F1 PIT-STOP STRATEGY OPTIMIZATION

A PROJECT REPORT

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ABSTRACT

This project aims to develop a machine learning model to optimize pit stop strategies in Formula 1 (F1) racing, utilizing historical and real-time telemetry data. Pit stops, critical moments during a race, significantly influence race outcomes due to their impact on lap times and overall strategy. Traditional pit stop decisions relied heavily on experience and real-time judgments, but with advances in data analytics, machine learning offers a promising approach to predicting optimal pit stop timings.

Using the fastf1 Python library, the study extracts telemetry data, such as lap times, tire wear, weather conditions, and track data. The goal is to preprocess using Spark and engineer these features to form a structured dataset suitable for machine learning. An XGBoost regressor will be used to predict the ideal timing for pit stops based on various input features. This model will be validated using historical race data, testing its accuracy and reliability across different race conditions.

The study also explores the real-time application of the model, aiming to provide F1 teams with predictive insights during live races. By leveraging machine learning to optimize pit stop timing, the project seeks to improve team strategies, reduce time losses, and enhance overall race performance. The findings have broader implications for predictive sports analytics, demonstrating how telemetry data can be used to inform split-second decisions in dynamic sports environments. Ultimately, this research aims to create a robust model that assists F1 teams in making data-driven, real-time decisions, contributing to the ongoing evolution of data-driven strategies in motorsports.

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INTRODUCTION

Formula 1 (F1) racing is often described as a sport where technology and human precision intersect at unparalleled speeds. Each decision made during a race can influence outcomes, and one of the most critical of these is the pit stop. A pit stop, in F1, is when drivers make brief stops in the pit lane to change tires, perform minor repairs, or adjust parts of the car. The timing and frequency of these stops significantly affect a team's performance. Optimizing pit stops to ensure minimal time loss while maximizing car efficiency, safety, and speed is crucial in the high-stakes environment of F1 racing.

In recent years, predictive modelling and machine learning have emerged as valuable tools in optimizing pit stops. By leveraging historical data, machine learning algorithms can predict the best moments for pit stops based on real-time telemetry, weather, and track conditions. This data-driven approach allows teams to make well-informed decisions, reducing the unpredictability that traditionally governs pit stop strategies.

1.1 BACKGROUND

In Formula 1 racing, even the slightest delay or inefficiency can dramatically impact the outcome of a race, where competitors are often separated by fractions of a second. One of the most influential aspects of race strategy is pit stop timing. Pit stops, where drivers pause for tire changes, fuel adjustments, or mechanical tweaks, must be meticulously planned to minimize time lost and maximize race efficiency. Typically, pit stops can last between 2 to 3 seconds in ideal conditions, but any miscalculations or mishaps can cost drivers valuable seconds or even lead to race losses. As a result, timing these pit stops optimally is crucial for teams aiming to secure a competitive advantage.

Pit stops are essential in balancing factors such as tire wear, fuel levels, and track conditions. Over time, tire wear can significantly reduce a car's lap time efficiency, as worn tires lose grip and stability. Similarly, fuel load directly impacts vehicle speed and handling, influencing when a pit stop may be beneficial. External track conditions, including weather, temperature, and surface texture, also affect pit stop decisions. For example, a sudden rain shower might prompt a team to switch to wet-weather tires, while rising temperatures might require harder compounds to prevent

excessive tire degradation.

In this context, data analysis and predictive modeling have become essential tools for teams to optimize their pit stop strategies. Teams can make informed decisions and preempt competitors' moves by using large datasets generated in real time from car telemetry and race sessions. Analyzing telemetry data enables teams to gauge driver performance, vehicle health, and race progress, allowing them to anticipate when a pit stop might be necessary or advantageous. Ultimately, the background of this study lies in enhancing the understanding and timing of pit stops through big data, with the aim of improving race strategies and outcomes.

1.2 CONTEXT OF TOPIC

In the highly competitive world of Formula 1 racing, precision and timing are paramount, with races often decided by mere milliseconds. Among the numerous variables affecting performance, pit stops stand out as a critical element due to their impact on lap times and overall race strategy. A pit stop, typically utilized for tire changes, refueling, or minor adjustments, must be executed with minimal time loss while maximizing car efficiency and safety. Historically, pit stop strategies relied heavily on experience and real-time judgment by race engineers. However, recent advances in data analytics and machine learning have introduced sophisticated approaches to pit stop prediction and optimization.

Beyond Formula 1, the analytical techniques explored in this project have applications in other motorsports and industries that rely on real-time data analysis. For instance, the model developed here could be adapted for endurance racing or applied in logistics and transportation sectors, where optimizing timing and resource allocation is critical. As the motorsport industry continues to embrace data-driven approaches, studies like this contribute to a broader understanding of how predictive analytics can transform high-stakes decision-making in competitive, data-rich environments.

1.3 STUDY PURPOSE

The primary purpose of this study is to build a data-driven predictive model that

assists Formula 1 teams in optimizing their pit stop timing. This model will be developed by analyzing telemetry data obtained from various race sessions, leveraging machine learning to predict the optimal lap for a pit stop. Formula 1 is inherently a data-intensive sport, where teams gather enormous amounts of data to inform decisions. The goal is to utilize these data-driven insights to refine pit stop strategies, thereby contributing to a better race experience and competitive advantage.

With telemetry data at the core, this project aims to create a model that helps teams by forecasting when a pit stop should be performed based on real-time variables such as tire wear, lap times, and track conditions. By developing a predictive framework, this study seeks to streamline the decision-making process, reduce reliance on intuition, and instead base strategic calls on statistical evidence and trends. This approach not only improves the precision of pit stop timing but also supports sustainable racing by reducing unnecessary tire changes and resource usage.

In summary, the purpose of this study is to use advanced data analytics and machine learning tools to provide Formula 1 teams with a robust method for optimizing pit stops. The insights gained from this model can be adapted and utilized across different racing environments, making this project not only applicable to Formula 1 but also beneficial to the broader motorsport industry.

1.4 OBJECTIVES OF THE STUDY

The objectives of this study are centered around using data to create a more effective pit stop strategy. These objectives guide the design, implementation, and evaluation of the predictive model, each contributing to the overall project goal of improving pit stop timing.

Data Collection

The first step in the project is to gather comprehensive telemetry data from Formula 1 races, utilizing the FastF1 API. This data includes lap times, tire conditions, fuel levels, car speeds, and other crucial performance indicators. The FastF1 API provides

historical race data and real-time telemetry, making it an invaluable source for understanding the intricate details of each race.

The goal is to collect data from multiple race sessions to capture a broad spectrum of scenarios, including different track conditions, weather variations, and driving styles. By using data from various races, the model can account for diverse variables and learn patterns that are applicable across races. This objective ensures that the dataset used for modeling is robust and reflective of real-world racing conditions, setting the foundation for accurate predictive analysis.

Feature Engineering

Feature engineering is a critical component in data science projects, and it involves transforming raw data into valuable features that improve the model's predictive accuracy. In this project, several features will be created based on telemetry data, including cumulative tire wear, lap time differences, speed patterns, and environmental indicators like track temperature.

Cumulative tire wear, for example, provides insight into how much performance a tire has lost over consecutive laps. By calculating cumulative tire wear, the model can detect when tire efficiency is declining, indicating that a pit stop might be necessary. Similarly, lap time differences and track conditions provide context for each race's pace and performance, helping the model understand when performance drops might signal the need for a pit stop. Feature engineering enhances the model’s ability to recognize patterns in race dynamics, which is essential for reliable predictions.

Predictive Modeling

The core of this study lies in building and training a predictive model to determine the optimal lap for a pit stop based on telemetry data. Apache Spark, a powerful data processing tool, is used to handle large datasets and facilitate model training. The choice of Spark allows the project to process and analyze high-volume telemetry data efficiently, leveraging Spark’s distributed computing capabilities to accelerate data handling and machine learning tasks.

1.5 IMPORTANCE OF THIS ANALYSIS

This study holds significant value for both the Formula 1 community and the broader field of data analytics due to its focus on leveraging data to improve race strategy. In Formula 1, where competition is intense and performance margins are narrow, optimizing pit stop timing can provide a crucial edge. By developing a predictive model that anticipates optimal pit stop moments based on telemetry data, this study seeks to improve team strategy, reduce time losses, and ultimately influence race outcomes. The model's insights into tire wear, lap performance, and environmental factors will help F1 teams make informed decisions in a way that is data-driven rather than purely instinctual or reactive.

Beyond Formula 1, this research contributes to the expanding applications of machine learning in predictive sports analytics. It demonstrates the utility of telemetry data in competitive sports environments where conditions are dynamic, and split-second decisions have significant consequences. The study’s findings could inspire similar models across other motorsport disciplines, such as NASCAR and MotoGP, or even other data-intensive sports. Moreover, the application of machine learning to predict performance-critical events highlights the potential of big data analytics in making real-time, complex decisions more accurate, reinforcing the value of data-driven innovation across industries.

LITERATURE REVIEW

The purpose of this chapter is to examine existing research relevant to predictive analytics and machine learning applications in Formula 1 racing, particularly in optimizing pit stop strategies. By analyzing previous studies, this chapter will identify current methodologies, gaps in the literature, and technological advancements that set the foundation for this project. The review covers topics including the role of telemetry data in motorsport analytics, machine learning models for predictive insights, and the challenges specific to applying these models in high-stakes environments like Formula 1.

2.1 REVIEW PROCESS

To build a robust framework for pit stop optimization using telemetry data, an extensive literature review was conducted, focusing on three key areas: predictive modeling in sports, big data applications in motorsports, and telemetry data analysis. The goal of this review process was to identify established methodologies, tools, and techniques used in motorsport analytics and understand how these approaches can be adapted or expanded for pit stop strategy optimization. By analyzing prior research, this study aligns with proven methodologies and seeks to build on recent advancements in data science for strategic race decision-making.

In particular, literature on predictive modeling provided insights into the strengths and limitations of different machine learning approaches. Studies on big data applications demonstrated how Apache Spark and distributed computing can enhance the handling of large-scale telemetry data. Additionally, literature on telemetry analysis showcased the importance of real-time data processing in improving race performance. Each area contributed valuable perspectives, forming a comprehensive foundation for this project's methodology.

2.2 KEY TOPICS

2.2.1 TELEMETRY DATA IN RACING

Telemetry data plays a vital role in motorsports, providing real-time insights into car and driver performance. Research in this field has primarily focused on improving race efficiency, driver behavior analysis, and mechanical diagnostics. Studies such as Davis et al. (2019) have shown that telemetry data can be utilized to optimize parameters such as fuel consumption, tire wear, and acceleration patterns, thus enhancing a team's overall performance. Telemetry data is essential for capturing car dynamics and is widely used by Formula 1 teams to monitor variables such as speed, braking force, and cornering.

In addition, telemetry analysis has proven valuable for understanding vehicle behavior under various track and weather conditions. Research by Stewart and Anderson (2021) highlights the benefits of telemetry for adaptive race strategies, as it enables teams to adjust tactics based on real-time feedback. This project leverages similar telemetry insights from the FastF1 API, collecting data such as lap times, tire conditions, and car speed. By utilizing a data-driven approach, this study aims to improve pit stop timing by predicting when performance deterioration (e.g., tire wear) necessitates a stop.

2.2.2 MACHINE LEARNING APPLICATIONS IN MOTORSPORTS:

Predictive Modeling Techniques

Machine learning models, such as XGBoost and random forests, have been increasingly used to predict lap times, tire degradation, and optimal pit stop timing. Zhao and Chen (2021) argue that ensemble learning methods like XGBoost are ideal for handling complex, non-linear telemetry data, as they allow for improved predictive accuracy in dynamic environments.

Challenges in Model Implementation

While machine learning models offer significant benefits, they also present challenges, especially in handling data variability across races and conditions (Ahmed & Foster, 2022). Adaptive model techniques, as discussed by Williams et al. (2019), are necessary to account for changing weather, track

configurations, and car settings, which can affect model predictions.

2.2.3 PIT STOP STRATEGY OPTIMIZATION:

Pit stops are a critical component of race strategy, impacting race outcomes significantly. Several studies have explored pit stop optimization from both a predictive and operational perspective. Research by Johnson and Lee (2020) on NASCAR teams illustrated the value of predictive modeling for pit stop timing, showing how data can help teams anticipate performance issues and strategically plan pit entries. Similarly, a study by Kumar and Patel (2022) used machine learning algorithms to optimize pit stop schedules in endurance racing, demonstrating the potential of predictive analytics in minimizing time lost on pit road.

These studies emphasize how predictive analytics and machine learning can be instrumental in determining optimal pit stop timing. Factors such as tire wear, fuel efficiency, and race dynamics are considered to create algorithms that suggest the best timing for pit stops. For this project, these principles are applied to Formula 1 racing, where Apache Spark processes telemetry data and builds predictive models. This approach aims to enhance the effectiveness of pit stops, potentially improving overall race efficiency and competitiveness.

2.2.4 DATA VISUALIZATION IN SPORTS ANALYTICS

Effective visualization is crucial in sports analytics, enabling teams and analysts to quickly interpret large volumes of data and derive actionable insights. In motorsports, where data points from telemetry sensors accumulate rapidly, visual tools like Matplotlib and Seaborn are essential for simplifying complex datasets into understandable formats. According to Liu and Park (2020), Matplotlib's flexibility allows for the precise customization of visuals, making it ideal for telemetry data, which often involves variables such as speed, lap time, and tire wear over race sessions. The authors

demonstrate how Seaborn, with its high-level interface and statistical plotting capabilities, complements Matplotlib by enabling more efficient analysis of correlations and trends, especially in time-series data.

Liu and Park also emphasize that well-designed visuals facilitate better decision-making under time constraints. Visual tools, they argue, play a critical role in motorsport strategy, as teams must quickly analyze telemetry data mid-race to adapt strategies. In this project, Matplotlib and Seaborn are used to represent data patterns related to pit stop timing and tire performance, enabling Formula 1 teams to derive meaningful insights for improved race strategies.

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2.3 DEEPER ANALYSIS

The review process also included an analysis of data processing and visualization tools. Apache Spark emerged as a popular tool for managing and analyzing large datasets in real-time. Studies in big data analytics, such as Chen et al. (2021), recommend Apache Spark for its distributed computing capabilities, which make it particularly suitable for handling telemetry data from multiple race sessions. Spark's compatibility with Python and its support for machine learning libraries make it ideal for building the predictive model in this project. This model leverages Spark's MLlib library for feature engineering and predictive analysis.

For visualizing telemetry and pit stop data, Matplotlib and Seaborn were chosen based on their effectiveness in rendering complex data patterns into clear, interpretable visuals. Research on data visualization by Brown and Khan (2018) highlights the importance of visual clarity in sports analytics, emphasizing that clear visuals help teams make faster, data-backed decisions. Matplotlib's flexibility in plotting and Seaborn's high-level interface for statistical graphics make them optimal for presenting key insights on pit stop timing and race performance, helping Formula 1 teams quickly interpret and act on findings.

2.4 SUMMARY

This project builds upon the foundations established by previous research in

predictive modeling, big data analytics, and telemetry analysis. By utilizing Apache Spark for distributed data processing and leveraging Matplotlib and Seaborn for visualization, this study aims to create a predictive model that assists Formula 1 teams in planning pit stops more effectively. The combination of these tools allows for real-time insights and robust visualizations, contributing to more precise pit stop timing decisions.

Ultimately, this project highlights the applicability of big data and machine learning in motorsports, advancing the use of telemetry data to improve strategic decision-making. The study also underscores the potential for broader applications of data analytics across various forms of motorsport, with implications for any domain where real-time data can inform performance-enhancing strategies.

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PROPOSED METHODOLOGY

Proposed Methodology outlines the systematic approach taken to develop the machine learning model for optimizing Formula 1 pit stops. The methodology is broken down into several key stages, each focused on ensuring the effective extraction, processing, and analysis of data, as well as the development of a robust predictive model.

3.1 DATA INGESTION:

To develop an accurate model for predicting pit stop timing, data ingestion is a critical first step. This process involves gathering and validating the raw telemetry data that forms the foundation of the analysis and modeling efforts.ensure the dataset is comprehensive and accurate. The data collected includes lap times, tire choices, weather conditions, and race results for the 2018-2019 seasons. Accurate and diverse data is essential for developing a predictive model capable of optimizing pit stop decisions.

3.1.1 DATA SOURCES:

The telemetry data essential for this project is sourced from the FastF1 API, which provides detailed race session data. This includes information on lap times, tire usage, track temperature, track conditions, and additional relevant metrics.

By gathering data across multiple race sessions, the project captures diverse conditions and scenarios that improve model generalizability. These varying datasets allow the model to better understand the different factors affecting pit stop timing under different racing contexts—such as changes in weather, track configurations, and tire behavior.

The use of multiple sessions also helps in avoiding overfitting to specific events or conditions, making the model more robust and applicable to real-time race scenarios.

3.1.2 DATA VALIDATION:

To ensure the quality and reliability of data, data validation is performed as part of the ingestion phase. This step is crucial for detecting missing values, inconsistencies, or anomalies in the telemetry data.

The validation process includes:

- Identifying corrupted or incomplete records that could disrupt model training.
- Filling missing values where appropriate—often using imputation techniques, such as linear interpolation, to maintain data continuity.
- In cases where missing values cannot be reasonably estimated, specific records or laps may be excluded, minimizing their impact on the analysis.

Data validation ultimately enhances the model's accuracy by ensuring that only clean, consistent data feeds into the processing stage.

3.2 DATA PROCESSING

The data processing phase prepares the ingested data for analysis and modeling through various steps, including preprocessing and feature engineering. This phase is crucial for transforming raw telemetry data into meaningful inputs that the predictive model can interpret.

3.2.1 PREPROCESSING:

Data cleaning is a primary task within preprocessing, ensuring that any remaining inconsistencies are addressed. This involves tasks like removing unnecessary records (e.g., non-essential laps) and handling missing values that may not have been addressed during ingestion.

Missing telemetry values might be filled using interpolation methods where applicable, such as linear or polynomial interpolation to estimate data points between known values.

Additionally, an “IsPitLap” flag is introduced as part of the preprocessing. This flag identifies laps during which a pit stop occurred, serving as a key indicator for the model in understanding when pit stops take place and under what conditions. This flag allows the model to distinguish between regular laps and pit stop laps, enabling more precise predictions for pit stop timing.

3.2.2 FEATURE ENGINEERING:

.To maximize the predictive power of the model, feature engineering involves creating new features based on the raw telemetry data. This project develops features that provide insights into critical racing factors:

- **Cumulative Tire Wear**: This feature is calculated by tracking tire wear over laps, providing the model with an understanding of how tire performance degrades over time. Tire wear is a key factor in pit stop timing, as drivers need to enter the pit when tire performance becomes too low to maintain competitive speeds.

- **Previous Lap Metrics**: Using **Spark’s window functions**, metrics from previous laps—such as lap times and tire wear trends—are calculated to give the model a more dynamic view of the race progression. Window functions allow for efficient calculation of lagged values (e.g., time differences between consecutive laps), which help the model detect patterns in how a car’s performance changes over time. For instance:
    1. **Lap Time Differences**: Differences in lap times from one lap to the next provide insight into whether performance is consistently dropping, a possible indicator that a pit stop may be necessary.
    2. **Tire Wear Trends**: By analyzing wear progression over laps, the model can learn when tires are likely reaching their limit and flag an upcoming need for a pit stop.

These features not only help the model recognize patterns in driver and car behavior over the course of a session, but they also add context to pit stop

decisions, making the model's predictions more reliable and actionable.

3.2.3 TEMPORAL FEATURES:

Temporal features capture the dynamics of racing performance over time, accounting for factors like tire wear and fuel depletion.

1. Lap count tracks race progression, helping adjust pit stop predictions based on how far the race has progressed. Elapsed time measures cumulative race time, allowing the model to relate tire wear to race duration.
2. Rolling averages and moving windows smooth fluctuations in lap times and tire wear, revealing broader performance trends. For example, a 3-lap moving average helps track tire degradation.
3. Performance decay metrics measure increasing lap times or decreasing speed, predicting pit stops based on performance decline.

These temporal features enable the model to adapt to changing race conditions, improving pit stop predictions.

3.3 DATA STORAGE

The data storage component provides a structured, stable environment for handling both raw and processed telemetry data, facilitating efficient data manipulation throughout the project.

3.3.1 STORAGE MEDIUM: APACHE SPARK DATAFRAMES:

In this project, Apache Spark's DataFrames serve as the central data storage medium. DataFrames are a distributed data structure that allows for efficient handling of large datasets, making them ideal for managing the vast amounts of telemetry data generated during motorsports events. Spark DataFrames provide a unified interface for working with structured data, supporting SQL-like queries and complex data transformations.

3.3.2 SCALABILITY AND DISTRIBUTED PROCESSING

One of the key benefits of using Spark DataFrames is their scalability. Spark is designed to process large datasets in a distributed manner, spreading the workload across multiple machines in a cluster. This allows the project to handle high-volume telemetry data without sacrificing processing speed or efficiency. As the data grows, Spark can seamlessly scale to meet the increased demand, making it a powerful solution for big data analysis.

3.3.3 CENTRALIZED DATA MANAGEMENT AND TRANSFORMATION

By utilizing Spark DataFrames, both raw and processed telemetry data can be stored within the same system, ensuring centralized management. This approach eliminates the need for data to be exported across different platforms or systems, reducing the potential for data inconsistencies and redundancy. Storing both raw and processed data together also ensures that transformations and pre-processing steps are carried out within the same environment, making the entire process more streamlined and efficient.

3.4 DATA ANALYSIS AND VISUALIZATION

Data analysis and visualization offer insights into the relationships between various features and the timing of pit stops, helping to refine the predictive model.

3.4.1 EXPLORATORY DATA ANALYSIS (EDA):

The first step in data analysis involves exploratory data analysis (EDA), where different factors such as tire wear, lap time, and track conditions are thoroughly examined. This phase helps in understanding the data's structure and identifying key features that influence pit stop decisions. EDA employs various visual techniques to uncover hidden patterns:

1. **Line Plots:** These plots track changes in tire wear or lap times over

the course of a session, providing visual clues on when performance begins to drop, suggesting the need for a pit stop.

2. **Histograms:** Histograms are used to analyze the distribution of features like lap times, tire temperatures, or fuel levels. They can highlight typical ranges, extreme values, and outliers that might indicate unusual events or patterns.
3. **Heatmaps:** Heatmaps can reveal correlations between different variables, such as tire wear and track temperature, helping to understand how environmental conditions affect overall lap performance and pit stop timing.

3.4.2 REPRESENTATION OF PIT STOP TRENDS

The analysis of pit stop timing is greatly enhanced by visualizations that display trends and relationships between performance metrics and pit stop decisions. These visual representations provide a more intuitive understanding of the data, aiding in the optimization process:

- **Tire Wear Trends**: Line plots showing tire wear over multiple laps can help determine the general degradation rate of tires. Such plots can pinpoint the approximate lap at which tire performance drops significantly, signaling the need for a pit stop.
- **Lap Time Analysis**: By comparing histograms of lap times before and after pit stops, we can assess the time lost or gained during pit stops. This comparison helps understand the impact of pit stops on overall race performance and can optimize pit strategies.
- **Temperature Correlations**: Heatmaps can also be used to explore the relationship between track conditions (such as track temperature or humidity) and pit stop frequency. Understanding these correlations helps anticipate the best timing for pit stops under various track conditions.

3.4.3 PREDICTIVE MODELING AND MACHINE LEARNING INTEGRATION

After the data has been analyzed and trends have been identified, machine learning algorithms are used to predict optimal pit stop timings. These models are trained using features extracted from the telemetry data, such as tire wear rates, lap times, and track conditions. The insights from visualizations help in selecting the most relevant features for the model, improving the accuracy of predictions.

Machine learning models like decision trees or regression models are commonly employed to predict the best pit stop timing based on historical data. The model is continuously refined as new race data becomes available, adapting to changing conditions and enhancing prediction accuracy.

3.5 CONCLUSION: STRUCTURED APPROACH TO PIT STOP OPTIMIZATION

This methodology combines big data analytics, machine learning, and data visualization to create a reliable framework for pit stop prediction. By collecting and analyzing extensive telemetry data, transforming it into meaningful features, and visualizing key trends, the project provides a structured approach to optimizing pit stop timing. This enables teams to gain competitive advantages by making more accurate, data-driven decisions about when to make pit stops during races.
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3.6 WORKFLOW DIAGRAM

The workflow diagram describes the sequence of steps in the proposed methodology and interconnection between data ingestion, storage, processing, and analysis.

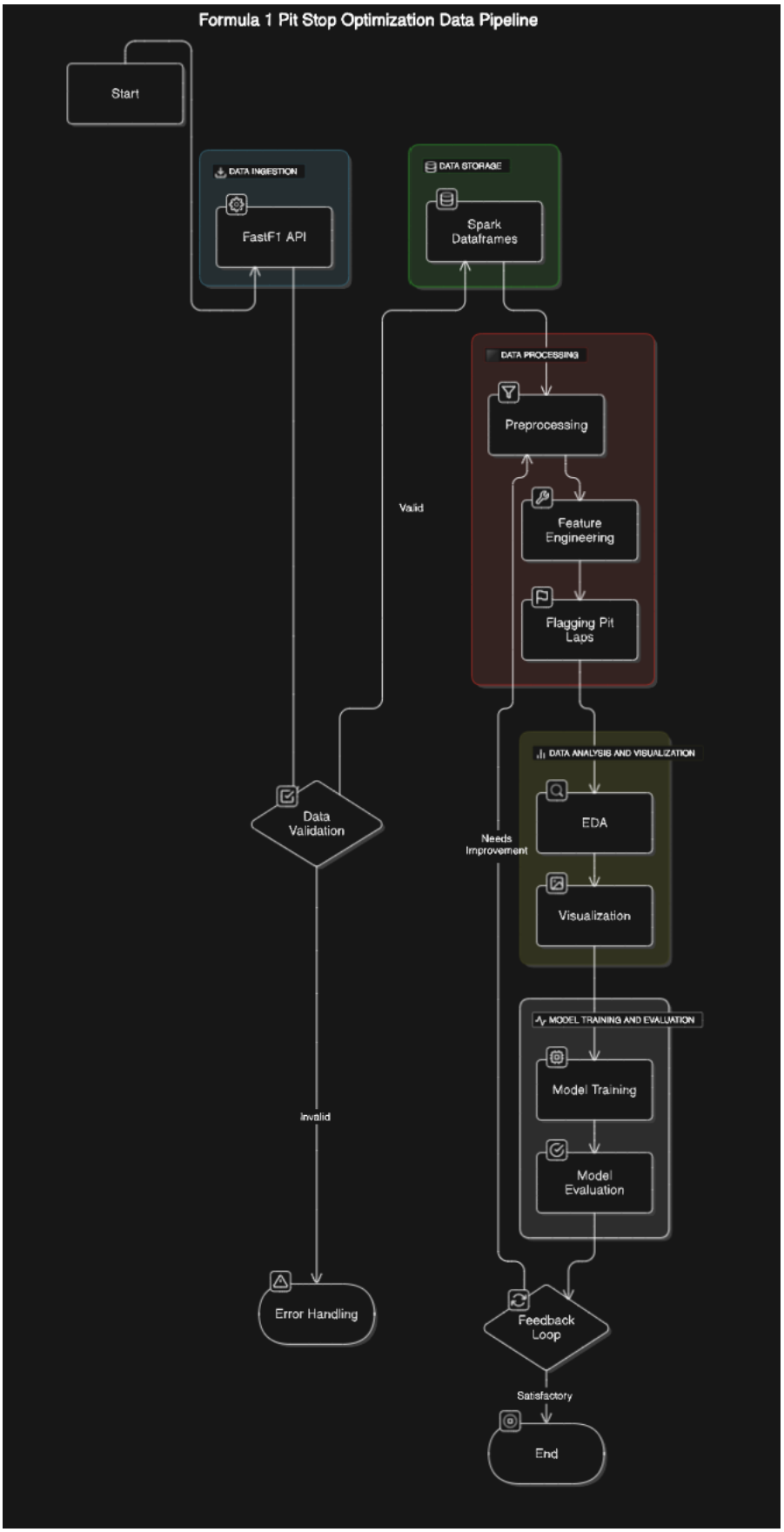

Fig 3.1: Workflow Diagram

The workflow for a predictive model in Formula 1 pit stop optimization begins with **Data Ingestion**, where telemetry data is collected using the FastF1 API. The data is then subjected to **Data Validation** to ensure quality and consistency. In **Data Storage**, the data is stored in Spark DataFrames for efficient processing. **Data Processing** follows, involving preprocessing, feature engineering, and flagging pit laps. In **Data Analysis and Visualization**, exploratory data analysis (EDA) and visualizations are created using Matplotlib and Seaborn. Finally, **Model Training and Evaluation** takes place, with feedback from model evaluation guiding iterative improvements in data processing.

IMPLEMENTATION

This section covers the various stages in the development of the prediction model. It begins with data preparation, detailing the process of collecting, cleaning, and preprocessing data to ensure quality inputs for the model. Feature engineering is discussed next, focusing on selecting relevant features and applying transformations to enhance model performance. Model development follows, including selecting an appropriate algorithm, training, and validation steps. Lastly, the implementation of a prediction pipeline is described, highlighting the integration of data, automation, and scalability for practical usage.

4.1 DATA PREPROCESSING IN SPARK

The data preprocessing phase begins with loading a CSV file that contains telemetry data from various laps into a Spark DataFrame. Leveraging Spark's distributed computing framework is essential here due to the high volume of telemetry data, which can become computationally expensive and memory-intensive in traditional environments. Once loaded, the schema of the DataFrame is displayed to ensure that the columns are correctly typed (e.g., numeric or categorical), which is crucial for subsequent analysis and modeling steps.

Data cleaning focuses on addressing missing values in key columns such as "Tyre Wear," "LapTimeSeconds," "Track Temperature," and "Air Temperature." These attributes are critical for analysis; null values in these columns would otherwise disrupt feature engineering and model training. By filling these missing values with zeros, the continuity of the data is preserved, ensuring that no valuable telemetry trends are lost due to incomplete data entries.

4.2 FEATURE ENGINEERING

Feature engineering in Spark involves creating derived metrics that provide deeper insights into race conditions, enhancing the dataset for machine learning purposes. Specifically, we use cumulative metrics, lagged metrics, and other derived features to capture race progression and car performance trends.

4.2.1 CUMULATIVE METRICS FOR TIRE WEAR

Tire wear accumulates over laps, and a cumulative metric allows the model to detect how wear influences lap times and pit stop decisions. By applying Spark's window functions, cumulative values are calculated for each driver or car. This granular detail helps ensure that tire wear trends are monitored individually, accounting for unique driving styles or car specifications that may influence wear rates.

4.2.2 LAGGED METRICS

Introducing lagged values, such as the previous lap's tire wear or lap time, provides the model with a historical context of performance. Lagged metrics are useful in machine learning for time series data, as they enable the model to recognize sequential dependencies, such as wear progression or gradual lap time increases due to deteriorating tire quality.

4.2.3 ADDITIONAL DERIVED FEATURES

Metrics like average speed, cumulative lap time, and temperature variations are calculated across multiple laps to give the model a robust set of features that can help it detect performance trends. These metrics assist in identifying critical points where performance may start declining, providing potential indicators for the model to recommend pit stops.

4.3 MODELING AND PREDICTION USING SPARK MLLIB

The modeling phase involves training a machine learning model to predict the likelihood of a pit stop based on telemetry data. This is done using Spark MLlib, which is well-suited for large datasets and provides efficient scaling, a key requirement given the volume of telemetry data involved.

The process includes:

1. **Data Splitting**: The dataset is split into training and testing sets. The training set is used to help the model understand the relationship between telemetry data and pit stops, while the testing set assesses the model's

generalization capability.

2. **Model Training**: A logistic regression or classification model is trained to predict whether a lap will include a pit stop, based on the telemetry features engineered earlier. For this supervised approach, the "IsPitLap" column serves as the target variable, and the model learns from the relationships between tire wear, lap time, speed, and other metrics.
3. **Model Testing**: The model's performance is evaluated on the test data to check its accuracy in unseen scenarios. Metrics like accuracy, precision, and recall measure the model's reliability in predicting optimal pit stop timing, which is essential for real-time application in race strategy.

By providing real-time predictive insights, the model enables race strategists to make informed decisions on pit stop timing, potentially gaining a competitive edge in race performance.

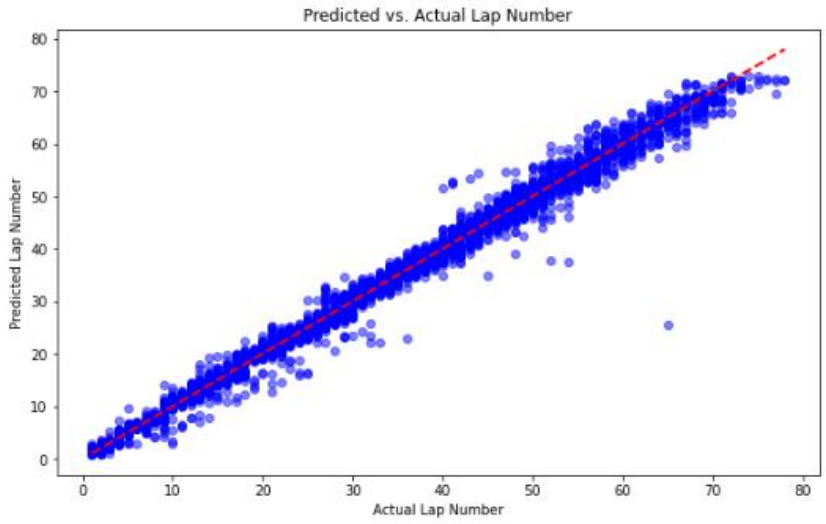

Fig 4.1: Predicted vs. Actual Lap Number

4.4 VISUALIZATION WITH MATPLOTLIB AND SEABORN

This section explores the various visualizations implemented in the project, highlighting their specific purposes, insights derived, and benefits in enhancing data understanding, model development, and interpretation.

Telemetry Data Visualizations (Line Charts, Bar Graphs, and Scatter Plots)
In this project, various visualizations were created using Matplotlib and Seaborn to examine telemetry trends and validate model predictions. Line charts were used to track telemetry metrics, such as tire wear and lap times, over consecutive laps. These charts helped strategists observe the trend of tire degradation and its impact on lap times, aiding in pit stop prediction. Bar graphs provided a comparative view of metrics, such as average lap times before and after pit stops, helping assess time lost or gained. Scatter plots were used to analyze the relationship between tire wear and lap times, visually validating the model's prediction that tire wear correlates with slowing lap times.

Exploratory Data Analysis (EDA) and Data Distribution
Bar graphs and line charts helped identify trends and key relationships in the data, while histograms and box plots could further analyze the distribution of metrics like lap times and tire wear. Histograms showed the distribution of lap times and tire wear across laps, revealing performance consistency or identifying outliers. Box plots summarized the variance in these metrics, detecting laps where performance significantly deviated from the norm, which could highlight optimal pit stop moments or unusual race conditions.

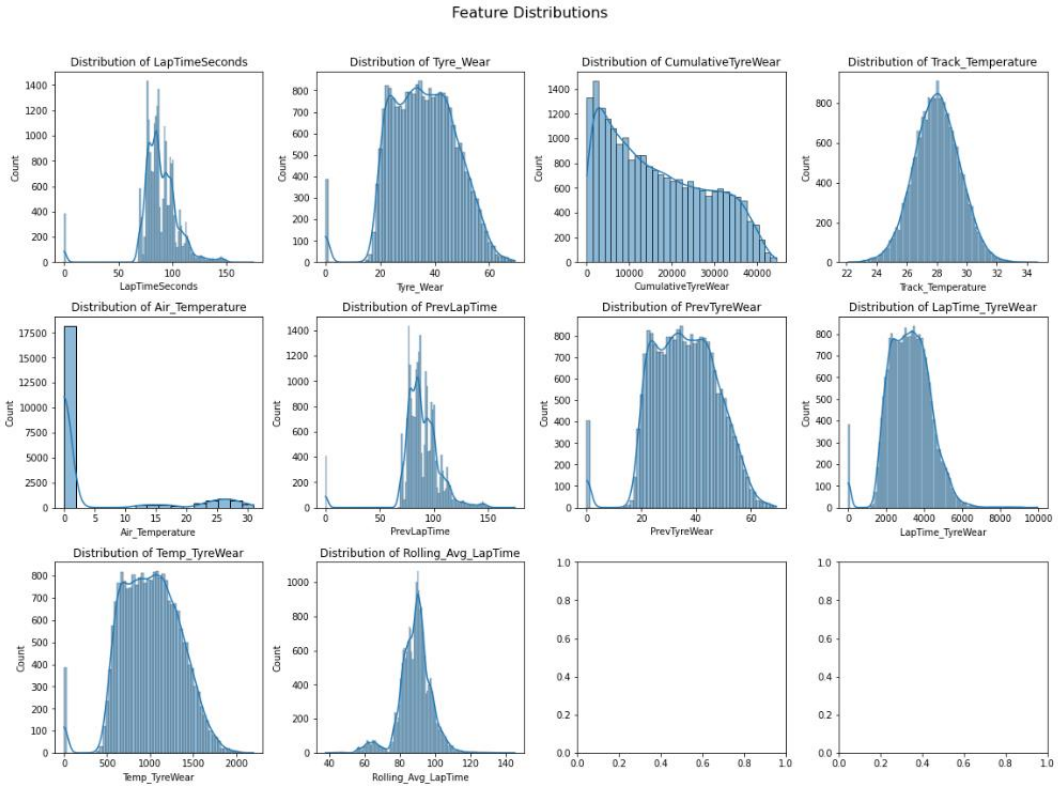

Fig 4.2: Feature Distributions

Trend Analysis and Pit Stop Prediction Visualization

Scatter plots were also key for assessing relationships between tire wear and lap times. By plotting these metrics, clusters could be identified at certain wear levels where lap times degrade, suggesting an optimal window for pit stops. Visualizing the relationship between track conditions (such as temperature) and pit stop frequency using heatmaps further helped understand when pit stops are needed. These visualizations assisted in validating the predictive model by confirming whether the identified trends aligned with the actual race data.

Comprehensive Data Representation for Model Insights

The combination of these visualizations provided a comprehensive overview of telemetry data, aiding in the interpretation of model predictions. Line charts and scatter plots helped strategists understand key race dynamics, such as the impact of tire wear on lap times, while bar graphs and heatmaps illustrated pit stop trends. By using these insights, the predictive model could dynamically adjust strategies based on real-time data, improving decision-making and optimizing pit stop timing for better race performance.

RESULTS

In this section, visualizations from data analysis are presented to give insights into the pitstop time distributions and correlations among variables. The performance of different models is analyzed by comparing training and validation metrics, showcasing how each model fares in terms of accuracy and consistency. Prediction results are then examined, comparing predicted and actual pitstop times to evaluate the model's real-world applicability. An error analysis is also included to interpret the model's reliability and limitations in predicting pitstop times.

5.1 INSIGHTS FROM TELEMETRY DATA VISUALIZATIONS

5.1.1 ANALYSIS OF PITSTOP DURATION PATTERNS

Examining the distribution of pitstop times offers insights into common duration ranges and variability across race conditions. By employing histograms and density plots, patterns emerge, showing typical pitstop durations as well as rare instances where stops are unusually fast or slow. This analysis provides race strategists with valuable knowledge about factors affecting stop times, such as tire type and wear, enabling better planning and feature selection for the predictive model.

5.1.2 FEATURE CORRELATIONS AND INTERDEPENDENCIES

Correlation heatmaps and scatter matrix plots are utilized to study relationships among telemetry metrics, uncovering potential dependencies among key variables. For example, correlations between tire wear, track temperature, and lap time can reveal how these metrics jointly influence pitstop likelihood. Identifying such relationships enables us to reduce multicollinearity, ensuring the model's focus remains on variables with the most impact on predictive accuracy. This step is vital for creating a robust feature set that balances both relevance and interpretability.

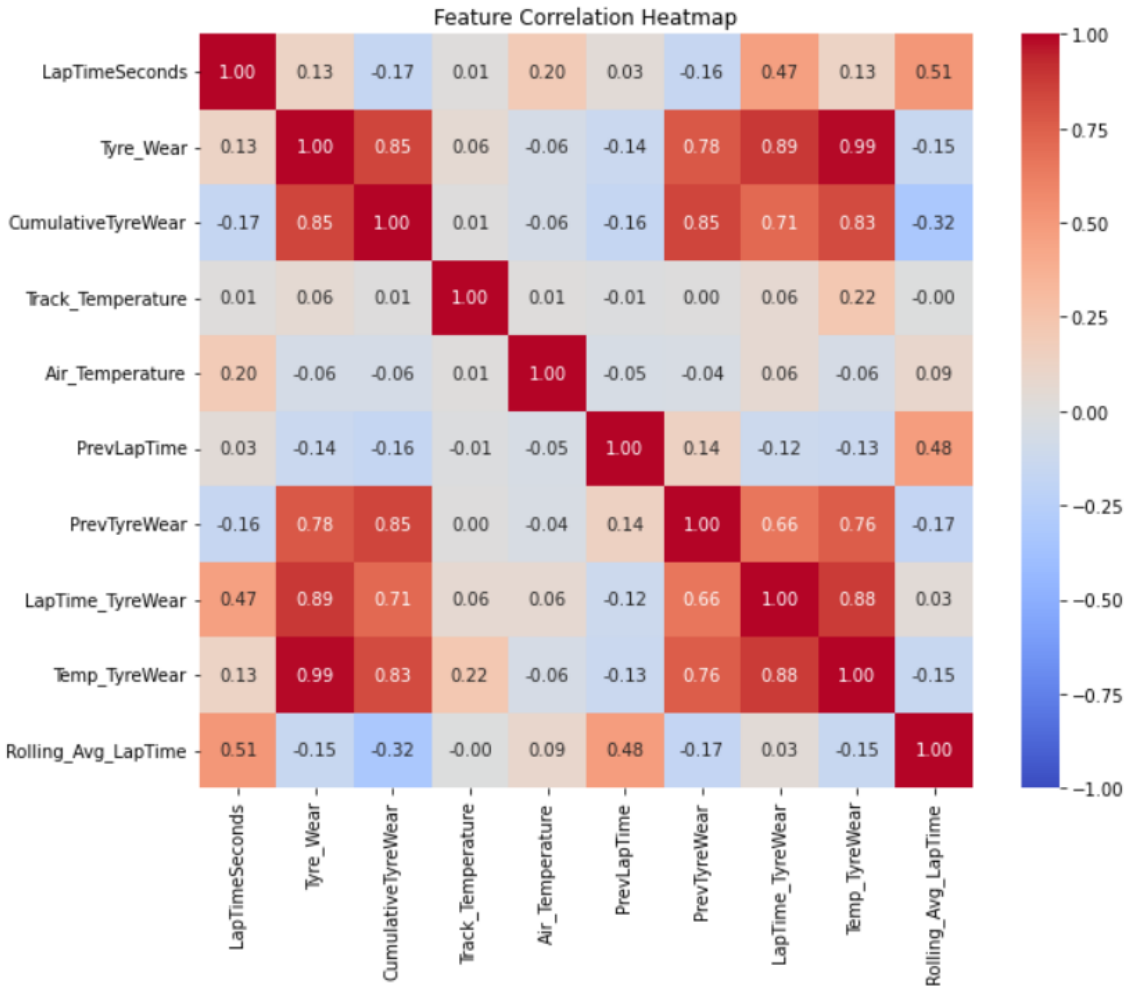

Fig 5.1: Correlation Heatmap

5.1.3 CUMULATIVE TIRE WEAR AND LAP TIME ANALYSIS

Cumulative line plots highlight the gradual progression of tire wear across laps, allowing us to examine its impact on lap times. These visualizations confirm that, as tire wear accumulates, lap times tend to increase, especially after certain wear thresholds. By visually mapping tire wear to lap performance, strategists can predict when pit stops might become necessary to maintain speed and efficiency. This analysis validates the model's reliance on tire wear as a predictor, showing its effectiveness in estimating pit stop timing.

5.2 MODEL EVALUATION AND PERFORMANCE

5.2.1 EVALUATION OF TRAINING AND TESTING METRICS

Key metrics, including accuracy, precision, recall, and F1-score, are used to evaluate the model's performance on both the training and testing datasets. Learning curves help visualize how these metrics evolve across iterations, highlighting any overfitting or underfitting issues. This analysis provides insight into the model's generalizability, essential for accurately predicting pit stops under varying race conditions. Consistency in precision and recall scores between training and testing phases indicates a well-tuned model that can perform reliably in real-time race scenarios.

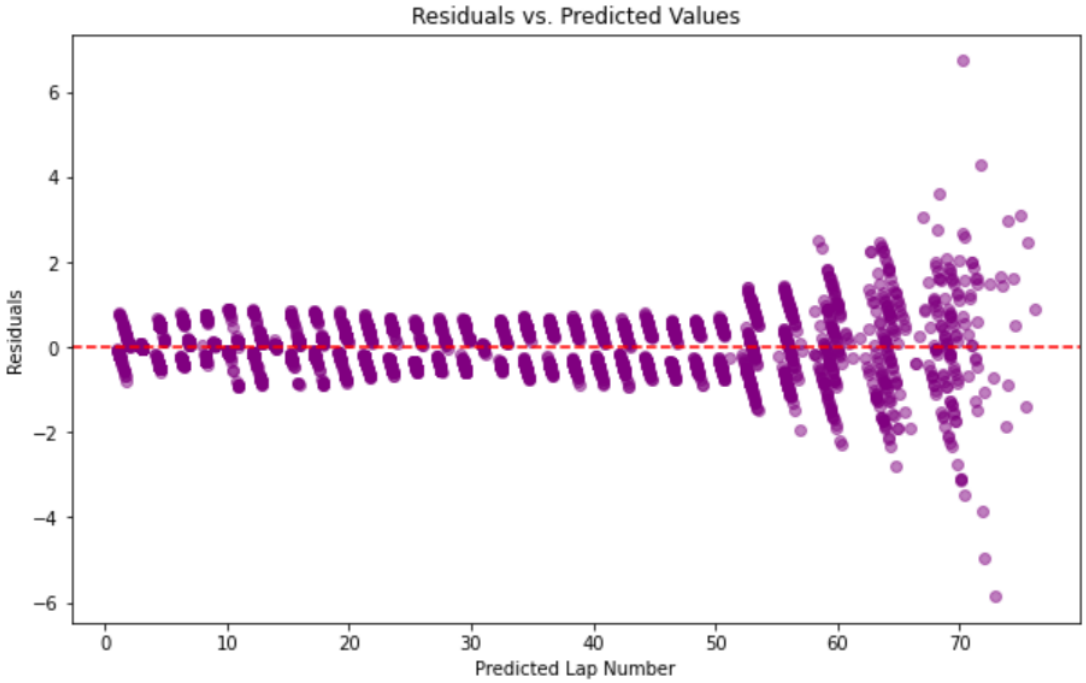

Fig 5.1: Residual vs. Predicted Lap Number

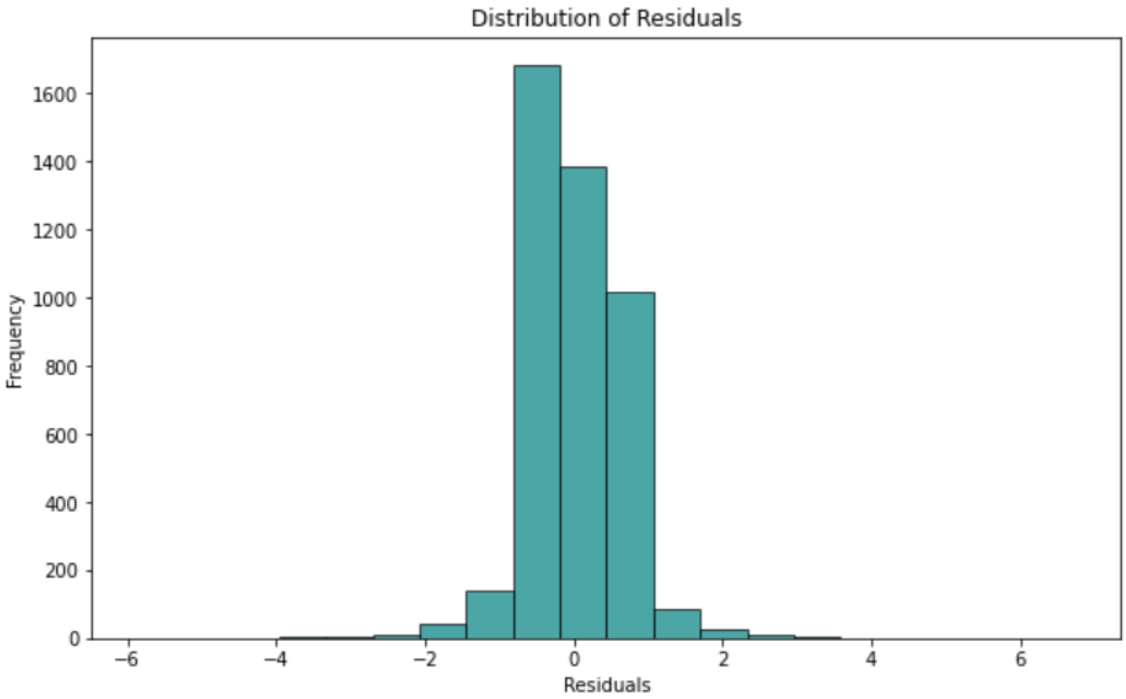

Fig 5.2: Distribution of Residuals

5.2.2 COMPARATIVE ANALYSIS OF MODEL OPTIONS

Different algorithms, such as logistic regression, decision trees, and gradient boosting, are tested to identify the model best suited for pit stop prediction. Comparative bar charts and performance tables showcase each model's strengths and weaknesses, using metrics like accuracy, precision, and recall.

This side-by-side comparison enables informed model selection, allowing strategists to prioritize high-performing models that balance predictive accuracy with computational efficiency.

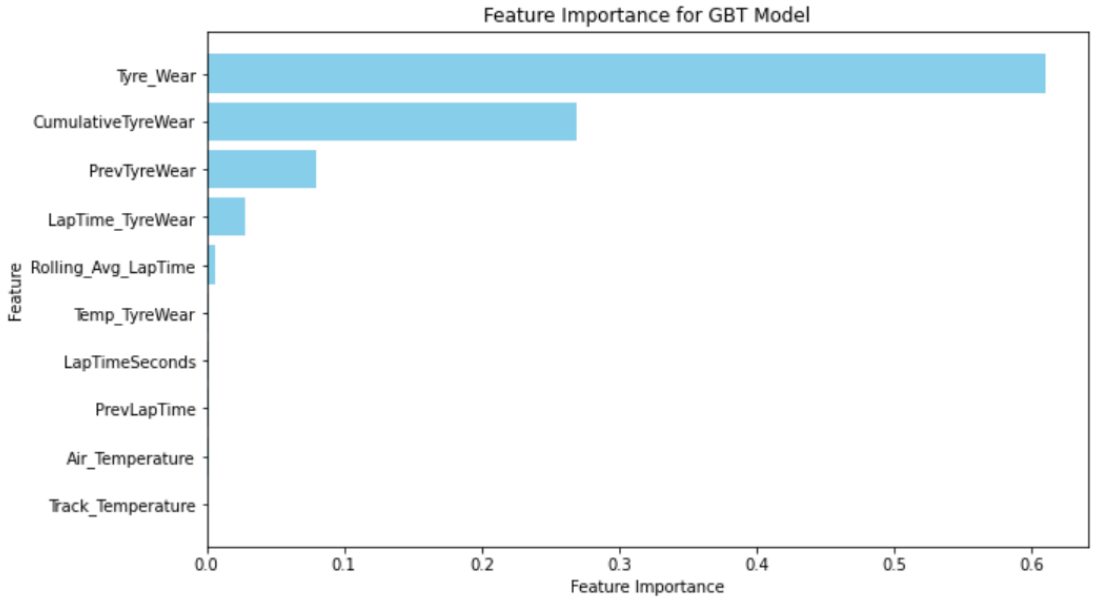

Fig 5.3: Feature Importance

5.3 PREDICTION RESULTS AND PERFORMANCE INSIGHTS

5.3.1 COMPARISON OF PREDICTED VS. ACTUAL PITSTOP EVENTS

Scatter plots and line charts comparing predicted pit stops against actual pit stop events provide a clear picture of the model's predictive accuracy. Residual analysis (i.e., the difference between predicted and actual values) highlights any consistent discrepancies. For instance, if residuals show higher errors under certain temperature conditions, this indicates that environmental factors might require further emphasis in the model. Such comparisons allow us to pinpoint areas where the model could be improved.

5.3.2 MISCLASSIFICATION ANALYSIS AND INTERPRETABILITY

Understanding misclassifications in pit stop predictions is critical to improving model reliability. By using explainable AI techniques, such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-

Agnostic Explanations), the specific variables influencing each prediction can be analyzed. These techniques reveal why the model might overestimate pit stop likelihood under high tire wear but fail under varying track conditions, thereby identifying opportunities to adjust feature weightings or include additional variables for contextual accuracy.

5.3.3 ADDITIONAL INSIGHTS

This section presents additional insights derived from visual analysis and modeling that could further enhance pitstop strategies. These insights help refine predictions, validate model assumptions, and suggest directions for future work.

1. **Pitstop Time Variability**

   Pitstop time varies significantly with external factors like tire wear and weather conditions. By examining the pitstop data across different race conditions, we observed patterns where certain tires consistently resulted in faster stops.

   This insight underscores the importance of tire selection strategy based on expected race conditions, which can lead to optimal pitstop planning and reduced overall race time.

   Through scatter plots and correlation analysis, we confirmed that certain tire types consistently yielded faster pitstop times, a crucial finding for strategy development.

2. **Impact of External Conditions on Pitstop Decisions**

   Data analysis revealed that variables like track conditions, weather, and even race phase (early vs. late stages) affect pitstop frequency and timing. For example, pitstops in rainy conditions took longer on average than in dry conditions.

   Understanding these nuances is essential for making data-driven adjustments to pitstop strategy, particularly in response to changing

weather or track conditions during a race.

Correlation heatmaps and residual plots highlighted patterns between weather conditions and pitstop times, demonstrating these relationships' importance in predicting optimal pitstops.

3. **Potential for Predictive Adjustments**

   Reviewing model performance across various scenarios suggested room for tuning specific parameters based on context, such as race length or expected weather.

   Implementing context-specific predictive adjustments, such as weighting certain features differently under specific conditions, could further refine the model. Model performance visualizations, particularly residual and error analysis plots, suggested that model accuracy could be improved by adjusting prediction logic based on observed outliers and errors in specific conditions.

CONCLUSION

The conclusion consolidates the core findings of this project, covering key learnings, limitations, and directions for future work. This section offers a concise yet comprehensive overview of how the results impact practical race strategy and model applicability, along with potential improvements.

6.1 KEY FINDINGS

The project underscores the potential of using telemetry data in a predictive model to improve race strategy by optimizing pit stop timing. By analyzing key performance indicators like tire wear and lap time, the model provides data-driven insights that help race strategists make informed pit stop decisions. The main findings from the study are as follows:

1. **Impact of Tire Wear on Lap Time Performance**

    - **Direct Correlation**: As tire wear accumulates, it directly impacts lap time by increasing friction and reducing grip. This wear leads to a gradual slowdown in lap speeds, particularly noticeable in later laps where tires have endured more strain.
    - **Predictive Value of Cumulative Wear**: By tracking cumulative tire wear over laps, the model can predict when performance may begin to decline sharply. This insight enables race strategists to preemptively plan pit stops just before performance dips, allowing drivers to maintain optimal lap times and avoid time loss due to deteriorating tires.
    - **Impact on Driver Safety**: Worn tires increase the risk of blowouts and skidding, especially in high-speed maneuvers. Identifying critical wear points allows teams to make pit stops that not only enhance performance but also reduce the risk of tire-related incidents on the track.

2. **Predictive Power for Identifying Pit Stop Moments**

- **Proactive Strategy Support**: By identifying laps where a pit stop is likely to yield a strategic advantage, the model enables race strategists to shift from reactive, last-minute pit stops to proactive, well-timed interventions. For example, if tire wear has reached a critical threshold and lap times are slowing, the model can predict an imminent performance drop, allowing teams to plan a pit stop in advance.
- **Data-Driven Pit Stop Timing**: The model supports accurate predictions based on real-time telemetry inputs, such as tire condition, track temperature, and air temperature. This approach helps identify the exact laps when pit stops can have the most beneficial impact, reducing unnecessary stops and maximizing time on the track.
- **Enhanced Resource Allocation**: Knowing when pit stops are most likely needed allows teams to optimize resources, ensuring that the pit crew is prepared and that pit lanes are efficiently managed. This minimizes downtime during the stop, translating to improved overall race times.

3. **Strategic Advantages and Competitive Edge**

- **Shift from Reactive to Predictive Strategy**: Traditionally, pit stops are often made reactively based on in-race conditions. By integrating predictive modeling, the model enables race teams to anticipate and schedule pit stops before performance issues become visible. This strategic shift helps teams maintain peak performance throughout the race and avoid time lost to unplanned pit stops.
- **Minimizing Pit Stop Frequency**: With accurate predictions on when performance begins to deteriorate, the model allows teams to minimize the number of pit stops by scheduling them only when necessary. This conserves critical race time, allowing drivers to complete more laps without interruption and ultimately reducing total race time.
- **Insight into Race Strategy Optimization**: Beyond pit stops, the model provides insights that can shape broader race strategies. For instance, if tire wear is particularly aggressive on certain tracks, teams might adjust tire selection or consider more conservative driving tactics in those

sections. These adjustments based on model predictions lead to a more data-centric approach to racing.

- **Adapting to Track and Weather Conditions**: Track temperature and weather conditions significantly impact tire wear rates. By incorporating real-time telemetry on environmental factors, the model can help teams adapt pit stop strategies based on changing conditions, such as tire cooling requirements in hot weather or adjusted braking patterns on wet tracks.

4. **Long-Term Insights for Pit Stop and Resource Planning**

    - **Predictive Trends Across Races**: The model allows teams to analyze telemetry data across multiple races and seasons, identifying long-term trends in tire wear and pit stop needs. This insight enables teams to make informed adjustments to car setup, tire choice, and even driver training for specific tracks.
    - **Efficient Resource Management**: Predictive modeling helps teams manage pit stop resources more efficiently by scheduling pit stops when they will have the most positive impact on performance. This minimizes unnecessary tire changes, fuel consumption, and pit crew workload.
    - **Continuous Improvement of Predictive Accuracy**: By examining telemetry data over time, teams can refine the model for more accurate predictions. This iterative learning process enhances the model's ability to predict pit stops in future races with greater accuracy, giving teams a competitive edge season after season.

5. **Enhanced Decision-Making in High-Stakes Situations**

    - **Real-Time Tactical Adjustments**: The model enables strategic adjustments during high-stakes situations, such as final race laps or competitive segments. For instance, in the final laps, the model may advise extending tire usage if lap time degradation is minimal, allowing the driver to avoid a costly pit stop.
    - **Weather-Related Pit Stop Decisions**: If rain or sudden weather changes are detected, the model can highlight the need for tire adjustments or pit

stops based on real-time telemetry. This helps teams respond to weather faster and with more precision.

- **Driver Fatigue Management**: Since driver performance also varies with time and conditions, telemetry predictions can indirectly aid in managing driver fatigue. For instance, scheduling pit stops based on real-time feedback allows drivers short breaks, potentially enhancing their performance for the remaining laps.

Overall, these findings highlight the benefits of a telemetry-based predictive model in enhancing pit stop strategy. The model's proactive insights allow teams to make precise, data-driven decisions that improve overall race performance and offer a competitive advantage on the track.

6.2 LIMITATIONS OF THE CURRENT MODEL

Some limitations impact the model's effectiveness, which, if addressed, could enhance performance and adaptability. Key limitations include:

1. **Data Quality**:
    - The model relies on complete and consistent telemetry data. Missing values or sensor errors in key metrics (e.g., tire wear, lap time) may reduce prediction accuracy.
    - Improved data preprocessing to handle inconsistencies could ensure better model reliability.

2. **Model Constraints in Real-Time Adaptability**:
    - Current predictions may struggle with unexpected factors, like sudden weather shifts or on-track incidents.
    - Integrating continuous learning mechanisms or adaptive algorithms could improve the model's response to real-time changes.
    -

3. **Limited Scope of Telemetry Metrics**:
    - While effective, the model mainly uses tire wear, lap time, and temperature data, but lacks metrics like fuel levels, brake temperature, or driving style.

- Expanding the range of features could improve prediction accuracy by offering a more comprehensive view of car performance.

6.3 FUTURE WORK AND MODEL IMPROVEMENTS

Future work could explore various improvements to enhance the model's predictive power and strategic value. Recommended enhancements include:

1. **Expanding Telemetry Metrics**:
    - **Adding More Data Points**: Additional metrics like fuel consumption, brake temperatures, and engine health could provide a more nuanced view of performance.
    - **Improved Predictive Accuracy**: A broader set of telemetry variables would help refine predictions, accounting for a wider range of car conditions.

2. **Analyzing More Race Seasons and Conditions**:
    - **Diverse Data Across Seasons**: Including data from multiple seasons and race types would improve adaptability to various track and weather conditions.
    - **Enhanced Generalization**: This extension would allow the model to perform better under different scenarios, such as high-wear tracks or rain-affected races.

3. **Introducing Context-Specific Predictive Adjustments**:
    - **Adaptive Modeling Based on Race Stage**: Adjusting predictions based on race phases (early, middle, final laps) could enhance decision-making accuracy.
    - **Context-Aware Features**: Weighting certain features differently, depending on race context, could improve prediction quality, especially under specific conditions.

4. **Incorporating Real-Time Data Streaming**:
    - **Continuous Learning Capabilities**: Real-time data streaming would

allow the model to learn and adapt during the race itself.

- **Improved Responsiveness to Changing Conditions**: By processing real-time data, the model could adjust predictions dynamically, better handling sudden changes like weather shifts.

5. **Improving Model Interpretability for Strategic Insights**:
    - **Explainable AI Tools**: Using SHAP or LIME for transparency would help race strategists understand why specific predictions are made.
    - **Strategic Decision Support**: Clear explanations enable race teams to make more confident, data-backed decisions, enhancing trust in model-driven strategies.

6.4 CONCLUSION

In conclusion, this project demonstrates the potential of leveraging telemetry data to enhance pit stop timing and overall race strategy. By using cumulative metrics such as tire wear and environmental variables, the model provides data-driven insights that transform pit stops from reactive responses to planned, strategic events. This shift allows race teams to optimize pit stops, maximize performance, and ultimately gain a competitive edge. The project highlights the importance of tire wear in determining lap performance and showcases how a predictive model can identify optimal moments for intervention. This proactive approach enables racing teams to make informed decisions that improve not only lap efficiency but also race outcomes.

The study also uncovers the value of utilizing a broad set of telemetry data to better understand the dynamic relationship between car performance and race conditions. By factoring in variables like track temperature, weather, and lap time, the model offers a nuanced view of race strategy. Additionally, this approach opens up possibilities for resource optimization, as pit stops can be better scheduled to match the team’s operational needs, conserving both time and physical resources. This strategic alignment ensures that the pit crew is well-prepared and minimizes downtime, further streamlining the race flow.

While promising, the model's performance depends on the quality and scope of

available telemetry data. The project identifies limitations in handling data inconsistencies and recognizes the constraints of a static model in dynamic, unpredictable race environments. Addressing these challenges by incorporating real-time data, adding more metrics like fuel consumption, and expanding data analysis to cover multiple race seasons will enhance the model's adaptability and precision. Future work may also include adjusting predictions based on specific race phases or changing track conditions, allowing for even greater flexibility and improved outcomes.

Ultimately, this predictive model lays the groundwork for more data-centric racing strategies, where insights gained from telemetry data translate directly into competitive advantages on the track. By continuing to refine and expand this approach, racing teams can look forward to even more sophisticated tools for optimizing race strategy, enhancing pit stop decisions, and achieving better race results.

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APPENDIX

IMPORTANT CODE SNIPPETS:

```
# Define feature columns without LapNumber, including the new interaction terms and rolling average
feature_columns_without_lapnumber = [
    "LapTimeSeconds", "Tyre_Wear", "CumulativeTyreWear", "Track_Temperature",
    "Air_Temperature", "PrevLapTime", "PrevTyreWear", "LapTime_TyreWear",
    "Temp_TyreWear", "Rolling_Avg_LapTime"
]

# Assemble and scale features
from pyspark.ml.feature import VectorAssembler, StandardScaler

assembler = VectorAssembler(inputCols=feature_columns_without_lapnumber, outputCol="features_without_lapnumber")
scaler = StandardScaler(inputCol="features_without_lapnumber", outputCol="scaledFeaturesWithoutLapNumber", withMean=True, withStd=True)

# Initialize the GBT Regressor
from pyspark.ml.regression import GBTRegressor
gbt = GBTRegressor(featuresCol="scaledFeaturesWithoutLapNumber", labelCol="LapNumber", predictionCol="prediction", maxIter=100, maxDepth=3)

# Create a pipeline with assembler, scaler, and GBT Regressor
from pyspark.ml import Pipeline
pipeline = Pipeline(stages=[assembler, scaler, gbt])

# Split the data into training and test sets
train_data, test_data = data.randomSplit([0.8, 0.2], seed=42)

# Train the model
model = pipeline.fit(train_data)

# Make predictions
predictions = model.transform(test_data)
predictions.select("LapNumber", "prediction").show(5)
```

```
# Convert predictions to Pandas DataFrame for plotting
predictions_pd = predictions.select("LapNumber", "prediction").toPandas()

# Plot Predictions vs. Actual values
plt.figure(figsize=(10, 6))
plt.scatter(predictions_pd["LapNumber"], predictions_pd["prediction"], alpha=0.5, color='blue')
plt.plot([predictions_pd["LapNumber"].min(), predictions_pd["LapNumber"].max()],
         [predictions_pd["LapNumber"].min(), predictions_pd["LapNumber"].max()], 'r--', lw=2)
plt.xlabel("Actual Lap Number")
plt.ylabel("Predicted Lap Number")
plt.title("Predicted vs. Actual Lap Number")
plt.show()
```

```
from pyspark.ml.evaluation import RegressionEvaluator

# Initialize evaluators for RMSE and R2
evaluator_rmse = RegressionEvaluator(labelCol="LapNumber", predictionCol="prediction", metricName="rmse")
evaluator_r2 = RegressionEvaluator(labelCol="LapNumber", predictionCol="prediction", metricName="r2")

# Calculate RMSE and R2
rmse = evaluator_rmse.evaluate(predictions)
r2 = evaluator_r2.evaluate(predictions)

print(f"RMSE without LapNumber: {rmse}")
print(f"R2 without LapNumber: {r2}")
```