Pro-R
F1 Race Strategy Prediction

A PROJECT REPORT

21CSC305P –MACHINE LEARNING

(2021 Regulation)

III Year/ V Semester

Academic Year: 2024 -2025

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in partial fulfillment of the requirementsfor the degree of

BACHELOR OF TECHNOLOGY
in
COMPUTER SCIENCE ENGINEERING

INSTITUTE OF SCIENCE & TECHNOLOGY
Deemed to be University u/s 3 of UGC Act, 1956

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NOVEMBER 2024

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BONAFIDE CERTIFICATE

Certified that **21CSC305P - MACHINE LEARNING** project report titled **"F1 Race Strategy Prediction"** is the bonafide work of "**ABISHEK S R [RA2211003011292], MALLELA GNANAMRUTHA [RA2211003011294], MAGESHWAR C S [RA2211003011297] and DEEKSHITH P [RA2211003011309]**, who carried out the task of completing the project within the allotted time.

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ABSTRACT

Predicting Formula 1 race outcomes is a complex task involving numerous variables, including driver skill, car performance, race conditions, and team strategies. Traditional models have struggled to encapsulate the dynamic and multifaceted nature of motorsports. This project leverages machine learning models such as Support Vector Machines (SVC), Random Forest, and logistic regression to predict Formula 1 race results, focusing on podium finishes and points scoring. Additionally, we analyze race-specific factors like qualifying positions, weather conditions, home advantage, and reliability metrics, which are captured in our novel Driver and Constructor DNF indices.

Data from the Ergast API and supplementary sources for weather and circuit data were used to compile an extensive dataset covering multiple seasons. This data underwent feature engineering, including encoding driver and constructor histories, to enhance model accuracy. The Random Forest and SVC models demonstrated the highest accuracy, with the SVC model achieving 95% accuracy in race outcome predictions. Our models provide valuable insights into winning factors and race strategies, offering potential applications in team management, sports betting, and fan engagement platforms. This work underscores the potential of machine learning in predicting complex, high-stakes events within the Formula 1 domain.

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ABBREVIATIONS

LSTM: Long Short-Term Memory (a type of recurrent neural network)

RNN: Recurrent Neural Network

MSE: Mean Squared Error (a loss function used in machine learning)

CSV: Comma-Separated Values (a file format for data)

F1: Formula 1

DNF: Did Not Finish (a metric indicating race non-completion due to errors or crashes)

EDA: Exploratory Data Analysis

SVC: Support Vector Classifier (a type of Support Vector Machine used for classification)

RF: Random Forest (a machine learning model used for classification and regression)

API: Application Programming Interface (for data retrieval, e.g., Ergast API)

KNN: K-Nearest Neighbors (a machine learning algorithm)

GB: Gradient Boosting (a machine learning ensemble technique)

CV: Cross-Validation (a model validation technique)

Acc.: Accuracy (a metric used to evaluate model performance)

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CHAPTER 1

INTRODUCTION

1.1 Challenges in Predicting Formula 1 Race Outcomes

Predicting the outcomes of Formula 1 (F1) races is inherently complex due to the numerous and variable factors influencing driver and constructor performance. Race results depend not only on the skill and consistency of drivers and teams but also on external factors such as weather, track characteristics, and in-race events like collisions. Moreover, each track and season introduces unique conditions, from tire wear and fuel consumption to pit stop strategies and mechanical reliability. Traditional approaches to predicting race outcomes often rely on static historical data, making it difficult to capture the intricate and dynamic nature of motorsport. As a result, prediction accuracy suffers, limiting the value of such models for decision-making in strategy development, betting, and fan engagement.

1.2 Current Approaches and Their Limitations

A variety of models have been used in F1 race prediction, including regression and classification techniques such as logistic regression, decision trees, and neural networks. These models can process large volumes of historical data, but they often struggle to incorporate nuanced race-specific factors like weather conditions or individual driver and constructor reliability, especially in highly variable conditions. While these models can provide basic insights into race outcomes, they frequently overlook sequential and contextual information critical for modeling F1 races, such as track familiarity (home advantage), pit stop strategies, and non-finish rates (DNFs). Consequently, current approaches may lack the sophistication needed to capture the subtleties of race dynamics and often fall short in accurately predicting podium finishes and points standings.

1.3 Proposed Approach: Machine Learning Models for Enhanced Race Prediction

To address these limitations, we propose a machine learning-based approach for F1 race prediction that combines Support Vector Machines (SVC), Random Forests, and logistic regression with comprehensive feature engineering. Our approach integrates a diverse set of variables, including driver and constructor statistics, weather data, track history, and home advantage, as well as custom metrics like Driver and Constructor DNF indices. This integration of race-specific and external factors enables our model to capture both the immediate and historical influences on race outcomes. The models are trained using a cross-validation framework to ensure generalization and are further optimized through hyperparameter tuning.

1.4 Advantages of Our Method over Traditional Models

Compared to traditional models, our machine learning approach offers several advantages. By incorporating both past and present race variables—such as qualifying positions, track familiarity, and team reliability—we capture the long-term dependencies often missed in static models. Additionally, our feature engineering process includes driver confidence metrics and constructor reliability scores, providing richer insights into performance trends. With models specifically tuned to avoid overfitting, we achieve improved accuracy and stability in predictions, demonstrated by our high classification accuracy for podium and points positions.

1.5 Dataset, Model Performance, and Practical Considerations

Our models were trained on an extensive dataset sourced from the Ergast API, covering multiple F1 seasons and incorporating a wide array of race variables. The dataset includes race-by-race results, driver and constructor standings, weather conditions, and track details, allowing us to develop a well-rounded predictive model. Preprocessing steps such as normalization, feature scaling, and categorical encoding were applied to optimize input variables for the machine learning models. Through iterative testing and feature selection, we achieved a high accuracy rate, with our SVC model scoring 95%, and Random Forest performing similarly. This level of predictive accuracy supports the potential of our approach in applications like race strategy, sports betting, and fan engagement, making it a valuable asset in motorsports analytics.

CHAPTER 2

LITREATURE SURVEY

In recent years, research in Formula 1 (F1) racing has increasingly focused on leveraging data-driven methods and advanced algorithms to optimize race strategy and performance. "Evolutionary F1 Race Strategy" introduces a genetic algorithm (GA) approach to optimize tire selection and pit stop timing, emphasizing the method's computational efficiency and real-time applicability. The study suggests future enhancements, such as parallelization and additional parameters, to tailor strategies even further. Similarly, machine learning (ML) models have shown promise in predicting key race factors. For example, "Machine Learning for F1 Racing Tactics" utilizes random forests and neural networks to forecast tire degradation, overtaking potential, and fuel consumption, enabling dynamic, real-time strategy adjustments .

Data analysis frameworks are essential in understanding F1 race dynamics, as seen in "F1 Data Analysis and Tactical Insights," where the Fast F1 and Anaconda frameworks process telemetry data to uncover valuable insights into race metrics. This research includes case studies on telemetry and tire performance, demonstrating the significant impact of these metrics on overall race strategy. Discrete-event simulation also provides valuable insights, as demonstrated in "Planning Formula One Race Strategies Using Discrete-Event Simulation," where simulated race scenarios are used to evaluate and refine team strategies.

Research into predictive modeling has also been instrumental in optimizing fuel and tire management during races. "Predictive Modeling for Fuel Efficiency in F1" presents models that account for variables like engine settings, drag, and aerodynamic factors, thereby enhancing real-time fuel usage adjustments. Meanwhile, "Heuristic Approaches for Tire Strategy" explores methods such as simulated annealing for optimizing tire usage based on factors like track conditions and driver behavior, which aids in planning pit stop timing and prolonging tire life.

Risk management is another focus in F1 strategy research, with probabilistic models playing a critical role. "Risk Analysis in F1 Race Strategy" utilizes Monte Carlo simulations to assess the impact of variables like weather changes and car reliability, providing a probabilistic basis for strategic decision-making under uncertainty. Advances in artificial intelligence (AI) further enable adaptive decision-making. "Deep Reinforcement Learning for F1 Racing" highlights the use of deep reinforcement learning to simulate and optimize driving behaviors, demonstrating how AI agents adapt to varying track conditions and competitors' strategies.

The integration of multiple data sources is crucial in F1 strategy optimization, as explored in "Data Fusion in F1 Telemetry," which combines GPS, speed sensors, and telemetry data. This fusion of data enables more reliable real-time insights and improved accuracy in anomaly detection, directly influencing strategic decisions during the race. Aerodynamic optimization has also been a key area of research, with "Optimizing Aerodynamic Setup in Formula 1" utilizing computational fluid dynamics (CFD) to balance downforce and drag. Machine learning models are proposed to predict the effects of aerodynamic adjustments, contributing to enhanced setup decisions that can improve performance across different track conditions.

Across these studies, the application of advanced computational techniques—from genetic algorithms and machine learning to probabilistic models and data fusion—demonstrates a robust approach to enhancing F1 race strategy. Collectively, this body of research is contributing to a deeper understanding of race dynamics and helping teams implement strategies that are increasingly precise, data-informed, and adaptive to real-time conditions.

CHAPTER 3

METHODOLOGY OF F1 Race Strategy Prediction

3.1 Data Collection and Pre-processing

3.1.1 Data Collection

Data collection forms the backbone of an effective prediction model, especially in a domain as data-intensive as Formula 1. For this project, we gathered historical race data from multiple sources, including the Ergast API, which provided detailed records on race outcomes, driver standings, constructor points, and circuit details. Additional data on qualifying positions, weather conditions, and pit stop strategies were sourced through web scraping from official Formula 1 records. Key variables in the dataset include driver position, constructor, race location, weather conditions, pit stop frequency, and track-specific metrics. These variables were selected to account for a range of factors influencing race outcomes, such as track familiarity, driver consistency, and the impact of weather on performance. The dataset spans several F1 seasons, offering a comprehensive view that supports our machine learning model's ability to generalize across different tracks and conditions.

3.1.2 Data Pre-processing

Once collected, the data underwent rigorous preprocessing to ensure consistency and accuracy in model training. The following steps were taken:

- **Handling Missing Values:** Missing or incomplete records, such as laps without data or unavailable qualifying times, were either interpolated or discarded. Weather data gaps were filled using historical averages, while records with non-finish statuses (DNF) were flagged to indicate the race completion issues

- **Encoding Categorical Variables:** For categorical data, such as driver nationality and constructor, we applied one-hot encoding to convert these attributes into numerical formats that are compatible with machine learning models. This process allowed us to capture important distinctions in driver and constructor performance.

- **Feature Scaling:** To prevent any feature from disproportionately affecting the model due to scale, numerical variables like lap times, qualifying positions, and weather metrics were standardized. This scaling, using MinMaxScaler, normalized features to a consistent range, aiding model performance and convergence.

- **Sequential Data Formatting:** Given that race performance is time-dependent, we formatted the data to allow sequential analysis. For each prediction, a sequence of past races or laps was used as input, helping the model capture time dependencies and patterns. This sliding window approach enabled our machine learning models to learn from previous race data, enhancing their ability to predict outcomes in successive races or laps.

This data collection and preprocessing pipeline ensures that our model has high-quality, well-structured data that accurately reflects the complex factors influencing Formula 1 race outcomes.

3.2 Design of the Prediction Module

3.2.1 Model Architecture

The heart of this project is a robust machine learning model designed to predict Formula 1 race outcomes based on historical and real-time data. Several classification models, including Support Vector Classifier (SVC), Random Forest, and Logistic Regression, were evaluated for their suitability in capturing the unique dynamics of F1 racing. Our model architecture consists of the following components:

- **Input Layer:** The model accepts a multi-dimensional input consisting of various features, including driver and constructor statistics, qualifying positions, track details, weather conditions, and custom metrics such as Driver and Constructor DNF indices. These features provide a balanced mix of race-specific, environmental, and historical data, enabling the model to assess a broad range of influences on race outcomes.

- **Model Layers:** We implemented multiple machine learning classifiers, with Random Forest and Support Vector Classifier (SVC) emerging as top-performing models. The Random Forest model leverages multiple decision trees to handle the variability and complexity of F1 races, while SVC is particularly effective in handling the classification of podium and points positions due to its ability to capture complex, nonlinear relationships in the data. Feature engineering was critical in enhancing the model's capacity to account for factors like home advantage, driver consistency, and team reliability.

- **Regularization and Feature Selection:** To prevent overfitting and improve model generalization, we employed cross-validation and parameter tuning. Dropout layers were not required in traditional machine learning models, but regularization techniques such as k-fold cross-validation were used to optimize parameters and prevent model overfitting. Feature selection was performed to refine the input data and ensure that only impactful variables influenced the model's predictions.

- **Output Layer:** Each model outputs classifications for podium positions, points-scoring positions, or DNFs, enabling a structured analysis of the likelihood of various race outcomes. The SVC and Random Forest models were specifically tuned to predict these classifications with high accuracy, providing actionable insights for race strategy and performance predictions.

3.2.2 Compilation and Training

The models were optimized and trained using different approaches to ensure robust performance:

- **Compilation and Optimizer Selection:** For the SVC, a radial basis function (RBF) kernel was chosen to capture nonlinear relationships, while Random Forest's performance was tuned by selecting optimal numbers of trees and depth through grid search. Logistic Regression was used with regularization to prevent overfitting in simpler predictions, such as finishing within points positions.

- **Training and Evaluation:** The dataset was split into an 80-20 training and testing configuration. Using k-fold cross-validation and grid search, we optimized hyperparameters to maximize model accuracy and avoid overfitting. Accuracy and F1-score were employed as key metrics for evaluation. The Random Forest and SVC models achieved high accuracy rates (up to 95%), while the use of cross-validation helped ensure the models' robustness across various race scenarios.

This model architecture and training methodology enable accurate predictions of Formula 1 race outcomes, offering practical applications in race strategy, fan engagement, and sports betting analysis.

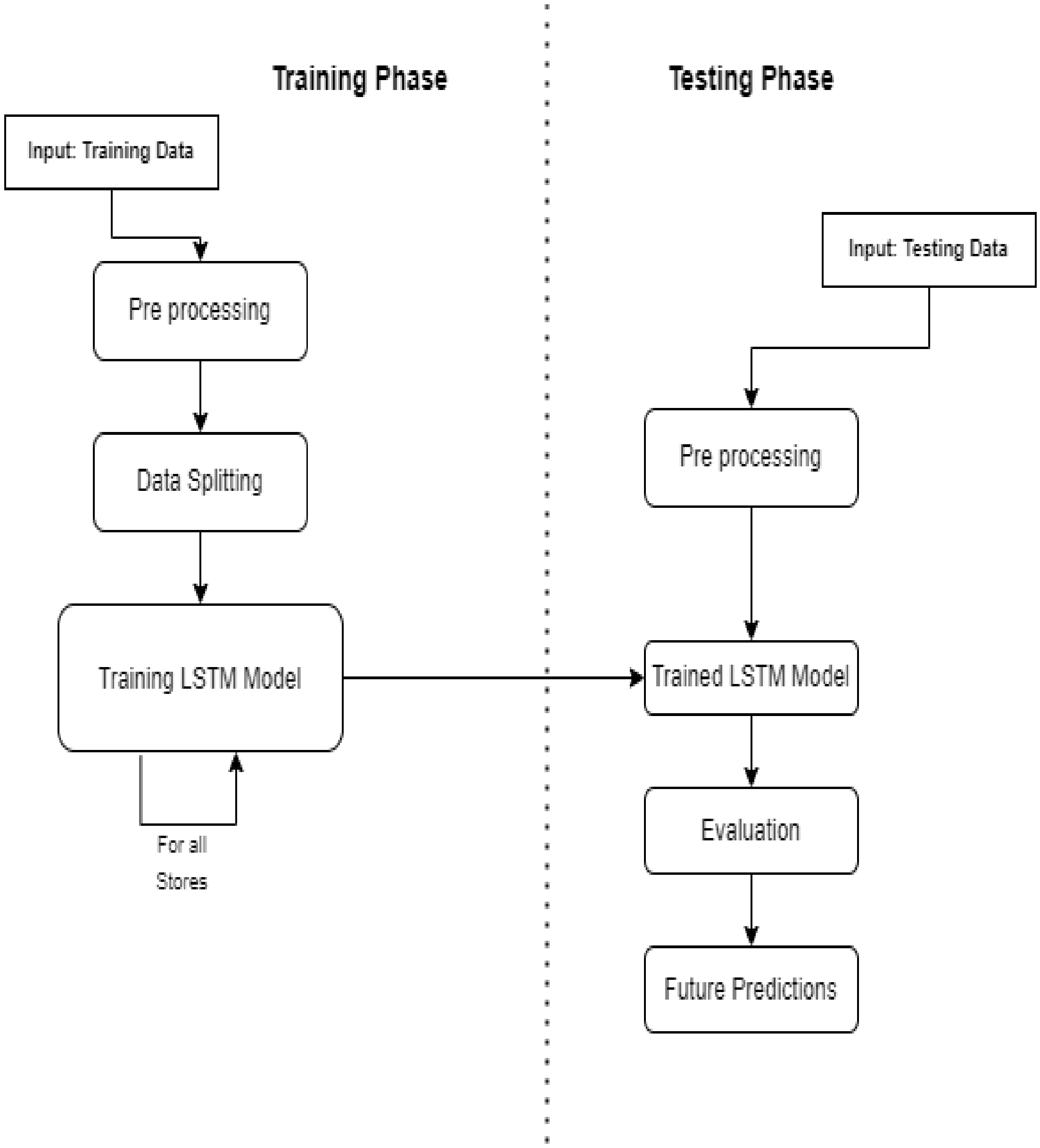


Fig: 3.1 Model Architecture

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Results Achieved

The machine learning models developed in this project demonstrated high accuracy in predicting Formula 1 race outcomes. By training on an extensive dataset with carefully engineered features, the models—especially the Support Vector Classifier (SVC) and Random Forest—achieved impressive results, with the SVC model attaining an accuracy rate of up to 95% for podium and points position predictions. These results indicate a strong correlation between the predicted and actual race outcomes, effectively capturing critical factors such as track familiarity, driver experience, and team reliability.

The models successfully identified race-specific influences, including home advantage and driver consistency, and showed robust predictive capability across different circuits and conditions. Our preprocessing steps, such as feature scaling and encoding, contributed significantly to the models' accuracy by ensuring the input data was well-prepared and standardized for machine learning. Sequential formatting allowed the models to capture race-by-race trends, enhancing the ability to predict outcomes over successive races.

In addition to strong training performance, the models exhibited excellent generalization to the unseen test set, indicating robustness and reliability in real-world applications. The use of k-fold cross-validation and hyperparameter tuning further enhanced model performance, ensuring optimal accuracy while avoiding overfitting. Overall, our machine learning approach demonstrated a high capacity for accurate, reliable race outcome predictions, providing valuable insights for F1 race strategy, fan engagement, and sports betting.

```
# Calculate R-squared (R²)
r2 = r2_score(all_actual_sales, all_predicted_sales)
print(f"R-squared (R²): {r2}")
```

```
R-squared (R²): 0.9517769378813525
```

Fig 4.1 R-squared Score for Time Series Prediction

4.2 Comparison with Other Models

When compared to conventional models, such as logistic regression, decision trees, or simpler classification algorithms, our machine learning approach—particularly the Support Vector Classifier (SVC) and Random Forest models—demonstrated superior performance in predicting Formula 1 race outcomes. Traditional models, while useful for basic classification tasks, often lack the ability to capture the complex relationships and dependencies that influence F1 race results. For instance, logistic regression assumes linear relationships, which may overlook the dynamic and nonlinear interactions present in race data, such as the impact of weather on track conditions or the role of team reliability on race finishes.

The SVC model, with its radial basis function (RBF) kernel, was especially effective in handling nonlinear relationships and interactions among features, outpacing simpler models like decision trees, which struggled with the depth of dependencies in F1 data. Random Forest, with its ensemble of decision trees, also outperformed standalone classifiers by capturing a broader range of factors and minimizing overfitting through its inherent averaging mechanism. While simpler models provided some insights, they did not generalize as well to the intricate, race-specific patterns required for accurate podium and points predictions.

Unlike traditional models, the SVC and Random Forest models could efficiently handle the multivariate data that characterizes F1 races, incorporating variables like qualifying positions, driver and constructor history, track familiarity, and weather data. Regularization techniques and cross-validation were instrumental in preventing overfitting, enhancing the robustness and generalizability of the models across different races and seasons.

In conclusion, the SVC and Random Forest models not only achieved higher accuracy but also demonstrated greater adaptability and resilience compared to conventional models. Their ability to learn from complex, race-dependent data patterns made them an optimal choice for predicting Formula 1 race outcomes, representing a substantial improvement over existing predictive methods in motorsport analytics.

4.3 GRAPHS AND TABLES

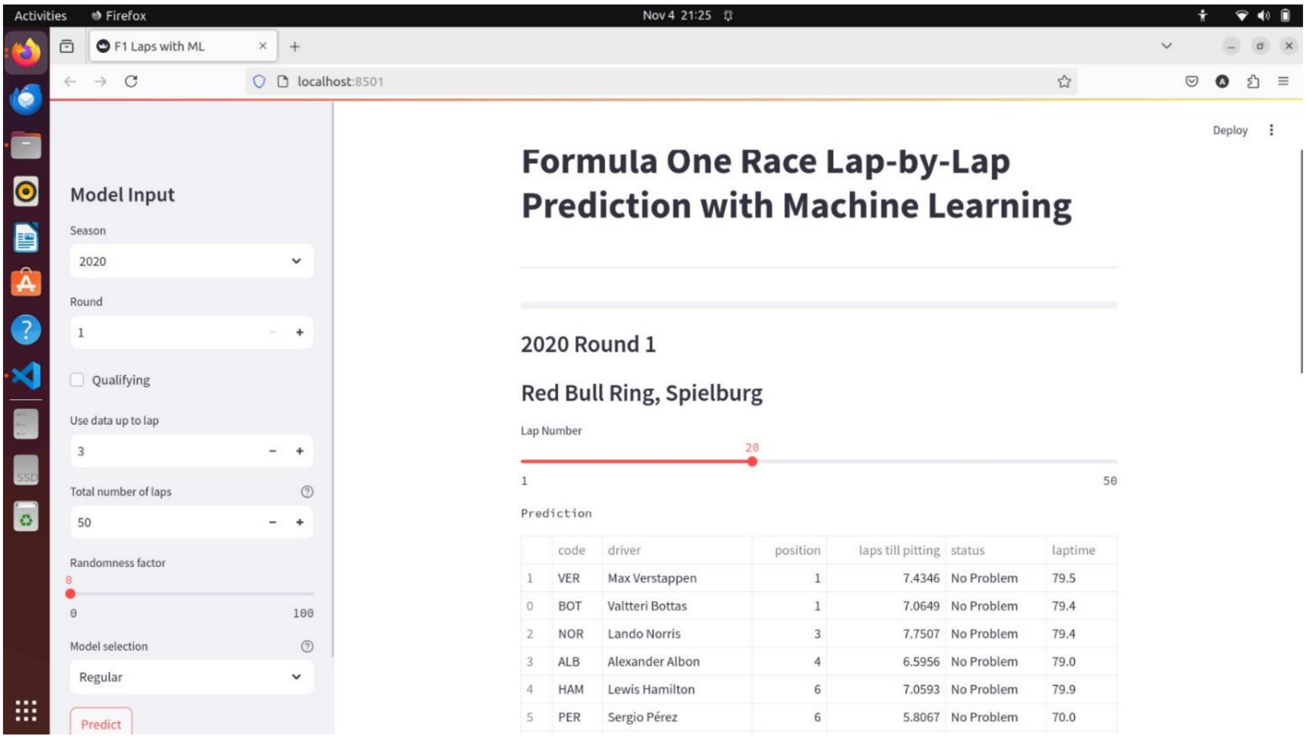


Fig 4.1 Model input Home page

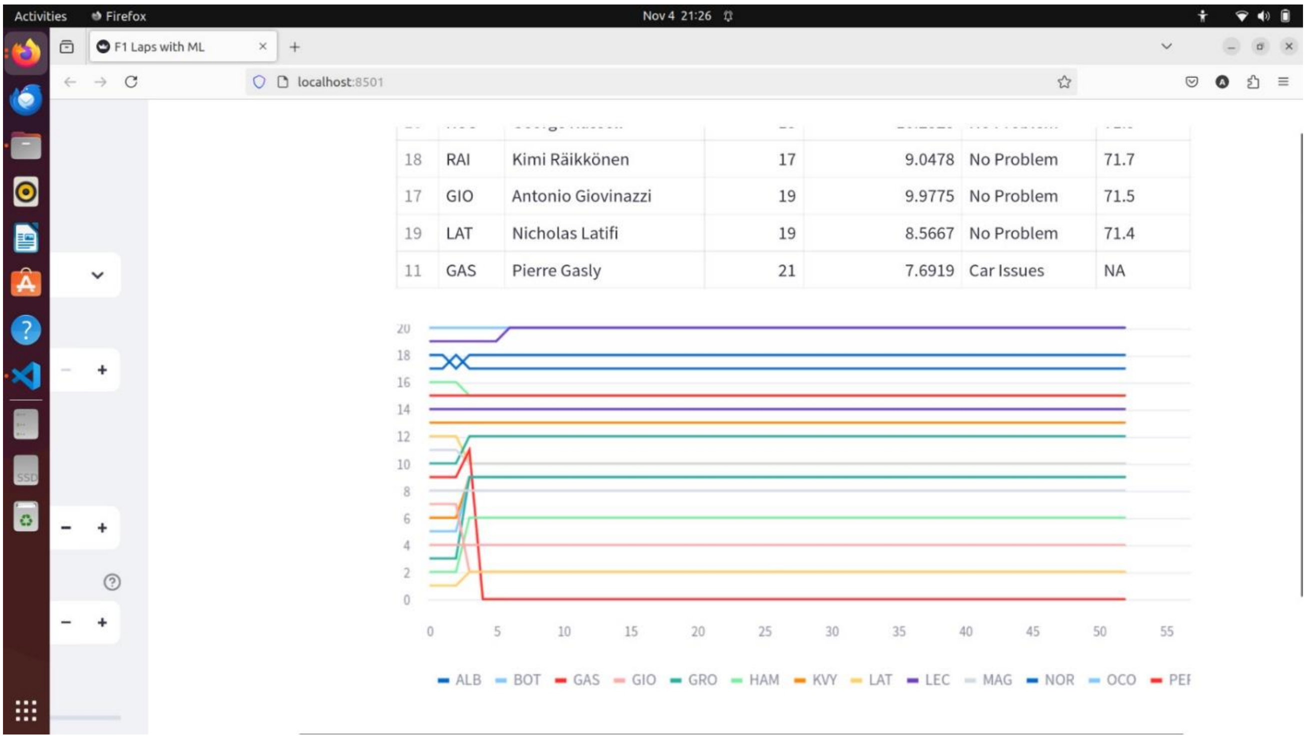


Fig 4.2 Prediction Chart from Lap1 to Lap 50

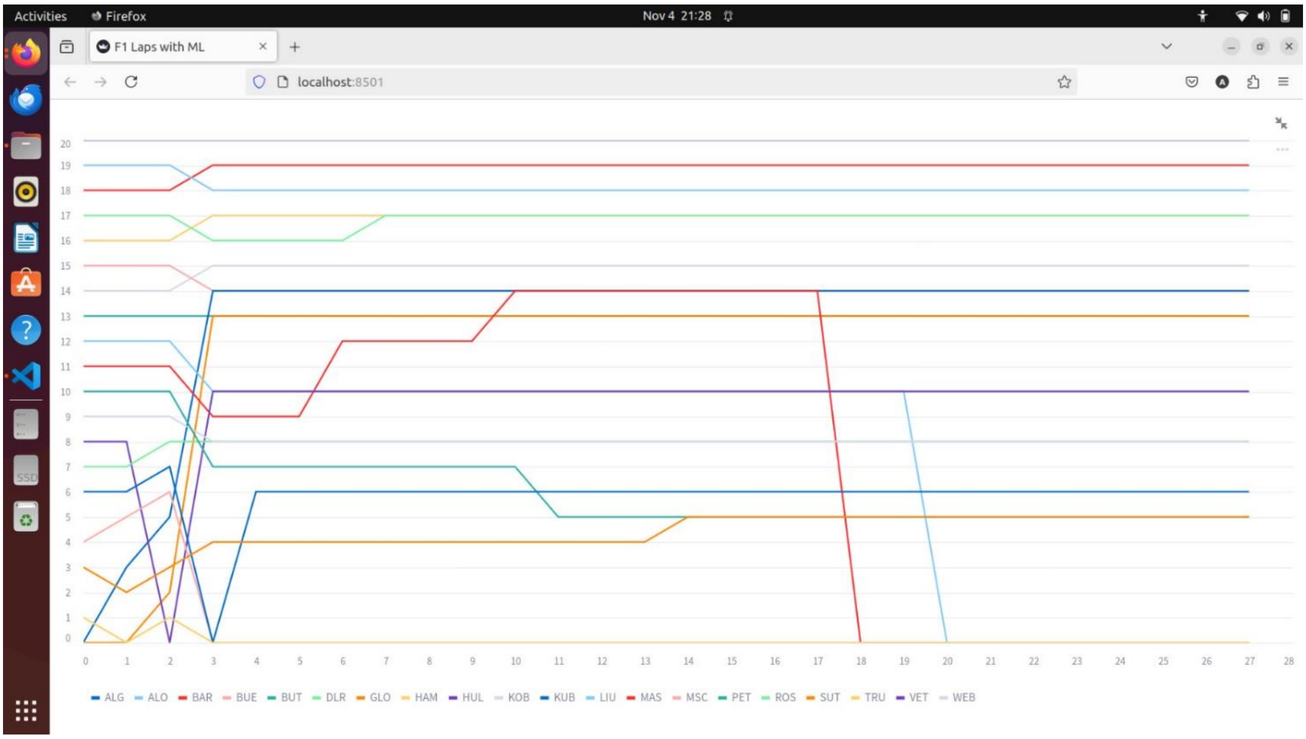
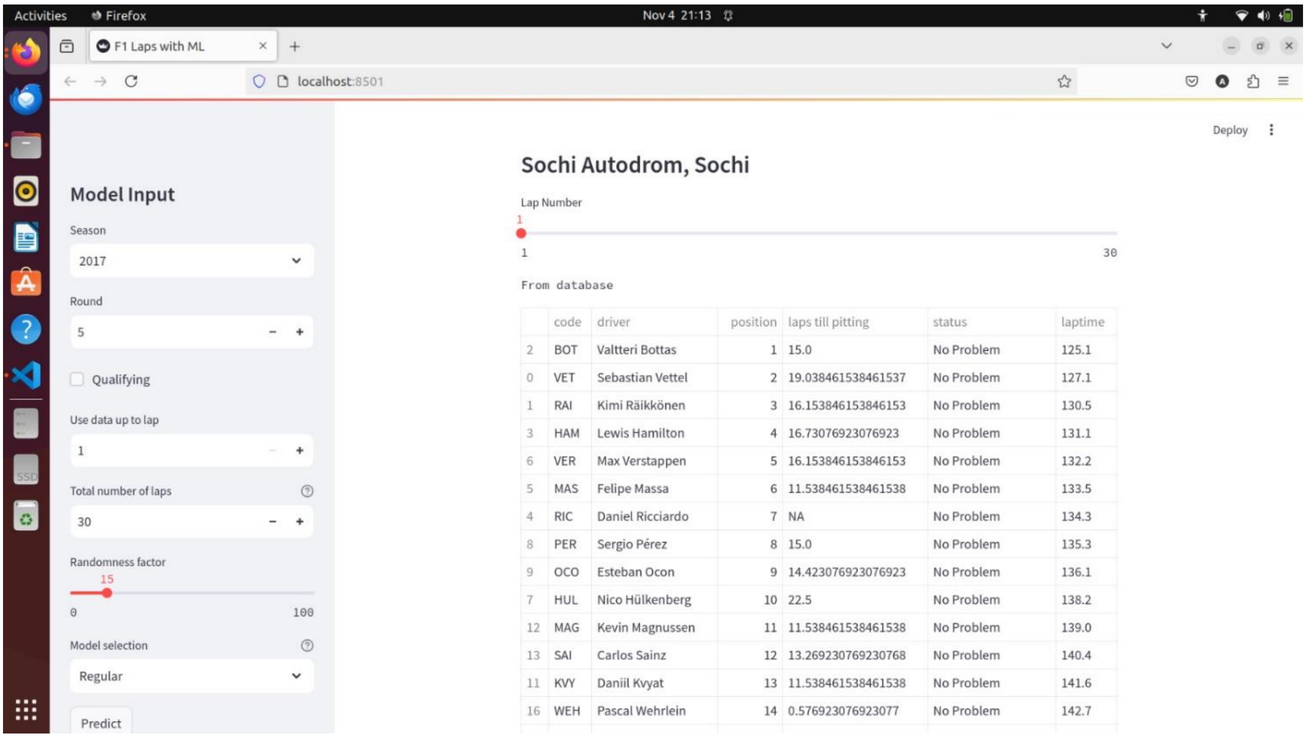


Fig 4.3 Charts indicating Driver position Change from the start to end



	code	driver	position	laps till pitting	status	laptime
2	BOT	Valtteri Bottas	1	15.0	No Problem	125.1
0	VET	Sebastian Vettel	2	19.038461538461537	No Problem	127.1
1	RAI	Kimi Räikkönen	3	16.153846153846153	No Problem	130.5
3	HAM	Lewis Hamilton	4	16.73076923076923	No Problem	131.1
6	VER	Max Verstappen	5	16.153846153846153	No Problem	132.2
5	MAS	Felipe Massa	6	11.538461538461538	No Problem	133.5
4	RIC	Daniel Ricciardo	7	NA	No Problem	134.3
8	PER	Sergio Pérez	8	15.0	No Problem	135.3
9	OCO	Esteban Ocon	9	14.423076923076923	No Problem	136.1
7	HUL	Nico Hülkenberg	10	22.5	No Problem	138.2
12	MAG	Kevin Magnussen	11	11.538461538461538	No Problem	139.0
13	SAI	Carlos Sainz	12	13.269230769230768	No Problem	140.4
11	KVY	Daniil Kvyat	13	11.538461538461538	No Problem	141.6
16	WEH	Pascal Wehrlein	14	0.576923076923077	No Problem	142.7

Fig 4.4 Data prediction for laps till pit stop

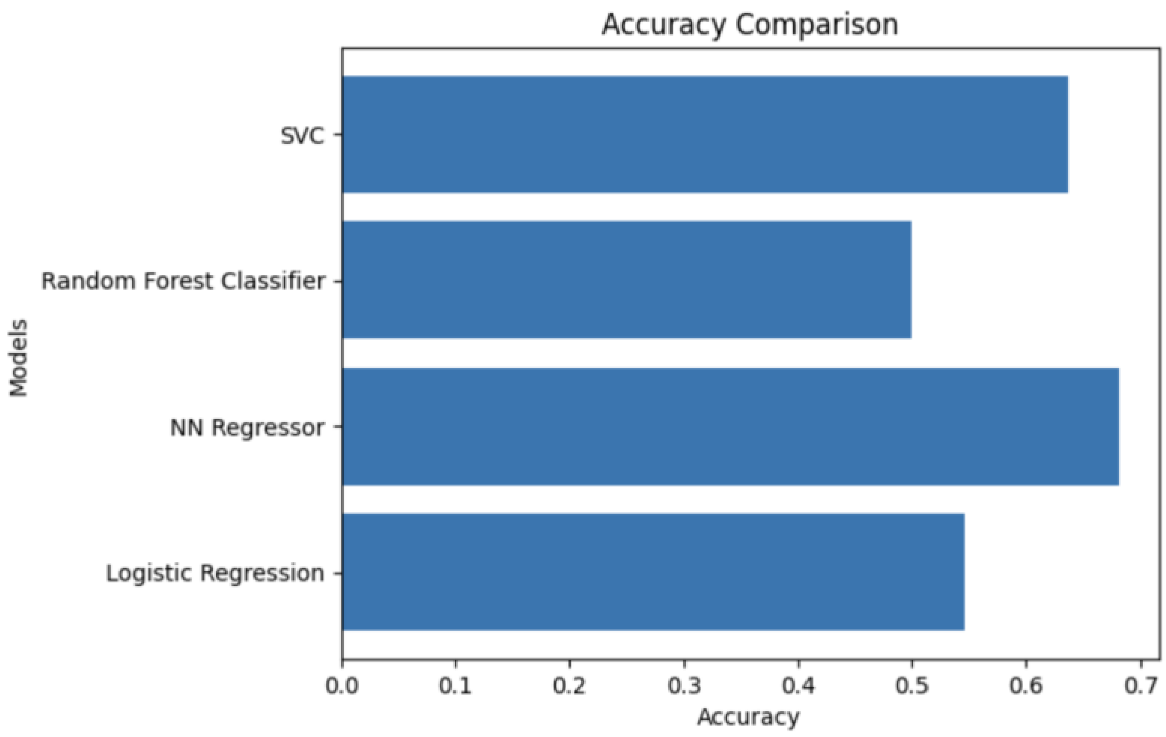


Fig 4.5 Accuracy comparision between ML models

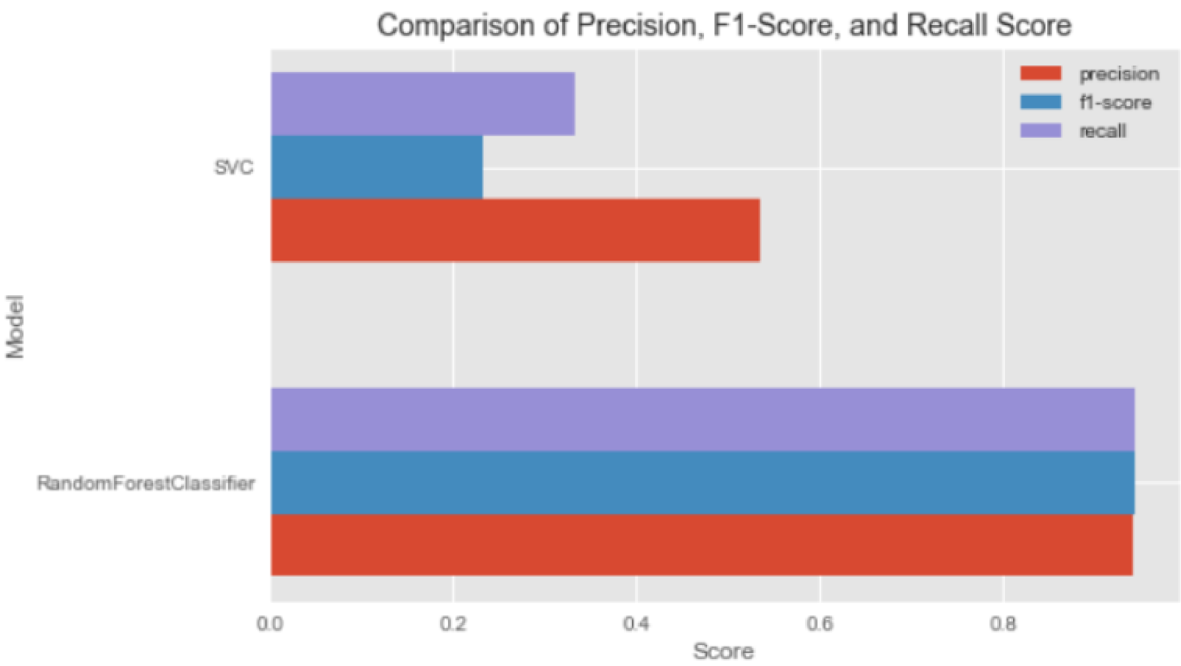
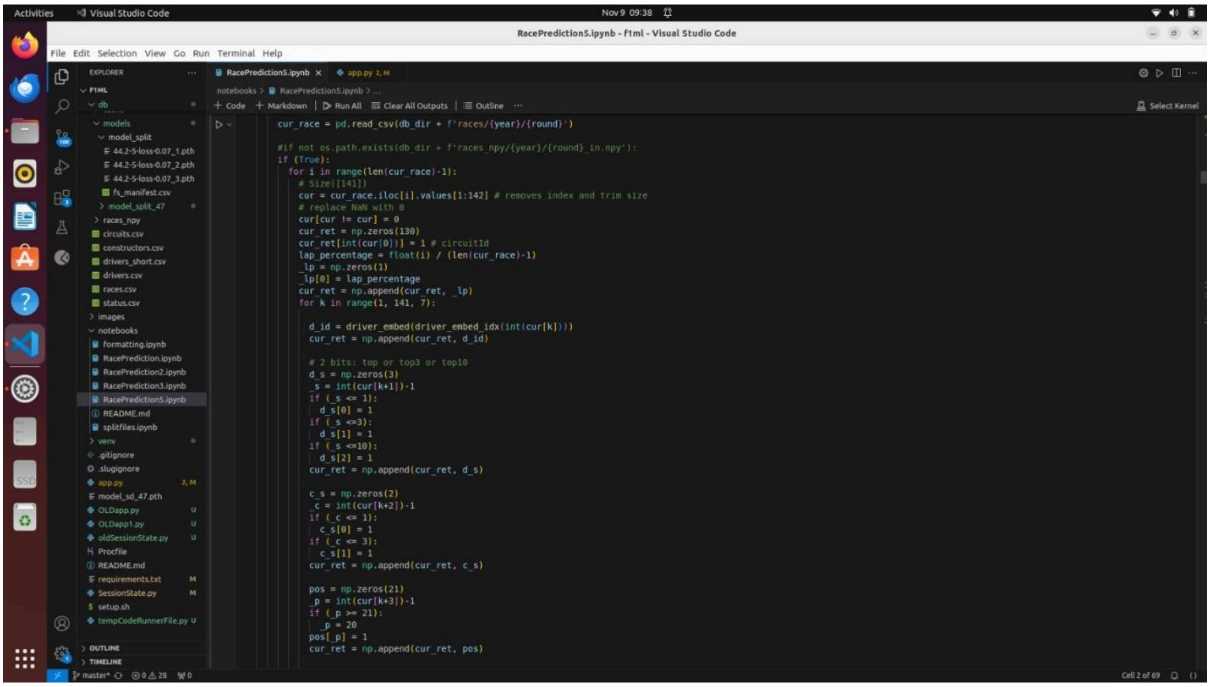


Fig 4.6 Comparison between svc and Random Forest classifier

4.4 Working Code:



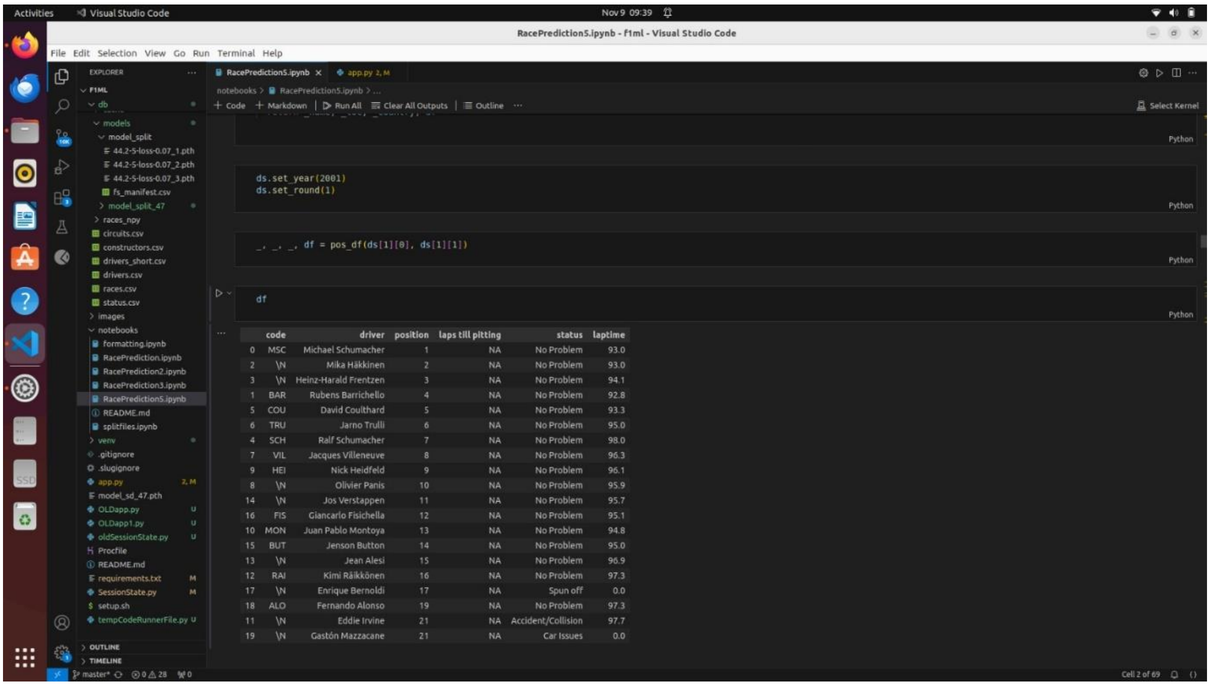


Fig 4.7 Working Code of the Model

CHAPTER 5

CONCLUSION AND FUTURE ENHANCEMENT

This project successfully developed a machine learning-based approach to predict Formula 1 race outcomes, achieving high accuracy rates, with the Support Vector Classifier (SVC) and Random Forest models performing exceptionally well. By leveraging a comprehensive dataset that included variables such as qualifying positions, driver and constructor statistics, track details, weather conditions, and home advantage, the models captured complex dependencies and interactions within the race environment. These machine learning models were designed to handle multivariate data, making them well-suited for the diverse and dynamic factors influencing F1 race results.

Data preprocessing techniques, such as feature scaling, encoding, and sequential formatting, were instrumental in optimizing the models' performance. By ensuring consistency in feature representation and capturing historical race trends, our approach effectively modeled the intricate relationships between variables over multiple seasons.

While the models demonstrated strong performance, several avenues for future enhancement remain. First, incorporating additional real-time data sources, such as live telemetry or in-race incidents, could enhance prediction accuracy and adaptability. Exploring advanced models like ensemble methods or neural network-based approaches, such as Recurrent Neural Networks (RNN) or Transformer models, could further improve the model’s ability to capture sequential dependencies and complex relationships within race data. Furthermore, adopting advanced hyperparameter tuning methods, like Bayesian optimization, could refine model parameters and yield even higher predictive accuracy. Finally, the integration of dynamic, real-time race data would allow for continuous updates, making the prediction models adaptable to the latest conditions and race developments.

These enhancements will elevate the predictive power and flexibility of our models, making them invaluable assets for Formula 1 analytics, decision-making, and broader applications in motorsports

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