
engine_condition	binary	1 = engine is in good condition and operational 0 = engine is degraded and non-operational

The chosen dataset helps answer the research question by providing IoT sensor data and corresponding vehicle status. The dataset providing a connection between sensor data and vehicle health is important because predictive maintenance models pair similar sensor data with machine learning methods to identify potential failures (Sengupta et al., 2023).

In this case, the IoT sensor data includes engine diagnostics such as rpm and oil pressure. These variables serve as critical indicators of vehicle status. They are a direct representation of the health of a vehicle while it is actively running. Furthermore, the dataset links engine diagnostic datapoints with unplanned maintenance events through the engine condition variable. This direct connection is crucial for the development of a predictive maintenance model because it provides information on how different diagnostics affect unplanned maintenance events like engine failure.

While not all unplanned maintenance events involve the engine, it is one of the most important and most vulnerable components of a ground combat vehicle. In fact, Narayanan and Padhy (2023) explain that unexpected engine failure during maneuver operations is the most catastrophic maintenance event that can occur for a ground combat vehicle. While engine failure would be detrimental in a combat scenario, Mohammadpour et al. (2012) explain that detecting faults early through the use of sensor data decreases the chance of a complete failure. The chosen dataset provides the data required to potentially detect these faults through a link between engine diagnostics and engine health. The dataset will help reveal insights into the relationships between various engine diagnostics, such as rpm and oil pressure, and engine failure.

Methods

Specific tools and models have been chosen to address the research question and hypotheses. All proceeding analysis will use a significance level of 0.05. First, two-sample t-tests will be used to determine if there is a statistically significant difference between vehicle diagnostic variables grouped by engine condition. These tests will show the magnitude of the differences in mean between groups and the statistical significance of these differences. The t-test task on SAS will be used to execute each of these two-sample t-tests.

Next, a binary logistic regression model will be developed. The vehicle diagnostic variables will be used as predictors for engine condition. The odds ratios from the model will show whether specific variables result in increased, decreased, or no change in odds of an unplanned maintenance event occurring (Harris, 2021). Model fit and predictive power will also be analyzed. The dataset will be partitioned into 70% training and 30% validation to ensure predictive power is properly analyzed. The SAS binary logistic regression task will be used to develop the model. R will be used to partition the data.

While the t-test and binary logistics regression tasks in SAS automatically generate plots, the ggplot2 package in R will be used to create additional visualizations such as side-by-side boxplots. These boxplots will help visually compare the measures of central tendency across engine condition. These visualizations help better illustrate the results of the t-test. In fact, Guetterman et al. (2021) explain that boxplots can reduce cognitive burden on the reader by making patterns in numeric statistics more apparent.

Limitations

The results of this project have the potential to improve the outcomes of the Army's maintenance program. However, all research contains certain limitations. Acknowledging these limitations allows for realistic interpretation of findings. Open acknowledgment of limitations also builds trust between researches and organizations. It helps manage expectations of the organization when applying findings to real-world scenarios.

The main limitation of this study is the simulated dataset. While the dataset is based on actual vehicle diagnostics pulled from IoT sensors, it does not include actual operational data from ground combat vehicles. The nuances of combat operations are not taken into account by the simulated data. This might result in a failure to capture complex operational factors faced by combat vehicles. These factors include specific combat stressors and environmental variables. A model built on simulated data will more than likely result in different levels of fit and predictive power when applied to real-world data.

While the use of simulated data does have limitations, it is necessary for this project due to the sensitive nature of operational data related to military equipment. Full visibility of combat vehicle maintenance predictors is not available due to the unavailability of classified maintenance records. The findings of this study might be valuable, but their applicability to actual military operations might be limited due to the use of simulated data. Stakeholders must interpret the proceeding results with caution. Instead of directly applying them to the Army's maintenance program, they should be used to prioritize which, if any, IoT sensors should be invested in. Once actual operational data becomes available, the predictive maintenance model should be recalibrated to ensure applicability to real-world conditions.

Ethics and Privacy Considerations

While predictive maintenance models can drastically improve the Army, ethics and privacy must also be taken into consideration when leveraging IoT data from ground combat vehicles. Altulaihan et al. (2022) explain that IoT technology can be an easy target for malicious actors due to a lack of basic information security features. However, user authentication and access control methods can be used to mitigate this lack of security (Altulaihan et al., 2022). Private, encrypted networks dedicated to the IoT sensors and corresponding database can also be used to increase security. While these methods are effective, they require additional investments and resources to implement.

Furthermore, while the IoT sensors in question focus on vehicle diagnostics such as oil pressure and coolant temperature, some sensors have the capability to capture video or sound, such as engine vibration sensors. Since these sensors will be used in vehicles operated by United States Soldiers, they may inadvertently collect data like personal conversations. If unauthorized data is collected, there must be systems and processes in place to ensure it is destroyed.

Similarly, a long-term data storage plan must be developed to ensure data preservation and disposal practices are conducted in an ethical manner.

Also, data use in joint military operations might cause friction points between various stakeholders. Guidelines must be developed to codify how data sharing between different militaries, government agencies, and defense contractors occur. Data sharing with defense contractors who are responsible for sourcing repair parts must face extra scrutiny to eliminate any possible conflicts of interest. These companies generate revenue through selling repair parts. Decreasing unplanned maintenance events may eventually decrease repair part sales. This conflict of interest must be kept in mind when sharing data. Finally, all efforts will be made to ensure this project is transparent and reproducible. All steps will be documented, and code will be made publicly available.

With limitations and ethics in mind, the study moves forward with an analysis of findings derived from the previously mentioned statistical tests. An in-depth understanding of the limitations of simulated data and an understanding of the ethical considerations involved with military data provides the context needed for the responsible interpretation of results. The next section presents detailed analytical outcomes that offer valuable insights into the use of predictive maintenance on ground combat vehicles.

Findings

Before conducting statistical tests on the research question, the dataset was cleaned and descriptive statistics tests were applied. Initially, the coolant temperature variable showed a high kurtosis value of 5.88. This was due to two extreme outliers. Due to the fact that the dataset consisted of 19,535 rows, the 2 rows that included the outliers were dropped. This resulted in the kurtosis value decreasing from 5.88 to -0.60 and skewness decreasing from 0.40 to 0.05. The other numeric variables did show some slight skewness. However, none of the variables have skewness values greater than the absolute value of 1.5 nor kurtosis values greater than the absolute value of 2.6. Histograms for each numeric variable are found below in Figure 1 to 6.

Figure 1

Histogram with Inset Statistics for rpm

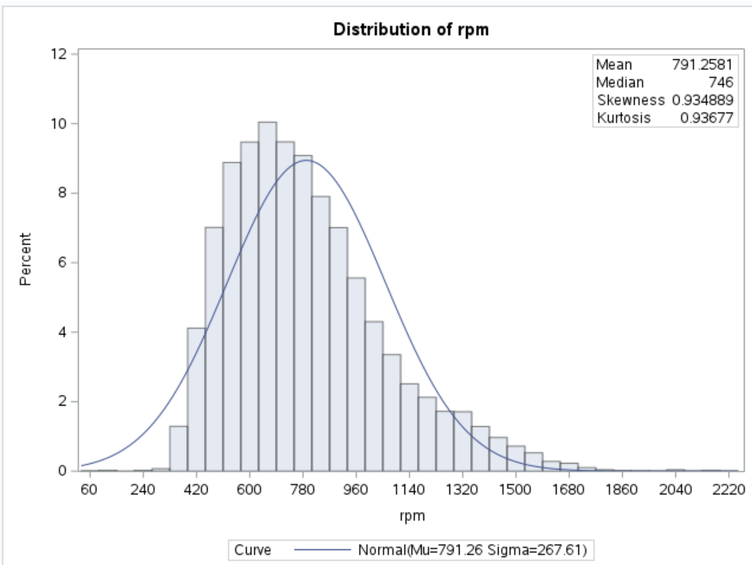


Figure 2

Histogram with Inset Statistics for Fuel Pressure

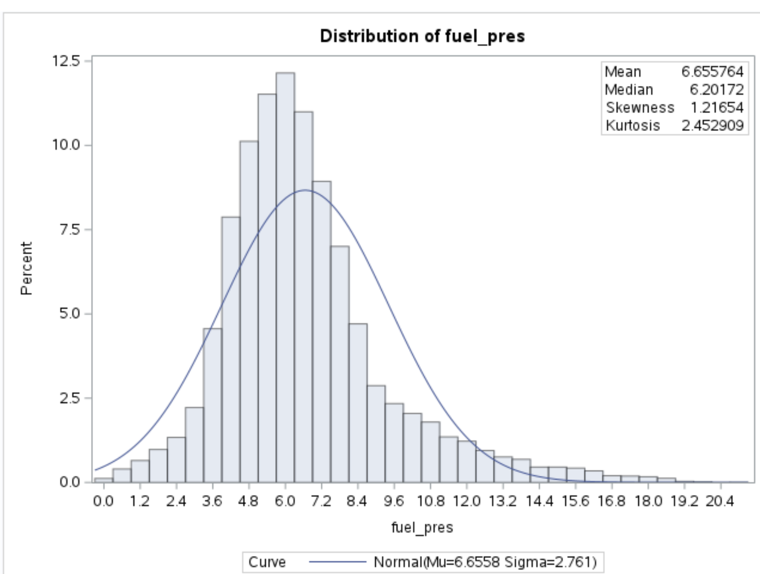


Figure 3

Histogram with Inset Statistics for Coolant Pressure

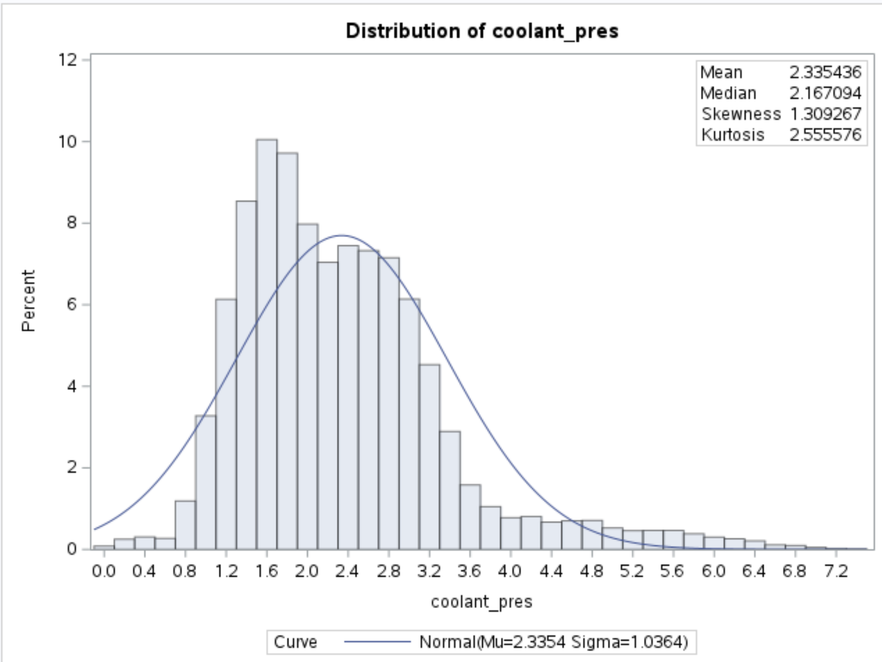


Figure 4

Histogram with Inset Statistics for Coolant Temperature

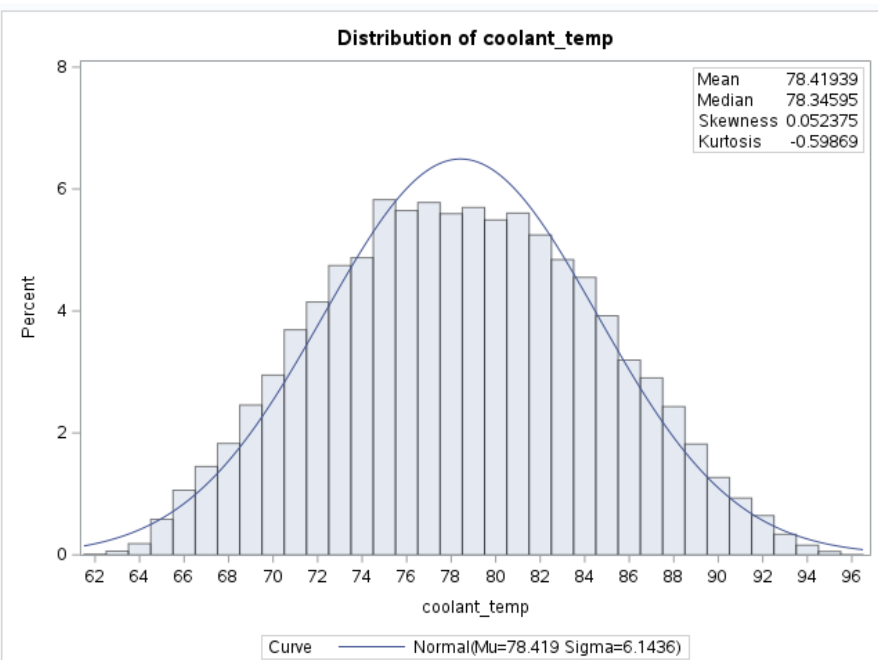


Figure 5

Histogram with Inset Statistics for Oil Pressure

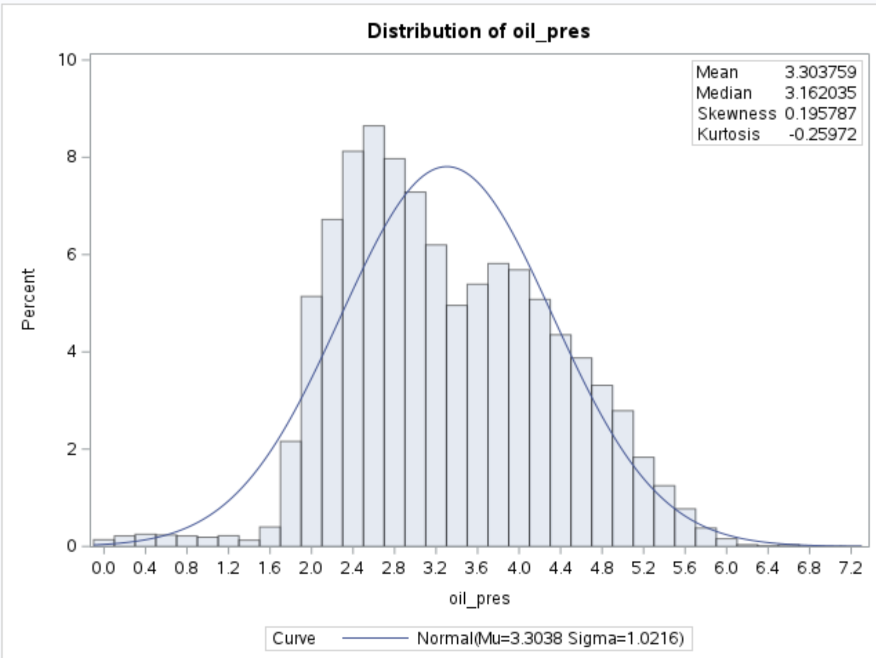


Figure 6

Histogram with Inset Statistics for Oil Temperature

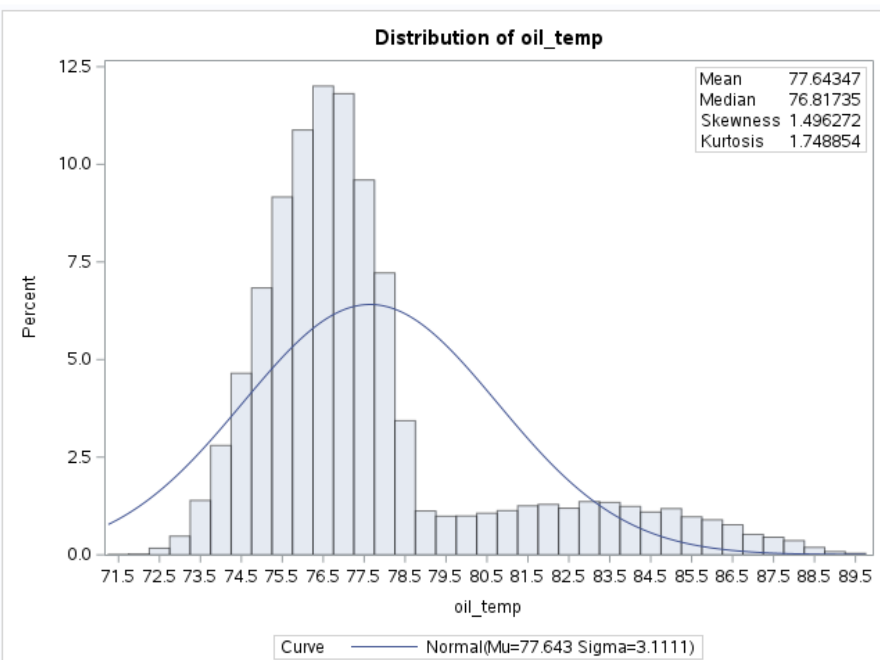


Figure 7 below shows the one-way frequency table for the engine condition variable. Normal engines make up 63.05% of the observations, and faulty engines make up 36.95%.

Figure 7

One-way Frequency for Engine Condition

engine_condition	Frequency	Percent
0	7217	36.95
1	12316	63.05

Since the goal is to create a logistic regression model, collinearity between predictors was analyzed. Figure 8 below shows the correlation matrix for all numeric variables.

Figure 8

Correlation Matrix

Pearson Correlation Coefficients, N = 19533						
	rpm	oil_pres	fuel_pres	coolant_pres	oil_temp	coolant_temp
rpm	1.00000	0.02498	-0.00155	-0.02503	0.05211	0.03113
oil_pres	0.02498	1.00000	0.04394	-0.00936	-0.00806	-0.06083
fuel_pres	-0.00155	0.04394	1.00000	0.03324	-0.02533	-0.04335
coolant_pres	-0.02503	-0.00936	0.03324	1.00000	-0.02077	0.03466
oil_temp	0.05211	-0.00806	-0.02533	-0.02077	1.00000	0.07400
coolant_temp	0.03113	-0.06083	-0.04335	0.03466	0.07400	1.00000

The matrix shows no correlation coefficients greater than the absolute value of 0.08. These low correlation coefficients mean collinearity is not a concern. All numeric variables will be used to create the initial logistic regression model.

Figure 9 below shows summary statistics grouped by the engine condition variable. There are differences in measures of central tendency between engine condition classes. However, the differences in mean between classes are small, with the exception of the rpm variable. T-tests and side-by-side boxplots are used to test the statistical significance of the differences and to visualize them as well.

Figure 9

Summary Statistics Grouped by Engine Condition

engine_condition	N Obs	Variable	Mean	Std Dev	Minimum	Maximum	Median	N Miss
0	7217	rpm	885.0123320	271.7376569	351.0000000	2239.00	843.0000000	0
		oil_pres	3.2222632	1.0102289	0.0078911	7.0513223	3.0670816	0
		fuel_pres	6.2368146	2.6813878	0.0031871	19.8589172	5.8241562	0
		coolant_pres	2.3680196	1.0872088	0.0024827	7.1684095	2.1818098	0
		oil_temp	78.0239545	3.2320304	72.2445544	89.5807955	77.0897425	0
		coolant_temp	78.7975470	5.9505925	62.4459553	94.7843922	78.7678377	0
1	12316	rpm	736.3194219	249.2993937	61.0000000	2172.00	690.0000000	0
		oil_pres	3.3515147	1.0252221	0.0033841	7.2655655	3.2146600	0
		fuel_pres	6.9012631	2.7774915	0.0507029	21.1383255	6.4209206	0
		coolant_pres	2.3163418	1.0050116	0.0156652	7.4785049	2.1580082	0
		oil_temp	77.4205048	3.0159611	71.3219737	89.2863016	76.6602498	0
		coolant_temp	78.1978002	6.2435429	61.6733247	95.8552834	78.1004904	0

The results of the two-sample t-test for rpm are found in Figure 10 below. The corresponding boxplot is found in Figure 11.

Figure 10

Two-sample T-test for rpm

engine_condition	Method	N	Mean	Std Dev	Std Err	Minimum	Maximum
0		7218	885.0	271.7	3.1983	351.0	2239.0
1		12317	736.3	249.3	2.2463	61.0000	2172.0
Diff (1-2)	Pooled		148.7	257.8	3.8217		
Diff (1-2)	Satterthwaite		148.7		3.9083		

engine_condition	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0		885.0	878.7	891.3	271.7	267.4	276.2
1		736.3	731.9	740.7	249.3	246.2	252.5
Diff (1-2)	Pooled	148.7	141.2	156.2	257.8	255.3	260.4
Diff (1-2)	Satterthwaite	148.7	141.0	156.4			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	19533	38.91	<.0001
Satterthwaite	Unequal	14085	38.05	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	7217	12316	1.19	<.0001

Figure 11

Boxplot for rpm Grouped by Engine Condition

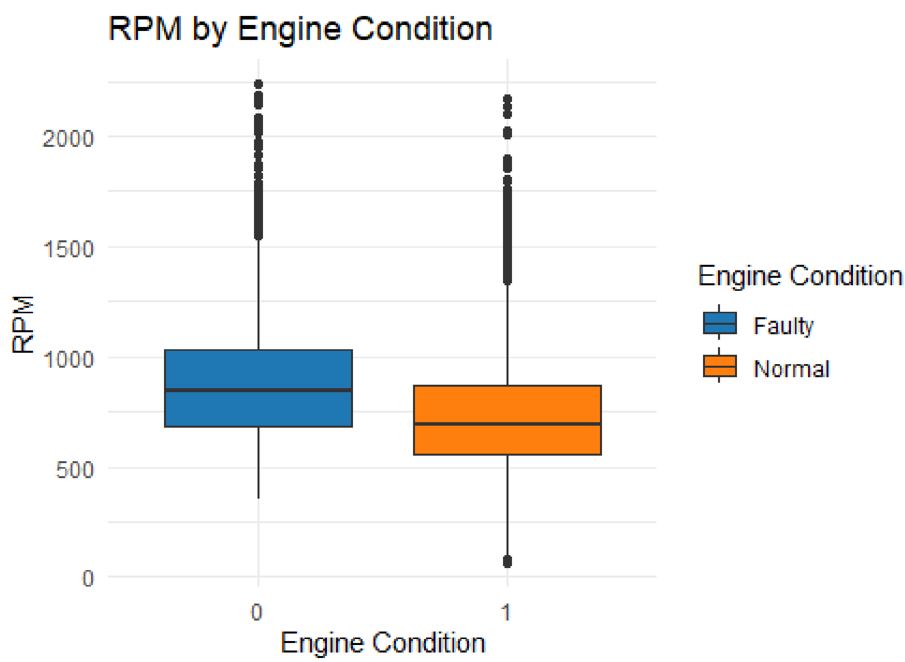


Figure 10 shows that the difference in mean rpm of engine condition 0 and mean rpm of engine condition 1 is 148.7. Figure 10 also shows that this difference in means is statistically significant with a p-value of < 0.0001. This result provides evidence that faulty engines have, on average, higher rpm readings than normal engines. This relationship is visualized in Figure 11.

The results of the two-sample t-test for fuel pressure are found in Figure 12 below. The corresponding boxplot is found in Figure 13.

Figure 12

Two-sample T-test for Fuel Pressure

engine_condition	Method	N	Mean	Std Dev	Std Err	Minimum	Maximum
0		7218	6.2363	2.6815	0.0316	0.00319	19.8589
1		12317	6.9013	2.7774	0.0250	0.0507	21.1383
Diff (1-2)	Pooled		-0.6650	2.7424	0.0407		
Diff (1-2)	Satterthwaite		-0.6650		0.0403		

engine_condition	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0		6.2363	6.1744	6.2982	2.6815	2.6385	2.7260
1		6.9013	6.8523	6.9504	2.7774	2.7431	2.8125
Diff (1-2)	Pooled	-0.6650	-0.7447	-0.5853	2.7424	2.7154	2.7698
Diff (1-2)	Satterthwaite	-0.6650	-0.7440	-0.5861			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	19533	-16.36	<.0001
Satterthwaite	Unequal	15544	-16.51	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	12316	7217	1.07	0.0008

Figure 13

Boxplot for Fuel Pressure Grouped by Engine Condition

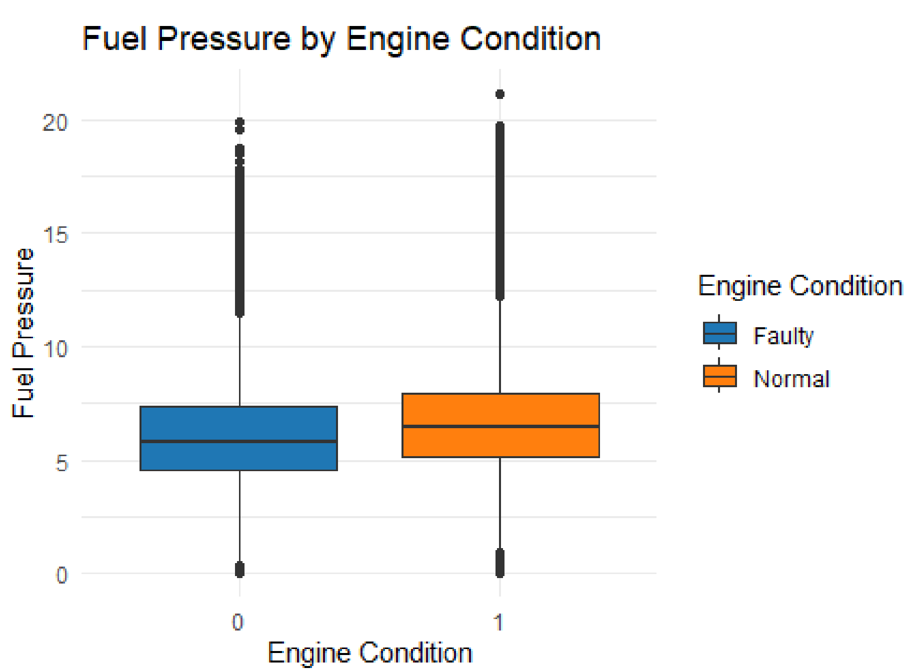


Figure 12 shows that the difference in mean fuel pressure of engine condition 0 and mean fuel pressure of engine condition 1 is -0.665. Figure 12 also shows that this difference in means is statistically significant with a p-value of < 0.0001. This result provides evidence that faulty engines have, on average, lower fuel pressure than normal engines. Figure 13 visualizes this relationship.

The results of the two-sample t-test for coolant pressure are found in Figure 14 below. The corresponding boxplot is found in Figure 15.

Figure 14

Two-sample T-test for Coolant Pressure

engine_condition	Method	N	Mean	Std Dev	Std Err	Minimum	Maximum
0		7218	2.3679	1.0872	0.0128	0.00248	7.1684
1		12317	2.3163	1.0050	0.00906	0.0157	7.4785
Diff (1-2)	Pooled		0.0516	1.0361	0.0154		
Diff (1-2)	Satterthwaite		0.0516		0.0157		

engine_condition	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0		2.3679	2.3428	2.3930	1.0872	1.0697	1.1052
1		2.3163	2.2985	2.3340	1.0050	0.9926	1.0177
Diff (1-2)	Pooled	0.0516	0.0215	0.0818	1.0361	1.0259	1.0465
Diff (1-2)	Satterthwaite	0.0516	0.0209	0.0824			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	19533	3.36	0.0008
Satterthwaite	Unequal	14172	3.29	0.0010

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	7217	12316	1.17	<.0001

Figure 15

Boxplot for Coolant Pressure Grouped by Engine Condition

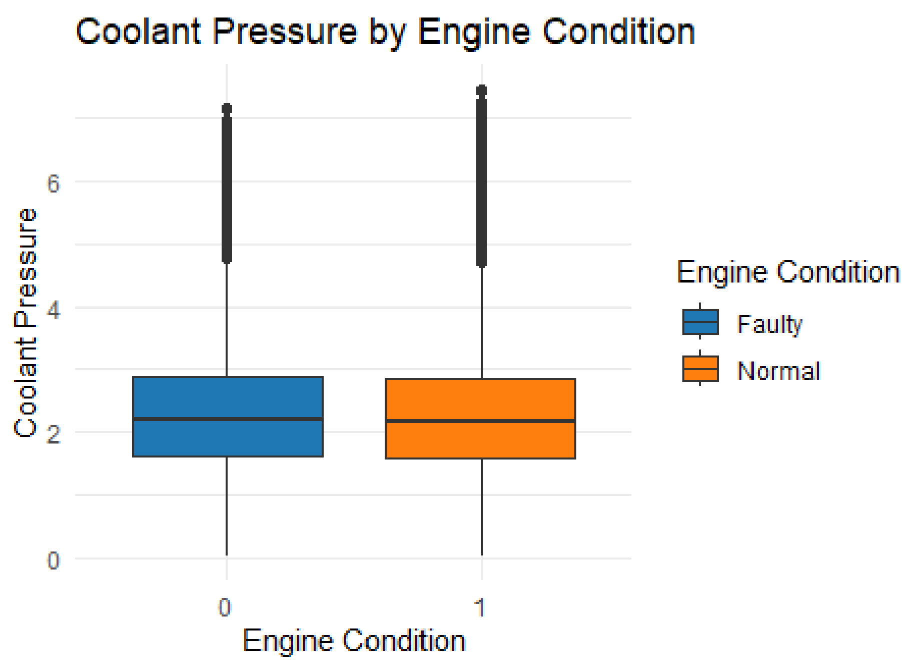


Figure 14 shows that the difference in mean coolant pressure of engine condition 0 and mean coolant pressure of engine condition 1 is 0.0516. Figure 14 also shows that this difference in means is statistically significant with a p-value of < 0.0008 for the Pooled method and a p-value of < 0.0010 for the Satterthwaite method. This result provides evidence that faulty engines have, on average, slightly higher coolant pressure than normal engines. Figure 15 visualizes this relationship.

The results of the two-sample t-test for coolant temperature are found in Figure 16 below. The corresponding boxplot is found in Figure 17.

Figure 16

Two-sample T-test for Coolant Temperature

engine_condition	Method	N	Mean	Std Dev	Std Err	Minimum	Maximum
0		7218	78.8030	5.9684	0.0703	62.4460	118.4
1		12317	78.2073	6.3322	0.0571	61.6733	195.5
Diff (1-2)	Pooled		0.5957	6.2002	0.0919		
Diff (1-2)	Satterthwaite		0.5957		0.0905		

engine_condition	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0		78.8030	78.6653	78.9407	5.9684	5.8726	6.0674
1		78.2073	78.0955	78.3192	6.3322	6.2541	6.4122
Diff (1-2)	Pooled	0.5957	0.4156	0.7759	6.2002	6.1394	6.2623
Diff (1-2)	Satterthwaite	0.5957	0.4183	0.7731			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	19533	6.48	<.0001
Satterthwaite	Unequal	15840	6.58	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	12316	7217	1.13	<.0001

Figure 17

Boxplot for Coolant Temperature Grouped by Engine Condition

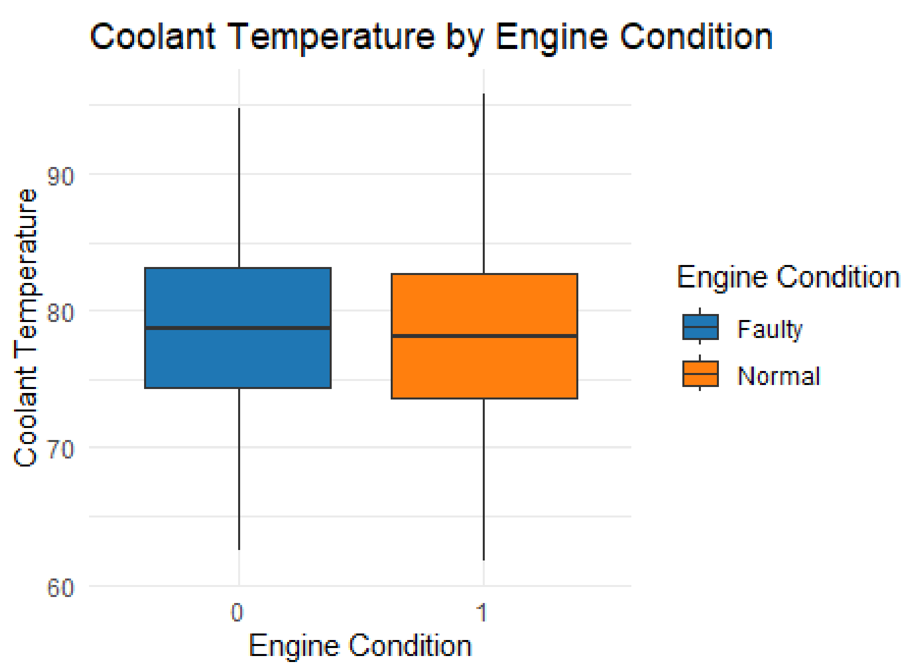


Figure 16 shows that the difference in mean coolant temperature of engine condition 0 and mean coolant temperature of engine condition 1 is 0.5957. Figure 16 also shows that this difference in means is statistically significant with a p-value of < 0.0001. This result provides evidence that faulty engines have, on average, higher coolant temperature than normal engines. Figure 17 visualizes this relationship.

The results of the two-sample t-test for oil pressure are found in Figure 18 below. The corresponding boxplot is found in Figure 19.

Figure 18

Two-sample T-test for Oil Pressure

engine_condition	Method	N	Mean	Std Dev	Std Err	Minimum	Maximum
0		7218	3.2225	1.0104	0.0119	0.00789	7.0513
1		12317	3.3514	1.0253	0.00924	0.00338	7.2656
Diff (1-2)	Pooled		-0.1289	1.0198	0.0151		
Diff (1-2)	Satterthwaite		-0.1289		0.0151		

engine_condition	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0		3.2225	3.1992	3.2458	1.0104	0.9941	1.0271
1		3.3514	3.3333	3.3695	1.0253	1.0126	1.0382
Diff (1-2)	Pooled	-0.1289	-0.1585	-0.0993	1.0198	1.0098	1.0300
Diff (1-2)	Satterthwaite	-0.1289	-0.1584	-0.0994			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	19533	-8.53	<.0001
Satterthwaite	Unequal	15292	-8.56	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	12316	7217	1.03	0.1637

Figure 19

Boxplot for Oil Pressure Grouped by Engine Condition

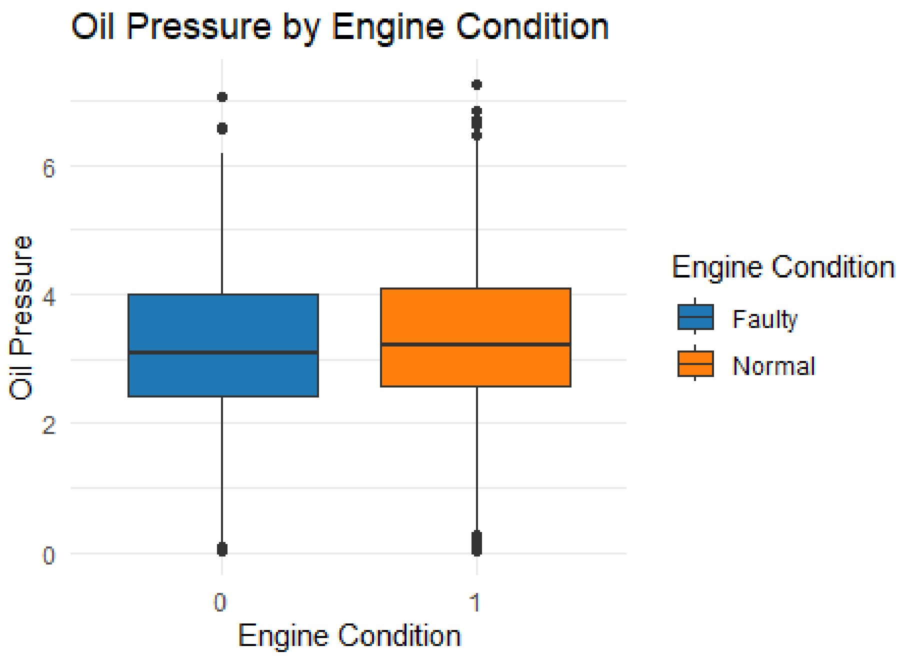


Figure 18 shows that the difference in mean oil pressure of engine condition 0 and mean oil pressure of engine condition 1 is -0.1289. Figure 18 also shows that this difference in means is statistically significant with a p-value of < 0.0001. While this result does provide evidence that faulty engines have, on average, lower oil pressure than normal engines, the equality of variances f-test p-value of 0.1637 provides evidence that the variances between the two samples are not equal. This violates one of the assumptions of a two-sample t-test and must be taken into consideration. Figure 19 visualizes the difference in mean oil pressure between the two groups.

The results of the two-sample t-test for oil temperature are found in Figure 20 below. The corresponding boxplot is found in Figure 21.

Figure 20

Two-sample T-test for Oil Temperature

engine_condition	Method	N	Mean	Std Dev	Std Err	Minimum	Maximum
0		7218	78.0239	3.2318	0.0380	72.2446	89.5808
1		12317	77.4204	3.0158	0.0272	71.3220	89.2863
Diff (1-2)	Pooled		0.6035	3.0974	0.0459		
Diff (1-2)	Satterthwaite		0.6035		0.0467		

engine_condition	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
0		78.0239	77.9494	78.0985	3.2318	3.1799	3.2854
1		77.4204	77.3672	77.4737	3.0158	2.9787	3.0540
Diff (1-2)	Pooled	0.6035	0.5135	0.6935	3.0974	3.0670	3.1284
Diff (1-2)	Satterthwaite	0.6035	0.5119	0.6951			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	19533	13.14	<.0001
Satterthwaite	Unequal	14283	12.91	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	7217	12316	1.15	<.0001

Figure 21

Boxplot for Oil Temperature Grouped by Engine Condition

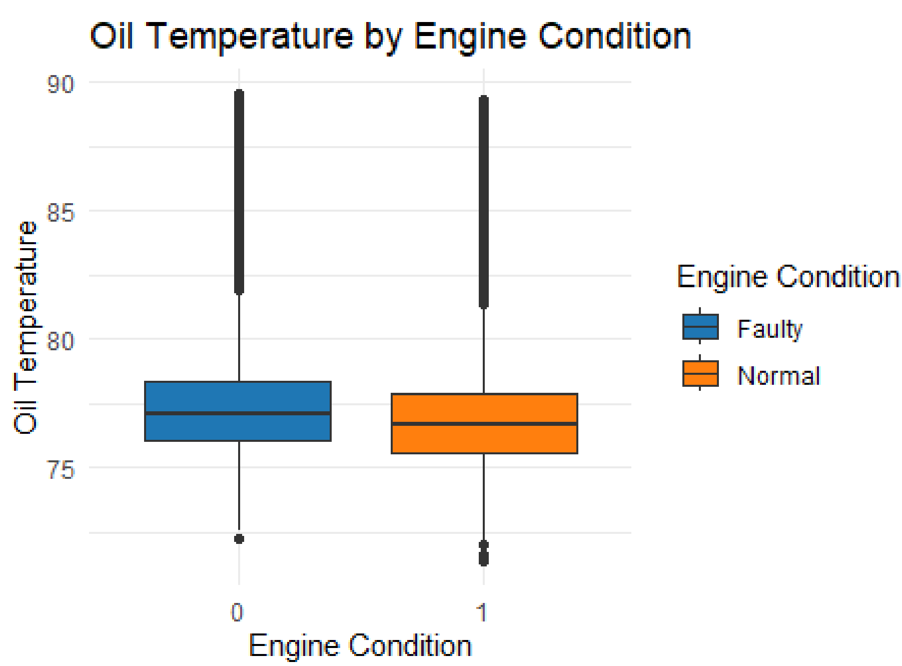


Figure 20 shows that the difference in mean oil temperature of engine condition 0 and mean oil temperature of engine condition 1 is 0.6035. Figure 20 also shows that this difference in means is statistically significant with a p-value of < 0.0001. This result provides evidence that faulty engines have, on average, higher oil temperature than normal engines. Figure 21 visualizes the relationship.

The two-sample t-tests have shown that all numeric variables have statistically significant differences in mean between engine condition groups. With these results in mind, the project moves forward to the logistic regression model. All six variables are used as predictors, but backward selection removed coolant temperature for not meeting the required confidence level of 0.05. The results of the model are found in Figure 22 below.

Figure 22

Logistic Regression Model

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-5.8970	0.4719	156.1773	<.0001
rpm	1	0.00223	0.000073	936.1432	<.0001
fuel_pres	1	-0.1057	0.00729	209.9626	<.0001
coolant_pres	1	0.0870	0.0179	23.6954	<.0001
oil_pres	1	-0.1368	0.0184	55.4951	<.0001
oil_temp	1	0.0580	0.00592	95.9441	<.0001

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
rpm	1.002	1.002	1.002
fuel_pres	0.900	0.887	0.913
coolant_pres	1.091	1.053	1.130
oil_pres	0.872	0.841	0.904
oil_temp	1.060	1.048	1.072

First, all five predictors are statistically significant with a p-value of < 0.0001. Next, while logistic regression coefficients are more difficult to interpret than linear regression coefficients, they still provide valuable information on the relationship between predictors and the dependent variable. The logistic regression equation is listed below.

Equation 1

Binary Logistic Regression Equation

$$Logit(engine\_condition = 0) = -5.897 + (0.00223)\mathrm{rpm} + (-0.1057) fuel\_pres + (0.0870)\mathrm{coolant\_pres} + (-0.1368)\mathrm{oil\_pres} + (0.0580)\mathrm{oil\_temp} \quad (1)$$

In this case, rpm, coolant pressure, and oil temperature have positive coefficients. Positive coefficients show that the probability of a faulty engine increases as the values of the variables increase. This means there is a positive relationship between the probability of engine failure and rpm, coolant pressure, and oil temperature. Fuel pressure and oil pressure have negative coefficients. Negative coefficients show that the probability of engine failure decreases as the values of the variables increase. This means there is a negative relationship between the probability of an engine failure and fuel pressure and oil pressure.

The odds ratios in Figure 22 provide more specific information on these relationships. The odds ratio of 1.002 for rpm means that an increase in 100 rpm increases the odds of engine failure by 22%. The odds ratio of 0.900 for fuel pressure means that a decrease of 1 bar decreases the odds of engine failure by 10%. The odds ratio of 1.091 for coolant pressure means that an increase of 1 bar increases the odds of engine failure by 9.1%. The odds ratio of 0.872 for oil pressure means that an increase of 1 bar decreases the odds of engine failure by 12.8%. Finally, the odds ratio of 1.060 for oil temperature means that an increase of 1 degree Celsius increases the odds of engine failure by 6%.

With these relationships in mind, the project now moves to analyze the fit and predictive power of the binary logistic regression model. The confusion matrix and performance metrics for the training data are found in Figure 23 and Figure 24, respectively. The confusion matrix and performance metrics for the validation data are found in Figure 25 and Figure 26, respectively. Figure 27 shows the Receiver Operating Characteristic curve for validation data.

Figure 23

Confusion Matrix, Training Data

	Predicted		All
	0	1	
	Count	Count	Count
Actual			
0	1576	3501	5077
1	1112	7484	8596

Figure 24

Performance Metrics, Training Data

Sensitivity	Specificity	Accuracy
31.04%	87.06%	66.26%

Figure 25

Confusion Matrix, Validation Data

	Predicted		All
	0	1	
	Count	Count	Count
Actual			
0	638	1502	2140
1	486	3234	3720

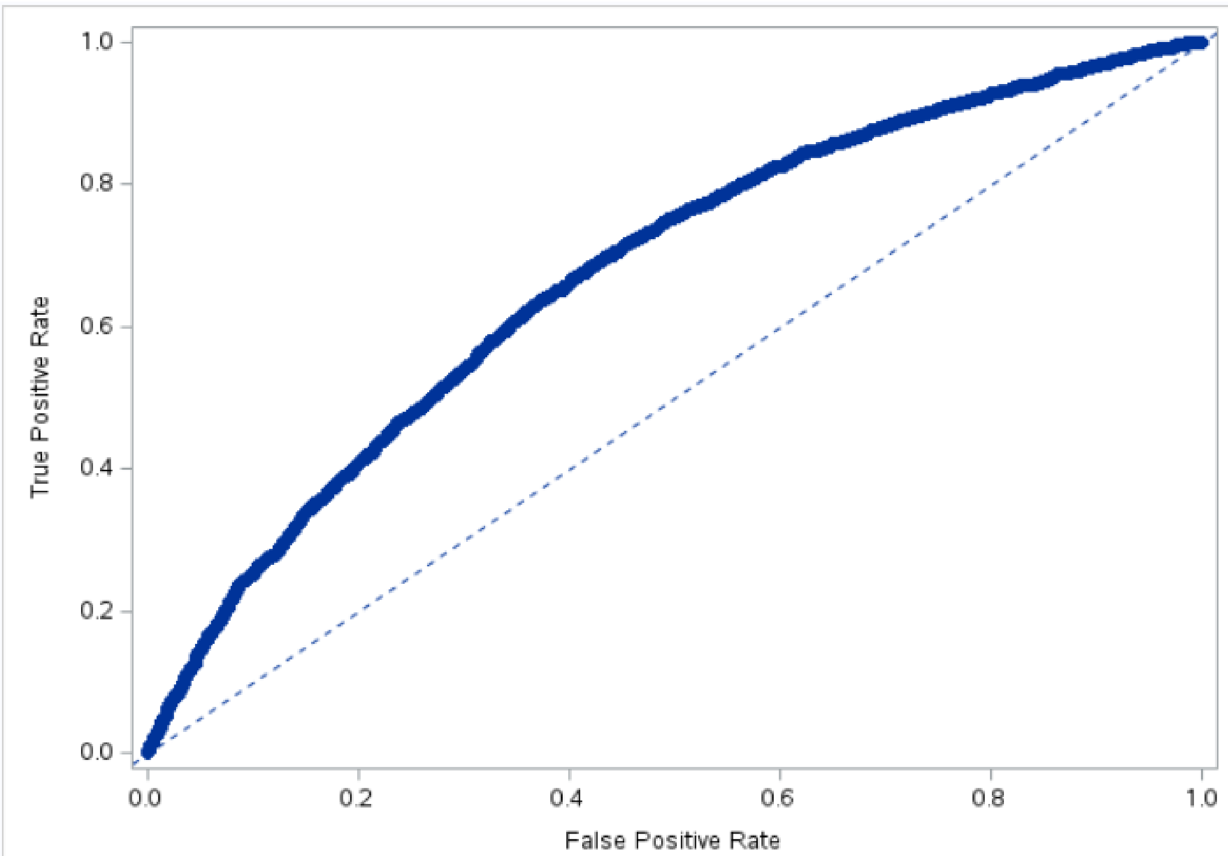
Figure 26

Performance Metrics, Validation Data

Sensitivity	Specificity	Accuracy
29.81%	86.94%	66.08%

Figure 27

Receiver Operating Characteristic (ROC) Curve, Validation Data



As a reminder, the positive condition is set as faulty, or engine condition = 0. Figure 24 shows that the model attains 66.26% accuracy on the training data. It also shows sensitivity of 31.04% and specificity of 87.06%. Comparing to the baseline accuracy of 62.87% for the training data, the model performs marginally better. The baseline accuracy is calculated by choosing the most frequent engine condition found in the data. This provides evidence that the model is somewhat recognizing meaningful patterns in the training data.

Furthermore, Figure 26 shows that the model attains 66.08% accuracy on the validation data. It also shows sensitivity of 29.81% and specificity of 86.94%. The small difference in accuracies when comparing the training accuracy to the validation accuracy provides evidence that the model is not overfitting the data. Comparing to the baseline accuracy of 63.48% for the validation data, the model also performs marginally better. The ROC curve found in Figure 27 provides further evidence that the model performs better than random selection. However, the low sensitivity is cause for concern. It shows that the model is correctly predicting only 29.81% of engine failures. While predicting 86.94% of healthy engines does have value, a predictive maintenance model is focused on predicting unplanned maintenance events.

With the t-test and logistic regression results in mind, the null hypothesis is partially rejected. The logistic regression model results in Figure 22 provide the bulk of the evidence needed to support this rejection. Five of the six predictors are statistically significant with p-values < 0.0001. Coolant temperature was removed through backward selection due to not meeting the required confidence level. While the model has significant room for improvement, the rejection of the null hypothesis suggests the dataset contains meaningful relationships between IoT sensor information and unplanned maintenance events. This provides evidence that data from IoT sensors capture patterns in vehicle performance which can be successfully leveraged for predictive maintenance purposes.

This finding identifies opportunities for overall model improvement, future investigation, and future analysis. Only six predictors were used for this model. However, ground combat vehicles rely on numerous mechanical and electrical components (Sengupta et al., 2023). Examples of these components include engines, transmissions, hydraulics, targeting systems, and on-board computers. With so many components, there are endless opportunities to test how other vehicle diagnostics affect the likelihood of unplanned maintenance events. In addition to vehicle diagnostics, other factors like environmental conditions, vehicle age, and historical maintenance records could be leveraged to make the model more effective as well. While including additional diagnostics and external factors has the potential to overcomplicate the model, it could help discover other variables that affect unplanned maintenance events. The model does have low accuracy and sensitivity; including additional variables has the potential to improve these results.

Furthermore, it is important to note that is possible results were influenced by factors outside the scope of this project. From a technological standpoint, variations in sensors or issues with sensor communication to the database can affect data quality and integrity. From an equipment standpoint, differences between vehicles due to model, age, or operating environments could also have influenced the results. Operator skill differences also have the potential to skew data.

Conclusion

In conclusion, unplanned maintenance events in ground combat vehicles require large expenditures on repair parts. In fact, maintenance of ground combat platforms like tanks makes up 6.56% of the total budget for the Army in Fiscal Year 2025 (Office of the Under Secretary of Defense, 2024). Furthermore, unplanned maintenance events negatively impact operational readiness and negatively impact the Army's ability to complete its mission. To help remediate these issues, this project focused on developing and analyzing a predictive maintenance model that leverages IoT sensor data to predict unplanned maintenance events.

The analysis conducted provided enough evidence to partially reject the null hypothesis. Unplanned maintenance events can be predicted through the use of IoT sensor data. More specifically, a binary logistic regression model can successfully leverage rpm, fuel pressure, coolant pressure, oil pressure, and oil temperature sensor data to predict engine failure. While the model and predictors were found to be statistically significant, the predictive power of the model has room for improvement.

The model identified key relationships in sensor data and maintenance events. For example, the odds ratio for rpm in Figure 22 shows that an increase in 100 rpm increases the odds of engine failure by 22%. This relationship provides valuable information to the Army regarding decision points to conduct maintenance and order repair parts. If sensors record a tank on the battlefield spiking the rpm reading, then that vehicle can be pulled back from the front for maintenance before a breakdown occurs.

Real-time operational data made available through IoT sensors can be used to trigger repair part replenishment orders and repair combat vehicles before they become nonoperational. The relationships between sensor data and maintenance event probability allow the Army to enhance ground combat vehicle readiness, optimize maintenance scheduling, and improve the repair part supply chain. Looking to the future, pairing IoT sensor technology with predictive maintenance models will allow the Army to maintain a competitive advantage on the battlefield. Future research should be conducted to identify IoT sensors that have a high impact on maintenance failures. Additional factors such as environmental conditions and operator skill levels should also be taken into account. Continuous refinement of the predictive maintenance program will improve decision-making accuracy and maintenance scheduling for the Army.

Recommendations

While the statistical tests and logistic regression model revealed valuable insights, the low accuracy must be taken into account by the organization. The recommended way forward is to invest in only the rpm sensor. This sensor had a relatively high impact on engine failure probability with odds of failure increasing by 22% for a 100 unit increase in rpm. Also, ground combat vehicles have internal rpm sensors installed. This one sensor would be more easily installed than the other sensors. This would minimize the initial financial investment while also jumpstarting the program. Once the organization has experience with the program and operators are trained on using the data, additional sensors can then be installed. This slow start method ensures the Army will not be overwhelmed by the adoption of a new maintenance program.

While the program is starting, additional analysis should be conducted to identify impactful IoT sensors. As mentioned previously, ground combat vehicles consist of numerous components. Studies should be done to see if sensors installed on other components like transmissions or on-board computers can improve the accuracy of the predictive model. Analysis of external factor sensors like weather, humidity, terrain, and operator information should also be conducted. Ground combat vehicles operate in austere and diverse environments. This additional research has the potential to make the predictive maintenance program more accurate and effective.

Next, the binary logistic regression model should be analyzed further. Changing the probability cut-off has the potential to improve the model's sensitivity. Finally, additional analysis should be done on model selection. While a binary logistic regression model is simpler to interpret, other models like classification trees, neural networks, or ensembles have the potential to outperform it. While some interpretability may be lost through the use of a more complicated model, it could result in a significant increase in accuracy which would be greatly beneficial to the organization.

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