FUEL EFFICIENCY, IN-CYLINDRICAL PRESSURE AND HRR PREDICTION

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report titled "**FUEL EFFICIENCY, IN-CYLINDRICAL PRESSURE AND HRR PREDICTION"** is the bonafide work of **DIKCHA SINGH [RA2011027010096] AND K SANTHANA LAKSHMI [RA2011027010129]** who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion for this or any other candidate.

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ABSTRACT

The escalating global vehicle count, particularly in emerging economies, poses significant challenges to energy reserves and environmental sustainability. This research endeavors to tackle this pressing issue by focusing on the identification of crucial intrinsic factors that influence fuel efficiency and the prediction of in-cylinder pressure within a mixture of fuels. Our comprehensive investigation delves into a range of machine learning models and formula-based calculations aimed at discerning the optimal fuel blends that not only maximize efficiency but also minimize harmful emissions. The study takes into account pivotal factors such as fuel density, calorific value, and brake power to construct models for predicting fuel efficiency and in-cylinder pressure. Our findings underscore the paramount importance of fuel mixtures and their profound impact on the efficiency of various brake power levels. Furthermore, this research involves a comparative analysis of multiple machine learning models, including Multiple Linear Regression, Random Forest Regressor, and Decision Tree Regressor,Gradient Boosting Regressor to offer valuable insights into their respective performance characteristics.

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ABBREVIATIONS

AI Artificial Intelligence
ML Machine Learning
AV Automotive Vehicle
SVM Support Vector Machine
KNN K Nearest Neighbour
OBD On Board Diagnostics
HRR Heat Release Rate
MPG Miles per Gallon
CNSL Cashew Nut Shell Oil
BP Brake Power
MAF Mass Air Flow
VS Vehicle Speed
RPM Revolutions Per Minute
TPS Throttle Position Sensor
IoT Internet of Things
GPS Global Positioning System
MII Mutual Information Index
KPI Key Performance Indicators
RMSE Root Mean Square Error
MSE Mean Square Error

CHAPTER 1

INTRODUCTION

As the number of vehicles on the planet experiences an unprecedented upsurge, especially in developing nations such as China and India, the resultant increase in the production of harmful greenhouse gasses and pollutants presents an immediate threat to the ecological balance of our planet. Simultaneously, the constant depletion of non-renewable resources, particularly petroleum, increases the need for creative and long-lasting solutions. In the midst of this environmental hell, smart route planning shows great promise as a potential solution to the ecological cost imposed by traditional transportation methods. However, a more thorough approach is necessary due to the complex terrain of vehicular dynamics.

To meet these demands, our research sets out on an ambitious and multi-pronged mission to decipher the complexities of combustion dynamics, forecast the illusive heat release rate, identify the ideal fuel efficiency, and precisely compute cylinder pressure at 720 angles. This quest for automotive enlightenment is supported by a strong framework that combines the formidable powers of machine learning algorithms with the clarity provided by advanced visualization techniques and the methodical approach of formulaic thinking, rather than being left to the whims of chance.

Our goal goes beyond simple scholarly curiosity as we explore the intersection of scientific research and technology innovation. We see a time where efficiency and sustainability coexist harmoniously, completely changing what it means to use cars. Our study aspires to be a catalyst for revolutionary change, leading the way for a peaceful cohabitation between humanity's automotive goals and the imperative of environmental stewardship through the synthesis of state-of-the-art technology and thorough scientific methods.

1.1 GENERAL

With developing nations such as China and India leading the way in the global automobile industry, the number of vehicles on the road is increasing at an unsustainable rate, leading to a serious depletion of non-renewable resources like petroleum. This unrelenting path is further exacerbated by the simultaneous production of undesired greenhouse gasses and emissions, posing a threat to the fragile ecological balance of our world.

Strategic route design becomes a powerful tool in the armory of limiting environmental effect in response to this vehicular juggernaut. A sophisticated strategy with the potential to reduce fuel use, this methodology struggles with its broad applicability. There isn't a single, universally applicable answer due to the complexity of various driving situations and infrastructure quirks.

In this context, by eschewing traditional fossil fuels, our research efforts pioneer a new direction in the field of sustainable mobility. We steer clear of the negative effects linked to conventional petrol and diesel in favor of the use of biofuels. Our two main goals in this revolutionary voyage are to determine the biofuels efficiency quotient for use in automobiles and to forecast the complex dynamics of cylinder pressure.

1.2 PURPOSE

Our scientific endeavors are driven by a tremendous mission to transform the field of engine performance prediction while pursuing efficiency and innovation at all costs. The idea to move beyond the conventional limitations of laboratory testing and usher in a time where engine performance can be predicted without physically operating the engines in controlled circumstances is at the heart of this audacious ambition. This paradigm change promises significant time and cost savings, but it also profoundly conserves the priceless energy and knowledge of our technical team.

We set out on a path that not only addresses the financial costs related to engine testing but also frees up the valuable time of our knowledgeable personnel by avoiding the need for lengthy laboratory experiments. Once tied to the demands of physical testing, this newly acquired financial and temporal capital can now be carefully diverted to more meaningful and creative endeavors. The benefits of this efficiency reach beyond our research labs and into domains where our technical workforce's combined knowledge and creativity can be used to tackle urgent problems, drive ground-breaking ideas, and make significant contributions to advancements outside of engine testing.

Essentially, our effort to forecast engine performance without requiring actual experiments constitutes both a responsible use of resources and a significant technological advancement. It is evidence of our dedication to effectiveness, sustainability, and the best possible use of human resources. As we navigate this unexplored area, we are focused not just on the revolutionary potential in our labs but also on the wider range of opportunities where the benefits of our vision might materialize in a more efficient, effective, and significant future.

1.2.1 SCOPE

Before moving on to the domain of real experiments, we can build a solid foundation by utilizing analogous outcomes from simulations. This method not only saves money and gives us the luxury of time, but it also acts as a tactical prelude to the practical stage. We may simplify our experimental design and concentrate resources on the most promising directions by using simulations to determine the points that perform the best. The precision rates achieved in the simulated environment instill confidence in the validity of our methodology, providing a robust basis for the upcoming real-world experiments. Essentially, this two-pronged strategy balances theoretical accuracy with real-world relevance, maximizing the effectiveness and efficiency of the research process.

1.2.2 NEED OF FUEL EFFICIENCY PREDICTION

This initiative is critical for a number of reasons. First of all, it directly tackles the critical issue of diesel engine fuel efficiency optimisation in cylindrical pressure scenarios, which is a cornerstone in many businesses and the transportation sector. Determining the optimal fuel mixtures for various loads is essential for enhancing overall engine performance and, in turn, operating economy.

Practical insights into real-world applications are offered by the inclusion of a wide variety of over 20 fuels and their combinations. This specificity is essential since it makes it possible to customize solutions for various sectors and circumstances, guaranteeing that the project's conclusions have quick and direct application.

Because diesel engines are widely used and biofuels have potential, there is a substantial focus on CNSL as the parent fuel along with other fuels like methanol and diesel. This project acts as a useful manual for putting biofuels into practice successfully, overcoming the challenges that come with using them directly, and proving that they are a competitive fuel substitute.

Not only is the combination of machine learning and data analytics a technological requirement, but it is also a luxury. A common shortcoming of mechanical engineers is their inability to precisely handle huge datasets. The project's use of these cutting-edge tools enables effective analysis, saving time and money while guaranteeing a degree of precision that is essential for making decisions.

Moreover, by reducing the hazardous pollutants that cars spew into the environment, the project directly supports environmental sustainability. Optimizing fuel combinations is a concrete step towards developing more environmentally friendly energy conversion processes that are in line with international initiatives to mitigate climate change and lower carbon footprints.

1.3 SUSTAINABLE TECHNOLOGY

We are firmly in the field of sustainability technology because of our participation in this project. As follows:

1. **Energy Efficiency Optimisation:** It helps optimize the energy efficiency of diesel engines by concentrating on determining the optimal fuel combinations and forecasting Heat Release Rate. This is a crucial component of sustainability since it lowers operating expenses and total energy usage.

2. **Integrating Biofuel:** The project focus on conventional fuels in addition to biofuels like CNSL is in line with sustainability objectives. Because they are frequently made from renewable resources, which lessens the need for non-renewable fossil fuels and lessens their negative effects on the environment, biofuels are thought to be more environmentally friendly.

3. **Decrease in Impact on the Environment**: The project's main objective, reducing the amount of hazardous pollutants that cars emit, directly tackles environmental issues. This emission decrease helps to develop more environmentally friendly and sustainable industrial and transportation methods.

4. **Accurate Machine Learning:** Using Data analytics and machine learning in your project is a technological advance that has consequences for sustainability. You help to reduce the total environmental impact of the research, minimize needless testing, and increase resource efficiency by optimizing the analysis process and increasing precision in identifying the best fuel combinations.

5. **Encouraging Eco-Aware Decision-Making**: Your initiative provides data-driven insights that can steer the transportation and industry sectors towards more environmentally friendly practices. This involves selecting gasoline blends that support wider environmental and sustainability goals while simultaneously improving performance.Our effort in figuring out the best fuel mixtures for diesel engines is essentially an application of sustainable technology in real life. It tackles the requirement for energy efficiency, investigates fuel substitutes that are less harmful to the environment, and uses cutting edge technology to make operations more sustainable. Research of this nature is essential to bringing in a day when sustainability and technology live side by side.

1.4 MOTIVATION

Meet both the ends of the most practical energy conversion device.One side is diesel engines are needed in various sectors like industry and transport since it is most reliable.

Other side we have biofuels that are on par with diesel but they have some drawbacks if directly used.

Through this project we can find which fuel combination at which load gives best performance and to predict the Cylindrical Pressure.Since Mechanical engineers don't know ML and Data Analytics it is difficult for them to work with huge datasets and precision.

In this project we have 20 + Fuels and its combination of Fuels.We are going to find which combination of amount of fuel gives best Efficiency with Several Loads such as 5.2 Brake Power, 4.16, 3.12, 2.08, 1.04 .Our parent Fuel is CNSL(Cashew Nut Shell Oil) combined with other Fuels like Cotton seed oil,Orange Peel oil etc.

1.4.1 PROBLEM STATEMENT

We have 20 + Fuels and its combination of Fuels.We are going to find which combination of amount of fuel gives best Efficiency with Several Loads such as 5.2 Brake Power, 4.16, 3.12, 2.08, 1.04 and to predict the cylindrical Pressure and HRR.Our parent Fuel is CNSL(Cashew Nut Shell Oil) combined with other Fuels like Coconut oil, Cotton seed oil etc.

CHAPTER 2

LITERATURE STUDY

The primary focus of this research paper [1] the authors M. Aditya Vamsi, B. Raja Rishita, M. Amin Qurishi, N. Siva Sandeep, K. Raghu Ram. are trying to develop sophisticated prediction models using advanced machine learning techniques for estimating the fuel efficiency, measured in Miles per Gallon (MPG), of diverse vehicles. The study employs a diverse set of machine learning algorithms, including Linear Regression, Random Forest, Decision Tree, and KNN. Additionally, it explores the application of deep learning concepts to assess their effectiveness in predicting fuel efficiency.A crucial aspect of the research involves the comprehensive comparison of these machine learning models. The evaluation criteria encompass error reduction and predictive accuracy. By scrutinizing models such as Random Forest, Decision Tree, KNN, and Linear Regression, the study aims to identify the model that not only minimizes errors but also demonstrates superior efficiency in predicting fuel consumption.To achieve these objectives, the research utilizes datasets that are pertinent to machine learning practitioners.

These datasets encompass a wealth of information about various cars, including key features such as the number of cylinders, displacement, horsepower, and weight. Leveraging these datasets, the models are trained and tested to ensure their accuracy and reliability in predicting fuel efficiency.The overarching goal of this research is to make a meaningful contribution to the automotive industry. By providing a tool that can assist car manufacturers in optimizing their processes for increased fuel efficiency, the paper aims to offer a valuable resource for enhancing competitiveness in the market. Accurate prediction models have the potential to provide manufacturers with a strategic advantage, enabling them to tailor their offerings to meet consumer demands and regulatory standards effectively.Motivations driving this research are multifaceted and closely tied to industry challenges and advancements in technology. The relentless increase in fuel costs serves as a primary motivation, pushing car manufacturers to seek innovative ways to optimize fuel efficiency.

Consumer preferences also play a pivotal role in motivating this research. As consumers become increasingly discerning about the features and performance of vehicles, there is a growing demand for fuel-efficient cars. Accurate prediction models can guide manufacturers in aligning their production processes with these consumer preferences, ensuring that the vehicles they produce are not only efficient but also align with market demands.In a highly competitive market, fuel efficiency becomes a crucial differentiator. Companies that can offer more fuel-efficient vehicles gain a significant edge over their competitors. Therefore, the research aspires to contribute to this aspect by developing models that can lead to the creation of more fuel-efficient and attractive vehicles, positioning manufacturers as leaders in the industry.

The incorporation of machine learning techniques is a response to the advancements in the field. Leveraging these techniques allows the research to enhance the accuracy of fuel efficiency predictions. This, in turn, enables better decision-making within the automotive industry, ens

During that time, manufacturers can optimize their processes and resources effectively.Lastly, the environmental impact is a key consideration. Beyond economic benefits, improving fuel efficiency has positive implications for environmental sustainability. By promoting the development of more fuel-efficient vehicles, the research aligns with a broader goal of reducing the overall carbon footprint associated with transportation.

In conclusion, this research endeavors to not only develop advanced prediction models for fuel efficiency but also to address industry challenges, consumer demands, and environmental concerns. By combining machine learning techniques with a comprehensive evaluation of models, the study aspires to contribute meaningfully to the automotive industry's ongoing pursuit of more sustainable and efficient vehicles.

The primary objective of this paper [2] the authors Xie, X., Sun, B., Li, X., Olsson, T., Maleki, N., & Ahlgren, F. are trying to develop precise fuel consumption prediction models for ships, employing both a white-box model based on mathematical methods and a black-box model based on machine learning. To ensure the accuracy of these models, a data preprocessing cleaning method is introduced, specifically based on the Kwon formula, aiming to eliminate noise generated during acceleration and deceleration processes.

The paper evaluates model performance using ship model test data and regression methods. It discusses the application of the data-cleaning method in preprocessing the black-box model and assesses its impact on overall model performance. Validation of the models under simulated conditions is a critical step, correlating predicted fuel consumption rates with ship speed to ensure their accuracy in representing real-world scenarios.

The ultimate goal is to enhance decision support for shipping companies. Accurate fuel consumption prediction models can play a pivotal role in navigation status analysis, energy conservation, and emission reduction, contributing significantly to the overall sustainability of maritime operations.

The motivation for this research stems from the increasing emphasis on environmental sustainability in the international shipping community. With a focus on reducing greenhouse gas emissions, there is a growing demand for accurate fuel consumption prediction models in the maritime industry. Shipping companies are keenly interested in improving the energy efficiency of their vessels to reduce fuel costs, a substantial portion of their operating expenses. The availability of vast amounts of data from sensors on ships further motivates the exploration of predictive models, offering opportunities to optimize energy usage.

In summary, this paper addresses the crucial need for accurate fuel consumption prediction models in the maritime industry, aligning with the global emphasis on environmental sustainability. The proposed models, supported by thorough evaluation and validation, aim to provide practical decision support for shipping companies, fostering improved fuel efficiency, reduced operating costs, and environmentally conscious decision-making in maritime operations.

This paper [3] the authors Mohamed A. HAMED, Mohammed H.Khafagy and Rasha M.Badry are aiming to enhance the accuracy of fuel consumption prediction models through the application of machine learning, specifically focusing on the Support Vector Machine (SVM) algorithm. The overarching objective is to contribute a robust model that predicts vehicle fuel consumption based on key parameters, including Mass Air Flow (MAF), Vehicle Speed (VS), Revolutions Per Minute (RPM), and Throttle Position Sensor (TPS) features.

The proposed model undergoes testing using a vehicle's On-Board Diagnostics (OBD) dataset, which encompasses 18 features. The primary goal is to achieve high accuracy in fuel consumption prediction, measured by the R-Squared metric. The paper asserts that the SVM algorithm, when applied to fuel consumption prediction, outperforms other related works utilizing the same algorithm.

The motivation behind this research is grounded in the significant impact of fuel consumption on individuals, businesses, and the global economy. Fluctuations in fuel prices can have far-reaching effects on economic factors, underscoring the importance of accurate fuel consumption prediction for effective planning and decision-making.

This study leverages machine learning, particularly the SVM algorithm, to address the motivation of developing a robust model for fuel consumption prediction. The incorporation of On-Board Diagnostics (OBD) data, part of the Internet of Things (IoT) technique, allows for real-time and remote monitoring of vehicles. By adopting a data-driven approach and employing machine learning techniques, the research aims to enhance the accuracy of predicting fuel consumption.

A notable contribution of the paper is the proposal of a model that considers both RPM_TPS-based and VS_MAF-based equations for fuel consumption prediction. The emphasis is on the significance of these equations and their parameters, asserting that they play a pivotal role in accurately measuring fuel consumption rates.

Additionally, the paper underscores the importance of feature weighting and selection in the context of SVM algorithm application. The motivation extends beyond predicting fuel consumption to identify and prioritize the most influential features contributing to accurate predictions.

In summary, the primary objective of this paper is to advance fuel consumption prediction models using the SVM algorithm, with a motivation deeply rooted in the broader implications for economic improvement, business optimization, and addressing global concerns related to fuel consumption through the application of machine learning techniques.

This study [4] the authors Yao, Y., Zhao, X., Liu, C., Rong, J., Zhang, Y., Dong, Z., & Su, Y. are aiming to develop a method for predicting vehicle fuel consumption based on driving behavior, focusing on leveraging data collected from mobile phone sensors. The escalating energy consumption of private cars in China underscores the urgency to address and reduce energy consumption in the transportation sector. The paper aims to contribute to the solution by investigating the correlation between driving behavior and energy consumption and utilizing mobile phone data to accurately predict fuel consumption.

The central objective is to construct a fuel consumption prediction model based on Global Positioning System (GPS) data obtained from smartphones. This model seeks to establish a connection between driving behavior data collected from mobile phones and fuel consumption data from On-Board Diagnostics (OBD) terminals. The intention is to improve real-time monitoring databases with enhanced error tolerance and provide a theoretical foundation for urban traffic fuel consumption management and policy effectiveness evaluation.

Motivated by the pressing need for sustainable urban transportation development in China, the study recognizes driving behavior as a crucial factor influencing energy consumption. While existing research has explored prediction models for energy consumption based on driving behavior, this study introduces a novel approach by incorporating data collected from mobile phone sensors. The motivation is to overcome limitations associated with traditional data sources, such as OBD devices and questionnaires, by leveraging mobile phone technology for larger-scale data collection, offering a more detailed and easily accessible dataset for analyzing driving behavior.

Acknowledging challenges related to potential inaccuracies in mobile phone data due to factors like phone placement and vibrations, the study proposes a method to calibrate and effectively utilize this data for predicting fuel consumption. The adoption of mobile phone terminals for data collection is seen as a cost-effective alternative to OBD equipment installation, providing a practical solution for traffic management departments to monitor urban traffic fuel consumption more accurately.

In conclusion, the motivation of this research lies in exploring the untapped potential of mobile phone data in predicting vehicle fuel consumption, considering its widespread use and potential for large-scale data collection. The study aims to bridge the gap between driving behavior and fuel consumption prediction, offering valuable insights for energy-efficient urban transportation management.

The primary objective of this study [5] the authors Yin, X., Li, Z., Shah, S. L., Zhang, L., & Wang, C.are trying to develop fuel efficiency prediction models for common automobiles, leveraging an extensive and informative vehicle database. The central focus is on identifying key characteristics that significantly influence fuel efficiency and employing machine learning techniques to construct accurate prediction models. The study explores five different machine learning techniques, with a specific emphasis on quantile regression, recognized for its superior performance compared to other methods. The overarching goal is to contribute valuable insights to car designers and manufacturers, facilitating enhancements in fuel economy by considering specific characteristics that impact fuel efficiency.

Motivation for this research emanates from the global surge in vehicle numbers, particularly in developing countries like China and India. This rise raises substantial concerns regarding energy resource consumption and environmental impact, with negative consequences including the consumption of non-renewable resources and the generation of greenhouse gasses. In response, effective strategies are imperative to reduce fuel consumption in vehicles. While route planning strategies show promise, their applicability is limited in many areas. Hence, this study aims to bridge the gap by identifying major characteristics affecting fuel economy and developing predictive models for fuel efficiency.

The motivation further extends to providing car designers and manufacturers with an objective model that guides improvements in fuel economy. The study leverages real-world vehicle data, delving into features such as engine displacement, vehicle size, weight, and aerodynamic performance to analyze and model fuel efficiency. The adoption of quantile regression as a prediction method is motivated by its demonstrated effectiveness in capturing nuances of fuel efficiency prediction compared to other regression methods.

Recognizing the challenges associated with fuel consumption models based on vehicle dynamics, which necessitate detailed knowledge of the physical structure of vehicles, the proposed approach focuses on using a Mutual Information Index (MII). This index serves to identify significant characteristics affecting fuel efficiency, offering a more adaptable and practical solution.

In summary, the motivation is grounded in contributing to the understanding of fuel efficiency in common automobiles, providing practical guidance for car designers, and offering predictive models that can enhance fuel economy by considering specific characteristics. The study not only aims to demonstrate the effectiveness of quantile regression but also highlights the relevance of identified features in predicting fuel efficiency accurately.

This research responds to a critical need in the face of escalating global concerns related to energy resource consumption and environmental impact. By identifying influential factors and leveraging advanced machine learning techniques, the study aspires to empower the automotive industry with tools and insights that can pave the way for more fuel-efficient vehicles, aligning with broader goals of sustainability and environmental stewardship.

This research seeks to contribute to the improvement of fuel efficiency in common automobiles by developing accurate predictive models based on an extensive vehicle database. Employing five machine learning techniques with a specific emphasis on quantile regression, the study aims to identify and analyze key characteristics influencing fuel efficiency, such as engine displacement, vehicle size, weight, and aerodynamic performance. Motivated by the global concerns of rising vehicle numbers, energy resource consumption, and environmental impact, the research addresses the need for effective strategies to reduce fuel consumption. By providing car designers and manufacturers with valuable insights and predictive models, particularly emphasizing the effectiveness of quantile regression, the study aims to guide improvements in fuel economy and promote sustainable practices in the automotive industry.

These research papers collectively demonstrate a comprehensive and multidimensional effort to address the critical challenges related to fuel efficiency and consumption prediction in various contexts, including automotive, maritime, and urban transportation. The adoption of advanced methodologies, diverse datasets, and a shared motivation to contribute to sustainability underscores the significance of these studies in shaping the future of energy-efficient transportation.

We are investigating the effects of biofuels on internal combustion engine efficiency, in-cylinder pressure prediction, and Heat Release Rate (HRR) in our study. The use of cutting-edge machine learning models to precisely forecast these biofuels' efficiency is the main goal. To determine the best model for biofuel efficiency prediction, we will use a variety of machine learning methods, including Random Forest, Decision Tree, Linear Regression. Next, our work moves on to the more complex work of in-cylinder pressure prediction, which is essential to comprehending the dynamics of biofuel combustion. The chosen machine learning model will be used to forecast pressure changes inside the engine during combustion after being thoroughly compared and validated. From the anticipated pressure data, the computed Heat Release Rate, a crucial variable in combustion analysis will next be obtained. Our project uses data visualization approaches to improve understanding by giving a visual depiction of the complex interactions between efficiency, Heat Release Rate, in-cylinder pressure, and biofuel properties. Researchers and experts in the industry can gain a greater understanding of the dynamics of biofuel combustion and make well-informed decisions in the search for efficient and sustainable energy solutions with the help of this visualization, which is a valuable tool.

CHAPTER 3

SYSTEM ARCHITECTURE AND DESIGN

3.1 ARCHITECTURE DIAGRAM

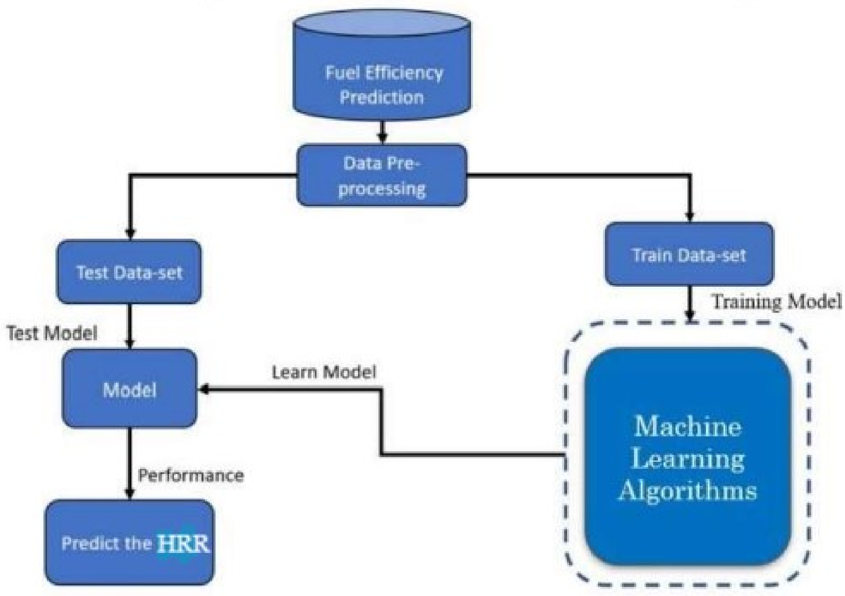


Fig 3.1 Architecture Diagram

The first stage in applying a machine learning model to predict pressure is gathering raw system data, which includes elements like calorific value,mass of fuel etc. Following feature selection and data cleaning, the dataset is split into training and testing sets. The selected machine learning technique is then trained on the training dataset to discover the correlations between input features and the target variable. Pressure is often a regression approach like linear regression or Random Forest Regressor. Metrics like Mean Absolute Error and Mean Squared Error are used to evaluate the model's performance using the test dataset. The selected features are entered into the model, which then uses the patterns it learnt during the training phase to generate predictions, and it may be used to forecast pressure based on fresh, unseen data after it has been trained and validated. Long-term accuracy in pressure prediction may require constant optimisation and monitoring.

3.2 USE CASE DIAGRAM

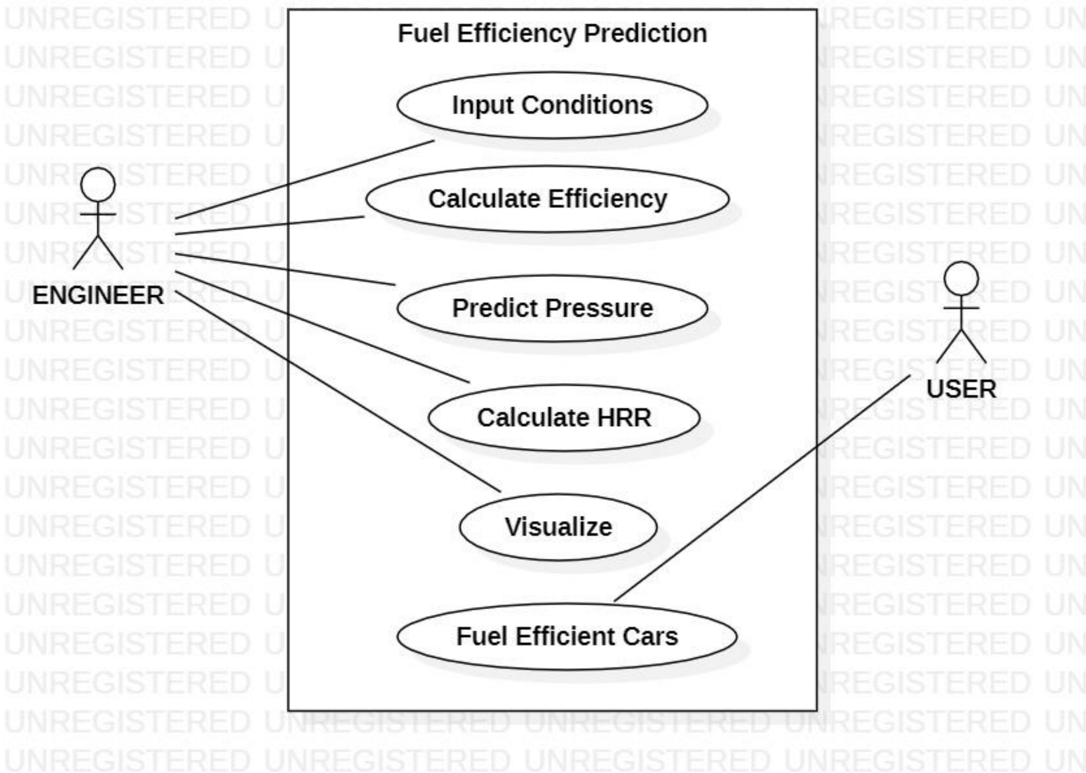


fig 3.2 Use Case Diagram

An engineer interacts with a complex system intended to improve comprehension and optimisation.The engineer starts the process by entering pertinent data into the system, such as calorific value, mass of fuel etc and other parameters. After that, the system uses machine learning models to do the complex tasks of estimating pressure, calculating efficiency, and calculating the heat release rate (HRR) based on the input.A data visualization component is incorporated into the system to enable a thorough comprehension of the outcomes. This facilitates effective interpretation and analysis of the results by the engineer, leading to well-informed decision-making. In the end, this use case gives engineers the ability to make data-driven decisions while working to create cars that are fuel-efficient.

3.3 DATA FLOW DIAGRAM

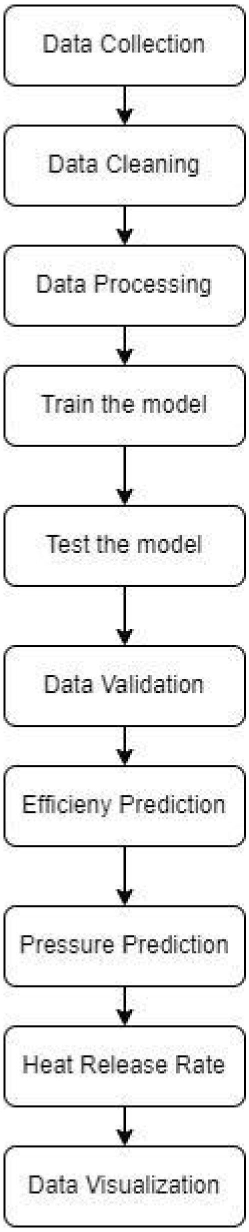


fig 3.3 Data Flow

The process of predictive modeling starts with data collection, which is the gathering of basic system data like mass of fuel, calorific value etc, affecting pressure and heat release rate.To address missing values and remove inconsistencies, the gathered data is carefully cleaned. Preprocessing procedures are used to get the dataset ready for modeling after data cleaning. To make the following training and assessment stages easier, the dataset is then split into training and testing sets. Using metrics like accuracy or Mean Squared Error, the selected machine learning algorithm is taught on the training dataset and its effectiveness is verified on the test dataset. If the model works well, it can be used to forecast the rate of pressure and heat release rate depending on fresh data inputs. Data visualization techniques can be utilized to improve interpretability and insights. This can help in understanding patterns and trends.

CHAPTER 4

PROPOSED METHODOLOGY

4.1 Data Collection:

1. **Data Variables:**

   The parameters like fuel types, fuel combinations, loads (Brake Power), pressure, calorific value, viscosity, volume, crank angle, density, mass of fuel, cetane number are collected.

2. **Data Sources:**

   The Data is collected from the Experimental setup and stored in the database.

4.2 Data Cleaning:

1. **Handling Missing Data:**

   Identify and address missing values in the dataset.Imputing missing values based on statistical measures, removing rows or columns with substantial missing data.

2. **Standardization:**

   Standardize the units of measurement to maintain consistency across different data points. This is crucial for accurate analysis and interpretation.

4.3 Data Processing:

1. **Data Integration:**

   Dataset is sourced from multiple places, we integrate the data to create a unified dataset. Ensured consistency in variable names, units, and formats.First Efficiency are found and the values are integrated for pressure dataset.

2. **Data Transformation:**

   Transformations to variables using mathematical operations (formula method) to find the efficiency by using the efficiency formula and to find the mass of fuel and HRR value identification.

3. **Normalization and Scaling:**

   Normalize or scale numerical variables on different scales. This ensures that all variables contribute equally to the analysis, preventing those with larger magnitudes from dominating the results.

4. **Data Splitting**:

   Dividing the dataset into training and testing sets. This ensures that the model is trained on one subset of the data and tested on another, providing a more robust evaluation of its performance.

4.4 TRAINING AND TESTING MODELS

The models considered in our analysis include:

1. **Multiple Linear Regression:**

   Multiple linear regression is a straightforward approach to modeling the relationship between multiple independent variables and a dependent variable, making it a suitable choice for our multi-factor analysis of In-cylinder pressure.

2. **Random Forest Regressor:**

   Random forests are an ensemble learning method known for their ability to handle complex relationships in data. They are capable of capturing non-linear patterns and interactions between factors, making them a valuable tool for predicting pressure.

3. **Decision Tree Regressor:**

   Decision trees are a simple yet effective model for regression tasks. We found that decision tree regressors performed well in capturing the impact of various factors on in-cylinder pressure.

4. **Gradient Boosting Regressor:**

   Gradient boosting is an ensemble technique that combines the predictions of multiple weak learners to create a strong predictive model. Gradient boosting regressors are known for their high accuracy in regression tasks.

4.5 IDENTIFICATION AND PREDICTION:

Efficiency is calculated using formula methods of efficiency and pressure is predicted using machine learning algorithms like Decision Tree , Random Forest , Linear Regression and Gradient Boosting and HRR calculated using the formula method of HRR.

1. **Conversion Brake Power to Equivalent Load Formula:**

   Brake Power =(2*pi*n*t) / 60000

   n=1500, r=0.185, t=w*r*9.81

2. **Efficiency Formula:**

   Mass of fuel 1 = ((amount of fuel 1 * 0.000001) / 60) * density of fuel 1

   Mass of fuel 2 =((amount of fuel 2 * 0.000001) / 60) * density of fuel 2

   Heat input = mass of fuel 1 * calorific value of fuel 1 + mass of fuel 2 * calorific value of fuel 2

   Efficiency = Brake Power / Heat input

3. **Heat Release Rate Formula:**

   HRR = (((1.35 / (1.35 - 1)) * (Pressure * ((Volume - dV) / 1))) + ((1 / (1.35 - 1)) * (Volume * ((Pressure - dP) / 1)))

4.6 Data Visualization:

Data visualization is a key component of the data analysis process, allowing to communicate complex patterns and insights in a visually accessible format.

1. **Normalization Visualizations:**

   - The paper discusses data normalization to facilitate analysis. Visualizing the effects of normalization, such as before-and-after plots, can help readers understand how scaling impacts the data and why it is essential for certain analyses.

2. **Regression Performance Plots:**

- For the regression models, visualizations like scatter plots comparing predicted fuel efficiency against actual values are likely included. This allows readers to assess the accuracy of the predictive models and understand how well they align with the observed data.

3. **Feature Importance Plots:**

   - In the context of machine learning model training, the paper may include visualizations highlighting the importance of different features in predicting fuel efficiency. This could be done through bar charts or other graphical representations.

4. **Validation Results Visualization:**

   - When presenting the results of model validation, the paper might include visualizations to compare predicted and actual fuel efficiency values. This helps in assessing the robustness and generalization capabilities of the predictive models.

4.7 Results and Accuracy :

Performance Matrix:

1. **Random Forest Regressor:**

   Mean Square Error: 0.234809795

   Root Mean Square Error: 0.484571765

   R Square: 0.998782242

2. **Decision Tree Regressor:**

   Mean Square Error: 0.33849539

   Root Mean Square Error: 0.58180357

   R Square: 0.998244513

3. **Gradient Boosting Regressor:**

   Mean Square Error: 0.840088763

   Root Mean Square Error: 0.916563562

   R Square: 0.995643176

4. **Linear Regression:**

   Mean Square Error: 151.1745303

   Root Mean Square Error: 12.29530522

   R Square: 0.215986548

CHAPTER 5

MODULE STUDY

5.1 Module 1: Data Preparation and Cleaning

1. **Data Collection and Cleaning:**
   - Handling missing values.
   - Standardizing the dataset.
   - Removing outliers using the z-score test.

5.2 Module 2: Efficiency Calculation

1. **Mass Calculation:**
   - Applying the provided formulas to calculate the mass of each fuel.
   - Converting brake power to equivalent load.
2. **Efficiency Iteration:**
   - Implementing a Python loop for efficiency calculations.
   - Setting and applying an efficiency threshold.
3. **Best Efficiency Identification:**
   - Storing the best efficiency fuel combination in an Excel sheet.

5.3 Module 3: Machine Learning for Pressure Prediction

1. **Data Preparation for Pressure Prediction:**
   - Selecting relevant features for pressure prediction.
   - Utilizing the best efficiency fuel combination data.
2. **Model Training and Validation:**
   - Splitting the dataset into training and testing sets.
   - Evaluating and selecting the best-performing machine learning model.
3. **Pressure Prediction:**

- Using the selected model to predict in-cylinder pressure for all 720 angles.

5.4 Module 4: Heat Release Rate (HRR) Analysis

1. **HRR Calculation:**
   - Applying the provided formula for HRR.
   - Incorporating pressure, volume, and relevant changes.
2. **Visualization of HRR:**
   - Creating visualizations to represent the calculated Heat Release Rate.

5.5 Module 5: Model Performance and Results

1. **Performance Metrics:**
   - Storing performance metrics for machine learning models.
   - Documenting accuracy and error rates.
2. **Results Storage:**
   - Compiling key results, predictions, and efficiency data in Excel sheets.

5.6 Module 6: Conclusion and Recommendations

1. **Summary of Findings:**
   - Summarizing the identified best efficiency fuel combination.
   - Highlighting pressure predictions and HRR analysis.
2. **Recommendations for Further Study:**
   - Suggestions for refining models or exploring additional factors.

5.7 Module 7: Documentation and Future Work

1. **Methodology Documentation:**
   - Detailed documentation of the methods and assumptions used.
   - Transparency in data processing and analysis.
2. **Future Work:**
   - Suggestions for potential future improvements or expansions on the study.

CHAPTER 6

CODING AND TESTING

6.1 DATA PREPROCESSING AND ANALYSIS

```python
# Supress Warnings

import warnings
warnings.filterwarnings('ignore')

# Import the numpy and pandas package

import numpy as np
import pandas as pd

# Data Visualisation
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
d = pd.DataFrame(pd.read_csv("pro1.csv"))
d.head(15)
```

	Unnamed: 0	FID	cf	Load	Fuel1	Fuel2	Total_Vol	Mass_Fuel	Heat_Input	BP	BTE
0	13	4	34500	4.19	17.658	1.962	19.62	0.000311	10.739879	1.22	11.359532
1	14	4	34500	6.63	22.041	2.449	24.49	0.000389	13.405690	1.92	14.322276
2	17	5	34200	3.48	15.264	3.816	19.08	0.000298	10.199002	1.03	10.099027
3	18	5	34200	7.36	18.224	4.556	22.78	0.000356	12.176796	2.14	17.574410
4	19	5	34200	11.05	22.400	5.600	28.00	0.000438	14.967089	3.16	21.112990
5	20	6	33800	5.34	16.912	7.248	24.16	0.000372	12.585085	1.56	12.395626
6	21	6	33800	7.41	18.648	7.992	26.64	0.000411	13.876931	2.14	15.421277

```
d.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48 entries, 0 to 47
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Unnamed: 0   48 non-null     int64
 1   FID          48 non-null     int64
 2   cf           48 non-null     int64
 3   Load         48 non-null     float64
 4   Fuel1        48 non-null     float64
 5   Fuel2        48 non-null     float64
 6   Total_Vol    48 non-null     float64
 7   Mass_Fuel    48 non-null     float64
 8   Heat_Input   48 non-null     float64
 9   BP           48 non-null     float64
 10  BTE          48 non-null     float64
dtypes: float64(8), int64(3)
memory usage: 4.2 KB
```

```
[ ] d.shape
```

```
(48, 11)
```

```
[ ] list(d.columns)
```

```
['Unnamed: 0',
 'FID',
 'cf',
 'Load',
 'Fuel1',
 'Fuel2',
 'Total_Vol',
```

First we need to load the datasets from the given csv files and analyze and normalize it to make data trained to make it easy for modeling over the algorithms.

```
d.describe()
```

	Unnamed: 0	FID	cf	Load	Fuel1	Fuel2	Total_Vol	Mass_Fuel	Heat_Input	BP	BTE
count	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000
mean	54.604167	14.416667	35985.416667	7.766667	16.168188	4.897021	21.065208	0.000326	11.700825	2.213750	18.600367
std	23.820909	6.235906	1596.270865	2.888487	3.414496	1.770067	3.828418	0.000060	1.938370	0.800565	5.060900
min	13.000000	4.000000	32000.000000	3.090000	11.277000	1.962000	14.270000	0.000223	8.399613	1.000000	9.431531
25%	34.750000	9.000000	34725.000000	5.700000	12.967500	3.496500	17.960000	0.000276	10.142955	1.650000	14.092301
50%	56.500000	15.000000	36600.000000	7.400000	15.850000	4.866500	20.710000	0.000322	11.531144	2.140000	19.638165
75%	75.250000	20.000000	36975.000000	10.870000	18.708750	5.745750	24.237500	0.000373	13.398800	3.060000	22.624036
max	92.000000	24.000000	38400.000000	14.620000	23.886000	8.940000	29.800000	0.000453	16.084606	4.000000	27.850374

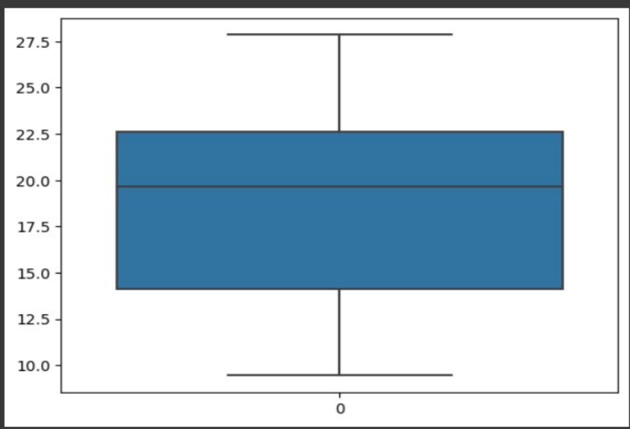
```
[ ] # Checking Null values
d.isnull().sum()
```

```
Unnamed: 0    0
FID           0
cf            0
Load          0
Fuel1         0
Fuel2         0
Total_Vol     0
Mass_Fuel     0
Heat_Input    0
BP            0
BTE           0
dtype: int64
```

```
d.isnull().sum()
```

```
Unnamed: 0     0
FID            0
cf             0
Load           0
Fuel1          0
Fuel2          0
Total_Vol      0
Mass_Fuel      0
Heat_Input     0
BP             0
BTE            0
dtype: int64
```

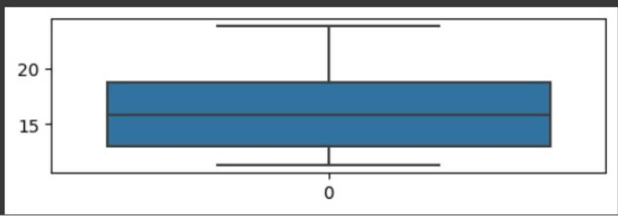
```
# Outlier Analysis

sns.boxplot(d['BTE'])
plt.show()
```

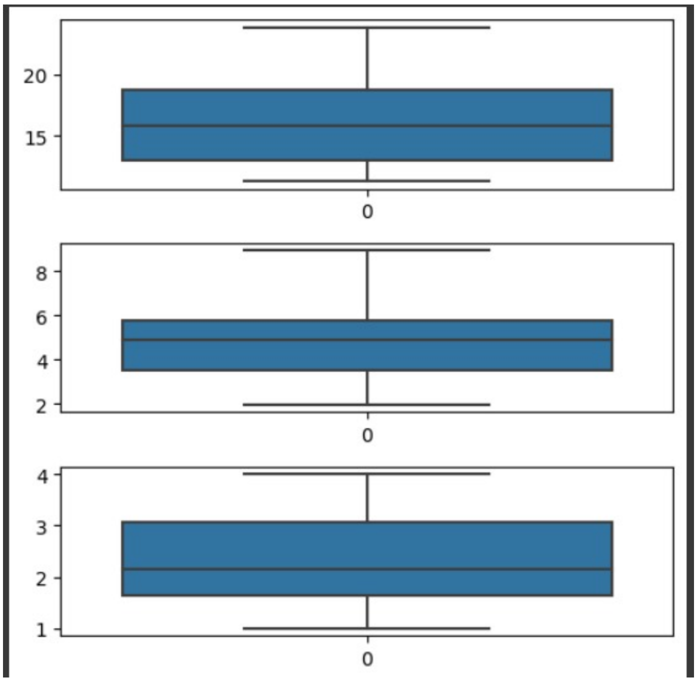



```
np.mean(d['BTE']),np.std(d['BTE'])
#max 34 & min 7
```

```
(18.600366825583333, 5.007904859637905)
```

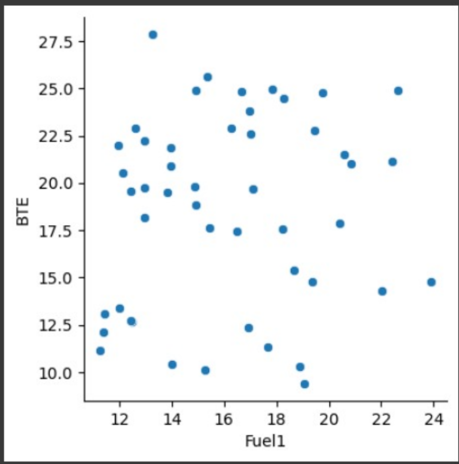
```
[ ] np.mean(d['Fuel1']),np.std(d['Fuel1'])
    #max=25 and min=11

    (16.168187500000002, 3.37874064098007)

    np.mean(d['Fuel2']),np.std(d['Fuel2'])
    #max=9 and min=1

    (4.897020833333333, 1.751531894865931)

[ ] np.mean(d['BP']),np.std(d['BP'])
    #max=4 and min=1

    (2.21375, 0.7921821786474792)

[ ] # Outlier Analysis
    fig, axs = plt.subplots(3, figsize = (5,5))
    plt1 = sns.boxplot(d['Fuel1'], ax = axs[0])
    plt2 = sns.boxplot(d['Fuel2'], ax = axs[1])
    plt3 = sns.boxplot(d['BP'], ax = axs[2])
    plt.tight_layout()
```



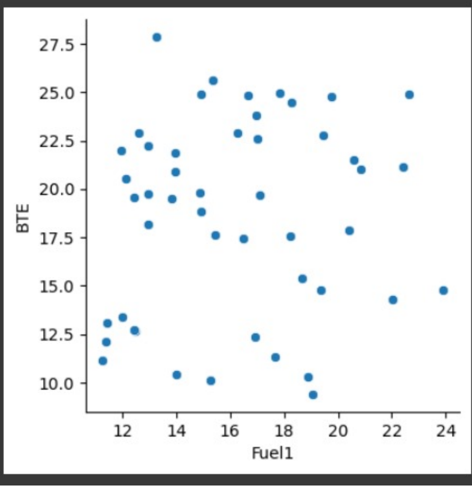


Since the dataset contains outliers we try to use box plots because box plots provide a quick visual summary of the variability of values in a dataset. They show the median, upper and lower quartiles, minimum and maximum values, and any outliers in the dataset. Outliers can reveal mistakes or unusual occurrences in data.

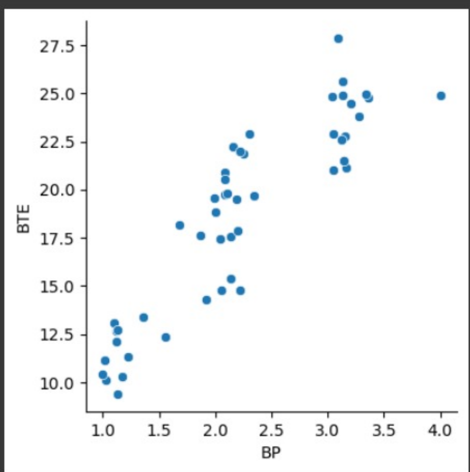
```
# Let's see how Sales are related with other variables using scatter plot.

sns.pairplot(d, x_vars=['Fuel1'], y_vars='BTE', height=4, aspect=1, kind='scatter')
plt.show()
```




```
sns.pairplot(d, x_vars=['Fuel1'], y_vars='BTE', height=4, aspect=1, kind='scatter')
plt.show()
```




```
sns.pairplot(d, x_vars=['BP'], y_vars='BTE', height=4, aspect=1, kind='scatter')
plt.show()
```



Here we are normalizing data and scaling it so that data is not scattered and tends to fall under a normal range for easy modeling.

```
[ ] dfa.to_csv('pro1.csv')
```

```
from sklearn.preprocessing import StandardScaler
import numpy as np
object = StandardScaler()
object.fit_transform(dfa)
```

```
array([[-1.68811057, -0.94040168, -1.2513529 ,  0.44093722, -1.67568792,
        -0.3814897 , -0.2563561 , -0.50099542, -1.2544463 , -1.4458811 ],
       [-1.68811057, -0.94040168, -0.39768065,  1.73816612, -1.39764559,
         0.90403765,  1.05548497,  0.88884318, -0.37081117, -0.85426753],
       [-1.52605196, -1.13032852, -1.49975753, -0.2676108 , -0.61718593,
        -0.52403278, -0.47850494, -0.78298545, -1.49429012, -1.69758406],
       [-1.52605196, -1.13032852, -0.14227871,  0.60845526, -0.19469861,
         0.45265125,  0.50331311,  0.24815076, -0.09309727, -0.20486752],
       [-1.52605196, -1.13032852,  1.14872564,  1.84441872,  0.40135105,
         1.83056764,  1.88844548,  1.70288888,  1.19448534,  0.50173146],
       [-1.36399334, -1.38356432, -0.84900738,  0.22014489,  1.34224171,
         0.816928  ,  0.77992534,  0.46101497, -0.82525209, -1.23898942],
       [-1.36399334, -1.38356432, -0.12478542,  0.7339458 ,  1.76701274,
         1.47157027,  1.42880027,  1.13452785, -0.09309727, -0.63481435],
       [-1.20193473, -1.57349117, -1.09041469, -1.23542703,  1.76929645,
        -0.2838213 , -0.39883016, -0.80986042, -1.07771927, -1.03795702],
       [-1.03987611, -2.5231254 , -0.15977199,  0.27401112,  1.38677416,
         0.88555985,  0.7622519 ,  0.09423082,  0.15936991,  0.21845591],
       [-1.03987611, -2.5231254 ,  0.66241235,  1.3886276 ,  2.30825324,
         2.30571122,  2.15101742,  1.45895637,  1.05562839,  0.48628401],
       [-0.8778175 , -0.43393009, -1.63620515, -0.64408244, -0.79874128,
        -0.94374294, -0.91772637, -1.08810287, -1.53216019, -1.63713461],
       [-0.8778175 , -0.43393009, -0.68107185, -0.21788814, -0.59320692,
        -0.46859936, -0.44188476, -0.57226741, -0.43392796, -0.19252342],
       [-0.8778175 , -0.43393009,  1.01227802,  1.05832702,  0.02225433,
         0.9541917 ,  0.98302557,  0.97237322,  1.44695252,  1.23157391],
```

Here we are standardizing data because in machine learning preprocessing is essential to ensure that features are on a consistent scale. This practice facilitates fair comparisons between features, enhances algorithm stability, and prevents biases in models sensitive to feature scales. By scaling features to a common mean and standard deviation, standardization improves the convergence speed of optimization algorithms, aids regularization techniques, and contributes to overall model interpretability. In essence, standardization is a fundamental step that promotes better model performance, robustness, and generalization across diverse datasets.

```
new_df = new_df[(new_df['Fuel2'] >= 1) & (new_df['Fuel2'] <= 9)]
new_df
```

	Unnamed: 0	FID	cf	Load	Fuel1	Fuel2	Total_Vol	Mass_Fuel	Heat_Input	BP	BTE
0	13	4	34500	4.19	17.658	1.962	19.62	0.000311	10.739879	1.22	11.359532
1	14	4	34500	6.63	22.041	2.449	24.49	0.000389	13.405690	1.92	14.322276
2	17	5	34200	3.48	15.264	3.816	19.08	0.000298	10.199002	1.03	10.099027
3	18	5	34200	7.36	18.224	4.556	22.78	0.000356	12.176796	2.14	17.574410
4	19	5	34200	11.05	22.400	5.600	28.00	0.000438	14.967089	3.16	21.112990
5	20	6	33800	5.34	16.912	7.248	24.16	0.000372	12.585085	1.56	12.395626
6	21	6	33800	7.41	18.648	7.992	26.64	0.000411	13.876931	2.14	15.421277
7	24	7	33500	4.65	11.994	7.996	19.99	0.000303	10.147454	1.36	13.402377
8	29	8	32000	7.31	17.094	7.326	24.42	0.000371	11.881566	2.34	19.694373
9	30	8	32000	9.66	20.860	8.940	29.80	0.000453	14.499209	3.05	21.035631
10	33	9	35300	3.09	13.992	3.498	17.49	0.000272	9.613765	1.00	10.401752
11	34	9	35300	5.82	15.432	3.858	19.29	0.000300	10.603174	1.87	17.636228
12	35	9	35300	10.66	19.744	4.936	24.68	0.000384	13.565907	3.36	24.767972
13	39	10	34800	7.58	12.936	5.544	18.48	0.000279	9.708524	2.16	22.248489
14	40	10	34800	12.00	17.850	7.650	25.50	0.000385	13.396503	3.34	24.931880
15	43	11	34500	4.19	18.891	2.099	20.99	0.000330	11.369093	1.17	10.291058
16	44	11	34500	8.07	20.421	2.269	22.69	0.000356	12.289887	2.20	17.900897

```
new_df = d[(d['Fuel1'] >= 11) & (d['Fuel1'] <= 25)]
new_df
```

1	14	4	34500	6.63	22.041	2.449	24.49	0.000389	13.405690	1.92	14.322276
2	17	5	34200	3.48	15.264	3.816	19.08	0.000298	10.199002	1.03	10.099027
3	18	5	34200	7.36	18.224	4.556	22.78	0.000356	12.176796	2.14	17.574410
4	19	5	34200	11.05	22.400	5.600	28.00	0.000438	14.967089	3.16	21.112990
5	20	6	33800	5.34	16.912	7.248	24.16	0.000372	12.585085	1.56	12.395626
6	21	6	33800	7.41	18.648	7.992	26.64	0.000411	13.876931	2.14	15.421277
7	24	7	33500	4.65	11.994	7.996	19.99	0.000303	10.147454	1.36	13.402377
8	29	8	32000	7.31	17.094	7.326	24.42	0.000371	11.881566	2.34	19.694373
9	30	8	32000	9.66	20.860	8.940	29.80	0.000453	14.499209	3.05	21.035631
10	33	9	35300	3.09	13.992	3.498	17.49	0.000272	9.613765	1.00	10.401752
11	34	9	35300	5.82	15.432	3.858	19.29	0.000300	10.603174	1.87	17.636228
12	35	9	35300	10.66	19.744	4.936	24.68	0.000384	13.565907	3.36	24.767972
13	39	10	34800	7.58	12.936	5.544	18.48	0.000279	9.708524	2.16	22.248489
14	40	10	34800	12.00	17.850	7.650	25.50	0.000385	13.396503	3.34	24.931880
15	43	11	34500	4.19	18.891	2.099	20.99	0.000330	11.369093	1.17	10.291058
16	44	11	34500	8.07	20.421	2.269	22.69	0.000356	12.289887	2.20	17.900897
17	46	12	36700	7.19	14.920	3.730	18.65	0.000289	10.611174	2.00	18.848055
18	47	12	36700	11.61	19.432	4.858	24.29	0.000377	13.820130	3.15	22.792839

```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 48 entries, 0 to 47
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Unnamed: 0   48 non-null     int64
 1   FID          48 non-null     int64
 2   cf           48 non-null     int64
 3   Load         48 non-null     float64
 4   Fuel1        48 non-null     float64
 5   Fuel2        48 non-null     float64
 6   Total_Vol    48 non-null     float64
 7   Mass_Fuel    48 non-null     float64
 8   Heat_Input   48 non-null     float64
 9   BP           48 non-null     float64
 10  BTE          48 non-null     float64
dtypes: float64(8), int64(3)
memory usage: 4.5 KB
```

```
c=['FID','cf',
 'Load',
 'Fuel1',
 'Fuel2',
 'Total_Vol',
 'Mass_Fuel',
 'Heat_Input',
 'BP','BTE']
dfa=new_df[c]
dfa
```

	FID	cf	Load	Fuel1	Fuel2	Total_Vol	Mass_Fuel	Heat_Input	BP	BTE
0	4	34500	4.19	17.658	1.962	19.62	0.000311	10.739879	1.22	11.359532
1	4	34500	6.63	22.041	2.449	24.49	0.000389	13.405690	1.92	14.322276
2	5	34200	3.48	15.264	3.816	19.08	0.000298	10.199002	1.03	10.099027
3	5	34200	7.36	18.224	4.556	22.78	0.000356	12.176796	2.14	17.574410
4	5	34200	11.05	22.400	5.600	28.00	0.000438	14.967089	3.16	21.112990
5	6	33800	5.34	16.912	7.248	24.16	0.000372	12.585085	1.56	12.395626
6	6	33800	7.41	18.648	7.992	26.64	0.000411	13.876931	2.14	15.421277
7	7	33500	4.65	11.994	7.996	19.99	0.000303	10.147454	1.36	13.402377
8	8	32000	7.31	17.094	7.326	24.42	0.000371	11.881566	2.34	19.694373
9	8	32000	9.66	20.860	8.940	29.80	0.000453	14.499209	3.05	21.035631
10	9	35300	3.09	13.992	3.498	17.49	0.000272	9.613765	1.00	10.401752
11	9	35300	5.82	15.432	3.858	19.29	0.000300	10.603174	1.87	17.636228

After the removal of outliers from the dataset, the refined set comprising Brake Power variables 1 to 4 and Fuel variables 1 to 9 is ready for storage in Excel sheets, marking a critical phase in the data preprocessing pipeline. This meticulous curation ensures that the data used for subsequent prediction and analysis is devoid of anomalous values that might skew the results.

6.2 EFFICIENCY CALCULATION

```python
#Butanol 10
fuel_1_range = [16.46,20.11,28.18,18.05,20.49,27.43,41.24,12.81,19.13,8.91,8.37,26.28,33.83,17.658,22.041,27.756,26.955,15.264,18.224,22.4,16.912,18.648,23.429,9.324,11.994,14.682,17.604,21.522,6.909,17.09
fuel_2_range=[]
for i in fuel_1_range:
  fuel_2_range.append(i*0.1)
 # Values from 1 to 40 (inclusive)
calorific_value1 = 35800
brake_power = 5.2
density1 = 958
density2=811.6
calorific_value2=33100
# Assuming you have the formulas defined as functions, for example:
def predict_efficiency(fuel_amount_1, fuel_amount_2, calorific_value1,calorific_value2, brake_power, density1,density2):
    # Your formula to calculate efficiency based on the given inputs
    mass_of_fuel1 = ((fuel_amount_1  * 0.000001) / 60) * density1
    mass_of_fuel2=((fuel_amount_2  * 0.000001) / 60) * density2
    heat_input = mass_of_fuel1 * calorific_value1 + mass_of_fuel2 * calorific_value2
    efficiency = brake_power / heat_input
    return heat_input
    # Limit efficiency to a maximum value of 32
    efficiency = min(efficiency, 32)

    return efficiency

# List to store combinations that meet the efficiency criteria
efficient_combinations = []

# Loop through all combinations of fuel_1 and fuel_2
for fuel_amount_1 in fuel_1_range:
      # Use the formula-based prediction function to get efficiency
      predicted_efficiency = predict_efficiency(fuel_amount_1, fuel_amount_1*0.1, calorific_value1,calorific_value2 ,brake_power,density1,density2)
      """if 23 <= predicted_efficiency <= 32:"""
```

```python
        """if 23 <= predicted_efficiency <= 32:"""
        efficient_combinations.append((fuel_amount_1, fuel_amount_1*0.1, predicted_efficiency))

  # Print the combinations that meet the efficiency criteria
  if efficient_combinations:
      for fuel_amount_1, fuel_amount_2, predicted_efficiency in efficient_combinations:
          eff=(brake_power/predicted_efficiency)*100
          if eff<33 and eff>31.999999999999:
            print(f"For Fuel 1 amount = {fuel_amount_1}, Fuel 2 amount = {fuel_amount_2}, "
                  f"Brake power = {brake_power}, "
                  f"Heat Input = {predicted_efficiency}, ",f"Efficiency={eff}")

  else:
      print("No combinations meet the efficiency criteria.")
```

```
For Fuel 1 amount = 26.28, Fuel 2 amount = 2.628, Brake power = 5.2, Heat Input = 16.198464647999998,  Efficiency=32.101807874995345
For Fuel 1 amount = 25.935, Fuel 2 amount = 2.5935, Brake power = 5.2, Heat Input = 15.985813571,  Efficiency=32.52884175650193
For Fuel 1 amount = 25.935, Fuel 2 amount = 2.5935, Brake power = 5.2, Heat Input = 15.985813571,  Efficiency=32.52884175650193
```

First we are calculating mass by applying the provided formulas to calculate the mass of each fuel. Then converting brake power to equivalent load.

fuel	fuel1	fuel2	brake power	heat power	efficiency	mass_of_fuel1	mass_of_fuel2	total
butanol10	26.28	2.628	5.2	16.19846465	32.10180787	0.000419604	0.00003554808	0.00045515208
	25.935	2.5935	5.2	15.98581357	32.52884176	0.0004140955	0.00003508141	0.00044917691
								0
diesel	26.955	0	5.2	16.038225	32.42254052	0.00037737	0	0.00037737
	27.12	0	5.2	16.1364	32.22527949	0.000433016	0	0.000433016

Fig.6.2.1 Mass of fuel after calculation

After mass calculation we are iterating efficiency by implementing a Python loop for efficiency calculations,setting and applying an efficiency threshold.

At last we are storing the best efficiency fuel combination in an Excel sheet.

6.3 PRESSURE PREDICTION USING MACHINE LEARNING ALGORITHMS

Crank_an	Volume	cf_value	density	viscosity	mass_of_f	load	pressure	cetane
1	40.16	42500	840	4.59	0.00028	10.44	1.45	50
2	40.34	42500	840	4.59	0.00028	10.44	1.45	50
3	40.65	42500	840	4.59	0.00028	10.44	1.42	50
4	41.09	42500	840	4.59	0.00028	10.44	1.38	50
5	41.65	42500	840	4.59	0.00028	10.44	1.38	50
6	42.33	42500	840	4.59	0.00028	10.44	1.31	50
7	43.14	42500	840	4.59	0.00028	10.44	1.25	50
8	44.07	42500	840	4.59	0.00028	10.44	1.25	50
9	45.12	42500	840	4.59	0.00028	10.44	1.18	50
10	46.29	42500	840	4.59	0.00028	10.44	1.15	50

fig.6.3.1 Dataset for pressure prediction

This is the data set for pressure prediction. The data variables are crank angle,volume,calorific value,density,viscosity,mass of fuel,load, pressure and cetane numbers.

1. FUEL: DIESEL
2. MODEL: GradientBoostingRegressor
3. MASS OF FUEL:0.00043

```
import pandas as pd
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

met
# Load the dataset
data = pd.read_csv("DIESEL.csv")  # Replace with the actual path

# Separate features and target
X = data[["Crank_angle", "mass_of_fuel", "Volume", "cf_value", "viscosity", "load","cetane"]]
y = data["pressure"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a Random Forest Regressor model
model1 = GradientBoostingRegressor(n_estimators=100, random_state=42)

# Fit the model to the training data
model1.fit(X_train, y_train)

# Make predictions on the test data
```

```
# Make predictions on the test data
predictions = model1.predict(X_test)

# Calculate the Mean Squared Error
mse = mean_squared_error(y_test, predictions)
print(f"Mean Squared Error: {mse}")
mass_values = [0.00043]
angles = list(range(1, 721))

# Create a DataFrame for new data
new_data_rows = []

for mass_value in mass_values:
    for angle in angles:
        new_data_rows.append({
            "Crank_angle": angle,
            "mass_of_fuel": mass_value,
            "Volume": data.at[angle - 1, "Volume"],
            "cf_value": data.at[angle - 1, "cf_value"],
            "viscosity": data.at[angle - 1, "viscosity"],
            "cetane": data.at[angle - 1, "cetane"],
            "load": 18.25
        })

new_data = pd.DataFrame(new_data_rows)

# Predict pressures for the new data
predicted_pressures = model1.predict(new_data[X.columns])  # Use the same columns as in X

# Reshape the predictions to matrices where each row corresponds to a mass of fuel
num_angles = len(angles)
num_mass_values = len(mass_values)
```

```
predicted_pressures_matrix = predicted_pressures.reshape(num_mass_values, num_angles, -1)

# Display predicted pressures for all angles and both mass values
for i, mass_value in enumerate(mass_values):
    print(f"Predicted Pressures for Mass of Fuel {mass_value}")
    for j, angle in enumerate(angles):
        pressures = predicted_pressures_matrix[i, j, :]
        print(f"Angle {angle}: Pressures {pressures}")
    print("\n")
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np

# Predict pressures for the new data
predicted_pressures = model1.predict(X)

# Compute metrics
mse = mean_squared_error(y, predicted_pressures)
rmse = np.sqrt(mse)
r2 = r2_score(y, predicted_pressures)

print(f"Root Mean Squared Error (RMSE): {rmse}")
print(mse)
print(f"R-squared (R2) Score: {r2}")
```

```
Mean Squared Error: 0.9635192635951386
Predicted Pressures for Mass of Fuel 0.00043
Angle 1: Pressures [0.99852942]
Angle 2: Pressures [0.99852942]
Angle 3: Pressures [0.99316126]
Angle 4: Pressures [1.26239005]
Angle 5: Pressures [1.41251009]
Angle 6: Pressures [1.60720309]
Angle 7: Pressures [1.54272751]
Angle 8: Pressures [1.54272751]
Angle 9: Pressures [1.47815268]
Angle 10: Pressures [0.76532476]
Angle 11: Pressures [0.62760149]
Angle 12: Pressures [0.62760149]
Angle 13: Pressures [0.62760149]
Angle 14: Pressures [0.79027304]
Angle 15: Pressures [0.78452616]
Angle 16: Pressures [0.78452616]
Angle 17: Pressures [0.77261799]
Angle 18: Pressures [0.75052811]
Angle 19: Pressures [0.60936016]
Angle 20: Pressures [0.75600074]
```

By using gradient boosting regressor we are predicting the pressures like this using 3 more algorithms mainly random forest regressor, linear regression and decision tree regressor. After which we will tabulate rmse, r square, mse in which we will select the model with lowest mse value.

1. FUEL: DIESEL
2. MODEL: RandomForestRegressor
3. MASS OF FUEL:0.00043

```
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt


# Load the dataset
data = pd.read_csv("DIESEL.csv")   # Replace with the actual path

# Separate features and target
X = data[["Crank_angle", "mass_of_fuel", "Volume", "cf_value", "viscosity", "load","cetane"]]
y = data["pressure"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a Random Forest Regressor model
model = RandomForestRegressor(n_estimators=100, random_state=42)

# Fit the model to the training data
model.fit(X_train, y_train)
```

```python
# Make predictions on the test data
predictions = model.predict(X_test)

# Calculate the Mean Squared Error
mse = mean_squared_error(y_test, predictions)
print(f"Mean Squared Error: {mse}")
mass_values = [0.00043]
angles = list(range(1, 721))

# Create a DataFrame for new data
new_data_rows = []

for mass_value in mass_values:
    for angle in angles:
        new_data_rows.append({
            "Crank_angle": angle,
            "mass_of_fuel": mass_value,
            "Volume": data.at[angle - 1, "Volume"],
            "cf_value": data.at[angle - 1, "cf_value"],
            "viscosity": data.at[angle - 1, "viscosity"],
            "cetane": data.at[angle - 1, "cetane"],
            "load": 18.25
        })

new_data = pd.DataFrame(new_data_rows)

# Predict pressures for the new data
predicted_pressures = model.predict(new_data[X.columns])  # Use the same columns as in X

# Reshape the predictions to matrices where each row corresponds to a mass of fuel
num_angles = len(angles)
num_mass_values = len(mass_values)
```

```python
predicted_pressures_matrix = predicted_pressures.reshape(num_mass_values, num_angles, -1)

# Display predicted pressures for all angles and both mass values
for i, mass_value in enumerate(mass_values):
    print(f"Predicted Pressures for Mass of Fuel {mass_value}")
    for j, angle in enumerate(angles):
        pressures = predicted_pressures_matrix[i, j, :]
        print(f"Angle {angle}: Pressures {pressures}")
    print("\n")
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np

# Predict pressures for the new data
predicted_pressures = model.predict(X)

# Compute metrics
mse = mean_squared_error(y, predicted_pressures)
rmse = np.sqrt(mse)
r2 = r2_score(y, predicted_pressures)

print(f"Root Mean Squared Error (RMSE): {rmse}")
print(mse)
print(f"R-squared (R2) Score: {r2}")
```

1. FUEL: DIESEL
2. MODEL: LinearRegression
3. MASS OF FUEL:0.00028

```python
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt


# Load the dataset
data = pd.read_csv("DIESEL.csv")   # Replace with the actual path

# Separate features and target
X = data[["Crank_angle", "mass_of_fuel", "Volume", "cf_value", "viscosity", "load","cetane"]]
y = data["pressure"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2 , random_state=42)

# Create a Random Forest Regressor model
model2 = LinearRegression()

# Fit the model to the training data
model2.fit(X_train, y_train)

# Make predictions on the test data
predictions = model2.predict(X_test)
```

```python
# Calculate the Mean Squared Error
mse = mean_squared_error(y_test, predictions)
print(f"Mean Squared Error: {mse}")
mass_values = [0.00028]
angles = list(range(1, 721))

# Create a DataFrame for new data
new_data_rows = []

for mass_value in mass_values:
    for angle in angles:
        new_data_rows.append({
            "Crank_angle": angle,
            "mass_of_fuel": mass_value,
            "Volume": data.at[angle - 1, "Volume"],
            "cf_value": data.at[angle - 1, "cf_value"],
            "viscosity": data.at[angle - 1, "viscosity"],
            "cetane": data.at[angle - 1, "cetane"],
            "load": 10.44
        })

new_data = pd.DataFrame(new_data_rows)

# Predict pressures for the new data
predicted_pressures = model2.predict(new_data[X.columns])  # Use the same columns as in X

# Reshape the predictions to matrices where each row corresponds to a mass of fuel
num_angles = len(angles)
num_mass_values = len(mass_values)

predicted_pressures_matrix = predicted_pressures.reshape(num_mass_values, num_angles, -1)
```

```
# Display predicted pressures for all angles and both mass values
for i, mass_value in enumerate(mass_values):
    print(f"Predicted Pressures for Mass of Fuel {mass_value}")
    for j, angle in enumerate(angles):
        pressures = predicted_pressures_matrix[i, j, :]
        print(f"Angle {angle}: Pressures {pressures}")
    print("\n")
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np

# Predict pressures for the new data
predicted_pressures = model2.predict(X)

# Compute metrics
mse = mean_squared_error(y, predicted_pressures)
rmse = np.sqrt(mse)
r2 = r2_score(y, predicted_pressures)

print(f"Root Mean Squared Error (RMSE): {rmse}")
print(mse)
print(f"R-squared (R2) Score: {r2}")
```

1. FUEL: DIESEL
2. MODEL: DecisionTreeRegressor
3. MASS OF FUEL:0.00037

```
import pandas as pd
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt


# Load the dataset
data = pd.read_csv("DIESEL.csv")    # Replace with the actual path

# Separate features and target
X = data[["Crank_angle", "mass_of_fuel", "Volume", "cf_value", "viscosity", "load","cetane"]]
y = data["pressure"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2 , random_state=42)

# Create a Random Forest Regressor model
model3 = DecisionTreeRegressor()

# Fit the model to the training data
model3.fit(X_train, y_train)
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np
```

```python
# Predict pressures for the new data
predicted_pressures = model3.predict(X)

# Compute metrics
mse = mean_squared_error(y, predicted_pressures)
rmse = np.sqrt(mse)
r2 = r2_score(y, predicted_pressures)

print(f"Root Mean Squared Error (RMSE): {rmse}")
print(mse)
print(f"R-squared (R2) Score: {r2}")
mass_values = [0.00037]
angles = list(range(1, 721))

# Create a DataFrame for new data
new_data_rows = []

for mass_value in mass_values:
    for angle in angles:
        new_data_rows.append({
            "Crank_angle": angle,
            "mass_of_fuel": mass_value,
            "Volume": data.at[angle - 1, "Volume"],
            "cf_value": data.at[angle - 1, "cf_value"],
            "viscosity": data.at[angle - 1, "viscosity"],
            "cetane": data.at[angle - 1, "cetane"],
            "load": 18.25
        })

new_data = pd.DataFrame(new_data_rows)
```

```python
# Predict pressures for the new data
predicted_pressures = model.predict(new_data[X.columns])  # Use the same columns as in X

# Reshape the predictions to matrices where each row corresponds to a mass of fuel
num_angles = len(angles)
num_mass_values = len(mass_values)

predicted_pressures_matrix = predicted_pressures.reshape(num_mass_values, num_angles, -1)

# Display predicted pressures for all angles and both mass values
for i, mass_value in enumerate(mass_values):
    print(f"Predicted Pressures for Mass of Fuel {mass_value}")
    for j, angle in enumerate(angles):
        pressures = predicted_pressures_matrix[i, j, :]
        print(f"Angle {angle}: Pressures {pressures}")
    print("\n")
```

	mass_of_fuel	model	mse	rmse	rsquare
Diesel	0.00028	GradientBoostingRegressor	0.7163811845	0.8463930437	0.9962463063
Diesel	0.00037	GradientBoostingRegressor	0.7163811845	0.8463930437	0.9962463063
Diesel	0.00043	GradientBoostingRegressor	0.7163811845	0.8463930437	0.9962463063
Diesel	0.00028	RandomForestRegressor	0.102447078	0.3200735509	0.9994631979
Diesel	0.00037	RandomForestRegressor	0.102447078	0.3200735509	0.9994631979
Diesel	0.00043	RandomForestRegressor	0.102447078	0.3200735509	0.9994631979
Diesel	0.00028	linear regression	149.4408675	12.22460091	0.216959838
Diesel	0.00037	linear regression	149.4408675	12.22460091	0.216959838
Diesel	0.00043	linear regression	149.4408675	12.22460091	0.216959838
Diesel	0.00028	DecisionTreeRegressor	0.1313038194	0.3623586889	0.9993119943
Diesel	0.00037	DecisionTreeRegressor	0.3536286764	0.1250532407	0.9993447461

fig.6.3.2 Tabulating errors after prediction

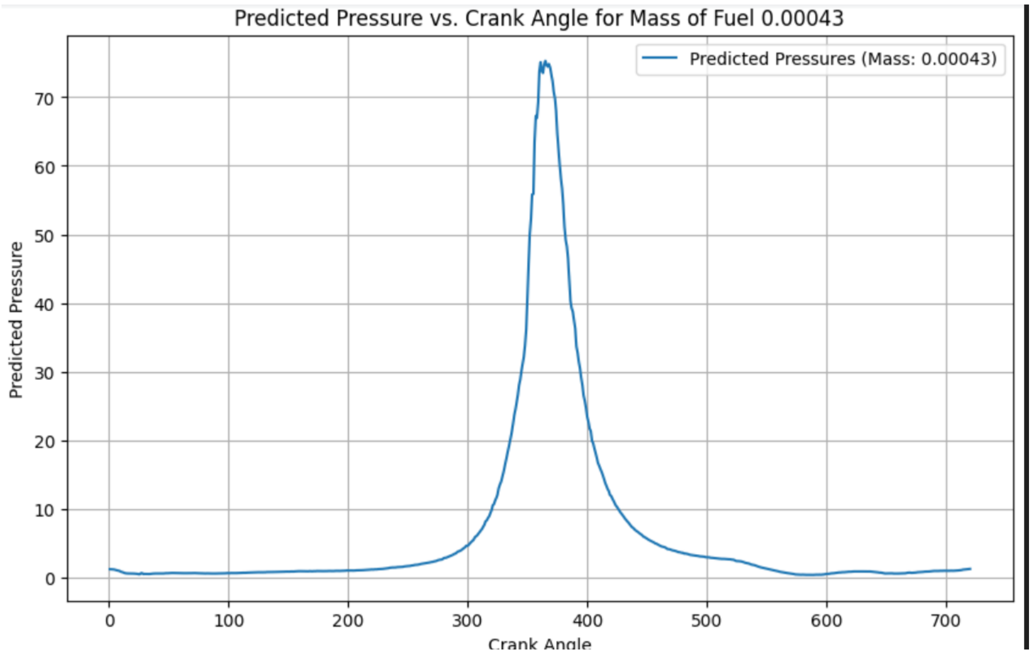
After applying machine learning algorithms like linear regression,decision tree regressor,gradient boosting regressor,random forest regressor.we could find the errors and tabulate them together so we can select the best model with the lowest error and use it for further HRR prediction.

6.4 HEAT RELEASE RATE PREDICTION OR ANALYSIS

```python
import pandas as pd

# Load the dataset from the CSV file
data = pd.read_csv("Diesel - trail - Sheet1.csv")

# Initialize an empty list to store HRR values
hrr_values = []

# Iterate through all angles in the data
for angle_index in range(len(data)):
    # Calculate HRR using the provided formula
    if angle_index == 0:
        # If it's the first angle, use a default value of 0
        hrr = 0
    else:
        # Calculate HRR using the formula
        pressure_current = data.iloc[angle_index]["pressure"]
        pressure_previous = data.iloc[angle_index - 1]["pressure"]
        volume_current = data.iloc[angle_index]["Volume"]
        volume_previous = data.iloc[angle_index - 1]["Volume"]

        hrr = ((3.85714285714 * (pressure_current * ((volume_current - volume_previous) / 1))) + (2.85714285714 * (volume_current * ((pressure_current - pressure_previous) / 1))))

    # Append the calculated HRR to the list
    hrr_values.append(hrr)

# Now you have a list of HRR values for all angles in the provided data

# Iterate through the angles and pressures to print them alongside HRR values
for angle_index in range(len(data)):
    angle = data.iloc[angle_index]["Crank_angle"]
    pressure = data.iloc[angle_index]["pressure"]
```

```python
# Iterate through the angles and pressures to print them alongside HRR values
for angle_index in range(len(data)):
    angle = data.iloc[angle_index]["Crank_angle"]
    pressure = data.iloc[angle_index]["pressure"]
    hrr = hrr_values[angle_index]
    print(f"Angle: {angle}, Pressure: {pressure}, HRR: {hrr}")
```

```
Angle: 1.0, Pressure: 1.45, HRR: 0
Angle: 2.0, Pressure: 1.45, HRR: 1.0067142857135782
Angle: 3.0, Pressure: 1.42, HRR: -1.7863714285692318
Angle: 4.0, Pressure: 1.38, HRR: -2.353942857139875
Angle: 5.0, Pressure: 1.38, HRR: 2.980799999997766
Angle: 6.0, Pressure: 1.31, HRR: -5.030057142851202
Angle: 7.0, Pressure: 1.25, HRR: -3.4900714285669214
Angle: 8.0, Pressure: 1.25, HRR: 4.483928571425248
Angle: 9.0, Pressure: 1.18, HRR: -4.244999999994536
Angle: 10.0, Pressure: 1.15, HRR: 1.2220714285715566
Angle: 11.0, Pressure: 1.04, HRR: -9.741999999988872
Angle: 12.0, Pressure: 1.04, HRR: 5.656114285710083
Angle: 13.0, Pressure: 1.01, HRR: 1.6673999999998808
Angle: 14.0, Pressure: 0.91, HRR: -9.119928571417951
Angle: 15.0, Pressure: 0.94, HRR: 11.079771428562012
Angle: 16.0, Pressure: 0.94, HRR: 6.852599999994926
Angle: 17.0, Pressure: 0.91, HRR: 2.094814285714027
Angle: 18.0, Pressure: 0.94, HRR: 12.865628571417702
Angle: 19.0, Pressure: 0.94, HRR: 8.12159999999399
Angle: 20.0, Pressure: 0.94, HRR: 8.520428571422265
```



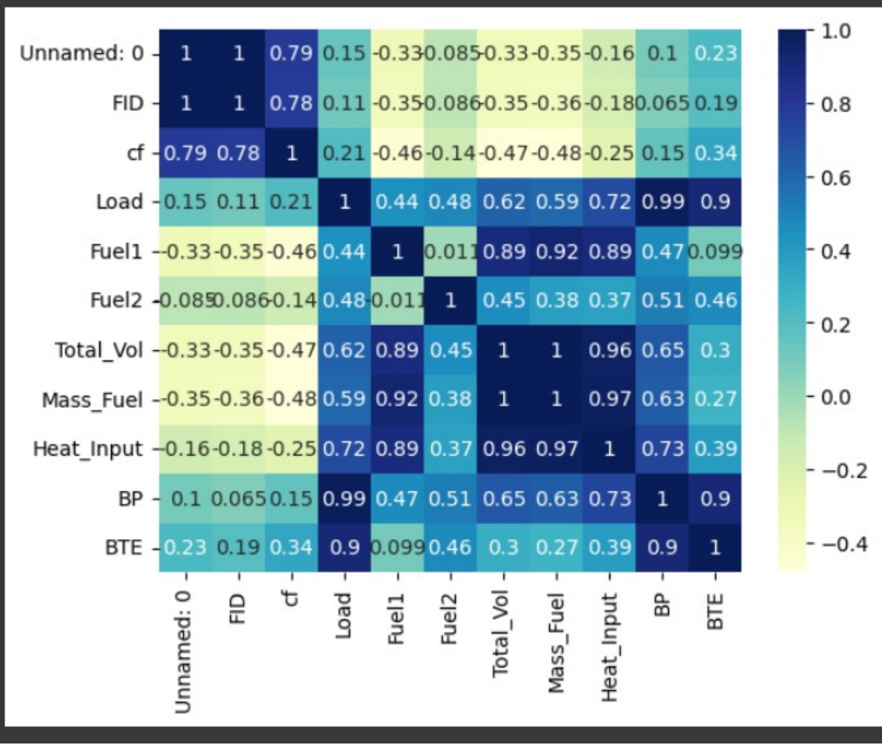
The process of Heat Release Rate (HRR) calculation involves applying a provided formula that considers pressure, volume, and relevant changes in a combustion system. Finally we visualize the HRR we found through the whole prediction process.

CHAPTER 7

RESULTS AND DISCUSSIONS

7.1 PERFORMANCE MATRIX

```
# Let's see the correlation between different variables.
sns.heatmap(d.corr(), cmap="YlGnBu", annot = True)
plt.show()
```



During analysis we create performance metrics because they serve as indispensable tools across diverse domains, offering a visual means to analyze and interpret complex data sets. By leveraging color gradients and matrix formats, these visualizations facilitate the identification of patterns, trends, and anomalies, providing valuable insights for decision-making and strategic planning. Whether applied in business analytics to compare the performance of different products or in sports to assess team dynamics, heatmaps condense intricate information into an accessible and user-friendly format. Beyond their aesthetic appeal, heatmaps are instrumental in highlighting correlations between variables, tracking Key Performance Indicators (KPIs), and optimizing processes by pinpointing bottlenecks. The visual clarity of heatmaps enhances communication, making them essential tools for conveying complex information to diverse audiences, ultimately aiding organizations in making informed decisions and driving continuous improvement.

7.2 RESULT

		Diesel				BUTANOL 10			
		0.00043		0.00037		0.00045		0.00044	
Angle	Cylinder Volume (cc)	Pressure	HRR	Pressure	HRR	Pressure	HRR	Pressure	HRR
Angle 1	40.16	1.2179	32.84015154	1.2179	32.84015154	0.7368	19.86	0.7368	19.86
Angle 2	40.34	1.2139	0.1303822	1.2139	0.1303822	0.7392	0.078	0.7392	0.078
Angle 3	40.65	1.206	0.235956	1.206	0.235956	0.7517	0.235	0.7517	0.235
Angle 4	41.09	1.189	0.4013702857	1.189	0.4013702857	0.7197	0.497	0.7197	0.497
Angle 5	41.65	1.155	0.65408	1.155	0.65408	0.6262	1.247	0.6262	1.247
Angle 6	42.33	1.0975	0.98328	1.0975	0.98328	0.5941	0.544	0.5941	0.544
Angle 7	43.14	1.0568	0.8318310857	1.0568	0.8318310857	0.5381	0.858	0.5381	0.858
Angle 8	44.07	1.0278	0.7338379714	1.0278	0.7338379714	0.4658	1.077	0.4658	1.077
Angle 9	45.12	0.9781	1.0368345	0.9781	1.0368345	0.3999	1.011	0.3999	1.011
Angle 10	46.29	0.8681	1.8465897	0.8681	1.8465897	0.3096	1.334	0.3096	1.334

fig.7.2.1 Final pressure and HRR

Upon the completion of machine learning predictions for the final Heat Release Rate (HRR) and pressure values, a crucial step is the systematic storage of this valuable information in Excel sheets. Organizing the predicted data in Excel facilitates a structured and accessible format for further analysis and comparison. This methodical approach ensures that the results of the machine learning model, capturing the dynamic relationships between variables, are readily available for comprehensive scrutiny and interpretation. By leveraging Excel's tabular structure, the predicted HRR and pressure values can be efficiently arranged, enabling easy reference and analysis. This organized storage not only streamlines subsequent data manipulation but also enhances the overall workflow for any future analyses, contributing to a more efficient and informed decision-making process based on the insights gleaned from the machine learning predictions.

CHAPTER 8

CONCLUSION

In this study, we have explored the prediction of fuel efficiency and In-cylinder pressure in a mixture of fuels. We considered various factors that influence these parameters, such as volume, mass of fuel, cetane number, crank angle, density, viscosity, and calorific value. We employed both formula-based calculations and machine learning models to predict fuel efficiency and In-cylinder pressure.

Our findings indicate that optimizing fuel mixtures can significantly enhance vehicle fuel efficiency across different brake powers. Additionally, the application of machine learning models, such as the Random Forest Regressor and Decision Tree Regressor, can lead to highly accurate predictions of In-cylinder pressure, which is crucial for improving engine performance and reducing emissions.

CHAPTER 9

FUTURE ENHANCEMENT

As we look ahead, there are several avenues for future research and development. The study can be extended to consider more complex fuel mixtures and real-world data from various engines and vehicle types. Furthermore, the application of the models and methodologies developed in this study within the automotive industry has the potential to drive the development of more environmentally friendly and fuel-efficient vehicles.

Future work may also explore the integration of sensor data and real-time feedback to optimize engine performance on the fly, taking into account changing operating conditions and fuel mixtures. This could lead to significant improvements in fuel efficiency and emission reduction, contributing to a more sustainable and eco-friendly transportation system.

CHAPTER 10

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