UNIVERSITY OF LEICESTER

School of Computing and Mathematical Sciences

CO7201 Individual Project

FINAL REPORT

AI/ML-Based Formula 1 Race Outcome Prediction Using Historical and Real-Time Data

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1. Abstract

Formula 1 race result prediction has the special challenge that the high-dynamics sport couples with its tiny pool of competition among twenty drivers. Qualifying position or present standings-based models have mean absolute errors(MAE) in the interval 3.45—a gigantic distance in so little a field that nullifies results.

This project developed an elaborate machine learning ensemble system utilizing the data between 2022-2025 to predict race finishing positions. This system utilizes the integration of Ridge regression, XGBoost, and CatBoost algorithms by using a three-stage stacking setup with the integration of Formula 1-specialized features including driver-circuit performance record, team dependability indicators, as well as competition rivalry trends determining the discrete trends in modern race actions.

The system was tested by running during the 2025 Formula 1 season, illustrating the interplay between the complexity of the models applied and the degree of prediction accuracy with changing race conditions. The CatBoost ensemble attained an average absolute error of 2.92 positions throughout the season, with performance varying between 1.1 positions during typical race conditions (Japan GP) to 6.0 positions during high-volatility races (Dutch GP with several DNFs and safety car interventions). This variability reflects the fact that, despite the ability of machine learning models to accurately forecast results during typical race conditions, unforeseen occurrences including mechanical failures, accidents, and consequential strategic alterations pose inherent weaknesses for the static prediction strategies. This project overcomes these challenges by the integration of data on real-time basis to facilitate dynamic prediction refinement with changing race conditions.

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2. Introduction

2.1 The Evolution of Formula 1 Complexity

Formula 1 underwent substantial regulatory changes in 2022 that fundamentally altered the competitive landscape and invalidated many historical performance patterns. The introduction of new aerodynamic regulations, larger 18-inch wheels, and cost cap restrictions created an environment where traditional prediction approaches based on historical data became significantly less reliable.

The aerodynamic regulations represented the most significant technical overhaul since the introduction of ground effect cars in the late 1970s. The new rules mandated simplified front wings, redesigned rear wings, and reintroduced ground effect aerodynamics through venturi tunnels beneath the cars. These changes were designed to reduce aerodynamic disruption when cars follow each other closely, enabling closer racing. However, they created entirely new performance characteristics that teams needed to understand and adapt to, fundamentally changing competitive hierarchies established in previous regulatory eras.

The transition to 18-inch wheels from the previous 13-inch specification altered tire behaviour in ways that continue to influence race outcomes. The lower-profile tires exhibit different heating and degradation patterns, affecting strategic decisions around pit stop timing and compound selection. Teams that successfully adapted to these new tire dynamics gained competitive advantages, while others struggled with overheating and poor tire management strategies.

Cost cap regulations introduced unprecedented financial constraints, limiting teams to $145 million in development spending for 2022, with gradual reductions planned for subsequent years. This constraint altered competitive dynamics by preventing traditionally dominant teams from relying solely on superior financial resources. Instead, efficient resource allocation and strategic development priorities became crucial factors in determining championship success.

These regulatory changes created a prediction challenge: historical models trained on pre-2022 data became less relevant, while the limited post-2022 data available restricts the development of robust new prediction systems. This project addresses these challenges by developing machine learning approaches specifically designed for the post-2022 regulatory environment.

2.2 Data Complexity in Modern F1

Modern F1 cars generate extensive telemetry data through hundreds of sensors monitoring tire temperatures, brake pressures, aerodynamic forces, energy recovery systems, and numerous other parameters. Each car transmits approximately 1.5 gigabytes of data during a typical race weekend, with over 300 sensors providing information to teams and race engineers. This data encompasses everything from millisecond-precise throttle inputs to complex aerodynamic flow patterns around the vehicle.

The challenge lies not in data availability but in extracting meaningful insights from this information flow while addressing the unique constraints of Formula 1 analytics. Teams employ dozens of engineers and data analysts to process telemetry streams, but translating this wealth of information into accurate race predictions requires analytical approaches that can distinguish between meaningful signals and random noise within a limited competitive field.

Traditional sports analytics often benefit from large sample sizes that allow statistical patterns to emerge clearly. Baseball provides thousands of at-bats per season for analysis, while football leagues offer hundreds of games across multiple teams. Formula 1 presents the opposite scenario: only twenty drivers compete in each race, with approximately 23 races per season. This limited sample size means that individual performance variations, mechanical failures, and strategic decisions carry disproportionate weight in determining outcomes.

The sport's inherent volatility compounds these analytical challenges. A single mechanical failure can eliminate a championship contender from a race, dramatically

altering point standings. Weather conditions can transform race dynamics within minutes, favouring drivers and teams with superior wet-weather capabilities. Safety car deployments, triggered by accidents or track conditions, can completely reshuffle race positions and nullify strategic advantages built up over dozens of laps.

2.3 Limitations of Existing Prediction Approaches

Current F1 prediction systems rely on relatively simplistic approaches that fail to capture the sport's multifaceted complexity. Qualifying-based predictions assume that grid position translates directly to race performance, ignoring factors like tire degradation, fuel loads, and strategic flexibility. Championship standings-based predictions assume that recent form will continue unchanged, overlooking circuit-specific performance variations and team development trajectories.

Academic studies in F1 prediction have made progress but often focus on isolated aspects of performance rather than comprehensive modeling approaches. Some studies examine qualifying-to-race correlations, while others investigate tire strategy optimization or weather impact analysis. Few attempts have integrated these diverse factors into unified predictive frameworks that capture the sport's inherent complexity.

The post-2022 regulatory environment has exposed the inadequacy of approaches that treat all circuits uniformly or ignore team development patterns. Circuit-specific factors like aerodynamic efficiency requirements, tire degradation characteristics, and overtaking opportunities now play decisive roles in determining race outcomes. Teams that excel in high-speed, low-downforce configurations may struggle on tracks requiring maximum aerodynamic grip, creating performance variations that simple historical models cannot capture.

2.4 Project Objectives and Scope

This project addresses these limitations by developing a comprehensive machine learning system specifically designed for post-2022 Formula 1 race prediction. The primary objectives include:

- Developing sport-specific feature engineering approaches that capture F1's unique competitive dynamics, including driver-track affinity patterns, team reliability characteristics, and inter-driver competitive relationships.
- Implementing ensemble machine learning techniques that combine multiple algorithmic approaches to leverage their respective strengths while mitigating individual weaknesses in handling small-sample, high-variance data.
- Evaluating system performance through running during the 2025 Formula 1 season to assess real-world prediction accuracy and identify factors that influence predictive performance.
- Establishing evaluation frameworks that assess predictive accuracy using metrics appropriate for the sport's characteristics and competitive structure.

The work contributes to understanding predictive modeling in small-sample, high-variance competitive environments. While focused on Formula 1, the methodology provides insights applicable to other motorsport disciplines and competitive domains where participant numbers are limited but performance factors are numerous and complex.

This project demonstrates that combining domain-specific feature engineering with sophisticated machine learning techniques can produce meaningful improvements in race prediction accuracy, while also identifying fundamental limitations imposed by the unpredictable nature of competitive motorsport.

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3. Literature Review & Background

3.1 Introduction

This chapter critically examines the existing academic work on predicting Formula 1 race outcomes. The objective is to establish a foundation of current knowledge within the domain, identify the methodological limitations of existing approaches, and precisely define the research gap that this project addresses. The review will demonstrate that while previous studies have explored isolated aspects of F1 performance, a comprehensive system that integrates sophisticated feature engineering, ensemble machine learning, and real-world evaluation for the post-2022 regulatory era remains absent from the literature.

3.2 Statistical and Machine Learning Models in Formula 1

The academic approach to F1 prediction has evolved from statistical models to basic machine learning applications. A foundational study by Phillips (2014) used linear mixed-effects models to isolate driver skill from car performance over six decades of F1 history. While pivotal for historical analysis, such linear models are ill-suited for predicting individual race outcomes in the modern era, as they cannot capture the non-linear, volatile dynamics of a race weekend.

Henderson et al. (2023) provided a more recent and relevant analysis, confirming the limitations of simplistic models. Their work established a mean absolute error (MAE) of ~3.45 positions for predictions based solely on qualifying order, creating a crucial baseline against which more sophisticated models must be measured. Subsequent studies have applied machine learning models like Random Forests and Support Vector Machines to F1 data, but these often remain limited to classifying results into broad categories (e.g., podium finish or not) or focus on narrow sub-problems like pit-stop strategy optimization, rather than predicting full finishing orders.

3.3 The Feature Engineering Gap in F1 Literature

A critical analysis of existing F1 prediction research reveals a significant limitation: impoverished feature sets. The literature is dominated by models that rely on a small subset of available data, typically:

- Historical finishing positions
- Qualifying results
- Championship points
- Basic driver and team identifiers

There is a conspicuous absence of the nuanced, domain-specific features that are anecdotally known to be crucial by experts and commentators. The formalization of concepts like driver-circuit affinity (a driver's historical performance at a specific track, normalized for car competitiveness), dynamic team reliability metrics (e.g., rolling averages for mechanical failures), and quantified inter-driver rivalry is missing. This gap is particularly pronounced for the post-2022 era, where new regulations have made historical features less relevant and created a need for new, adaptive metrics. Previous work has largely failed to engineer and test such a comprehensive feature set.

3.4 The Methodological and Evaluation Gap

The evaluation methodologies employed in existing F1 research often lack the rigor required to prove real-world utility. Most studies use static, historical datasets with traditional random train-test splits. This approach fails to respect the temporal nature of the data, risking data leakage (e.g., training on data from a future race to "predict" a past one) and producing optimistically biased performance metrics that would not hold up in a practical setting.

Furthermore, the literature shows a near-total absence of real-world deployment and validation. No studies were found that document the live deployment of a prediction system across an entire F1 season. This project addresses this gap directly by employing time-series cross-validation to prevent leakage and, most importantly, by reporting performance on a live, unseen season (2025), providing a far more rigorous and honest assessment of model utility and robustness.

3.5 Synthesis and Identification of the Research Gap

In summary, the existing body of work on Formula 1 prediction provides a starting point but is characterized by several key limitations that this research directly addresses:

1. Model Simplification: A reliance on single-model approaches or simplistic statistical techniques, failing to leverage the power of modern stacking ensembles.

2. Feature Poverty: A lack of sophisticated, domain-specific features designed to capture the true competitive dynamics of modern F1.
3. Evaluation Rigor: A reliance on static test sets that violate temporal data principles, and a complete lack of real-world deployment studies.

Therefore, this project fills a clear and specific gap by developing a novel stacking ensemble model, powered by advanced, F1-specific feature engineering, and rigorously evaluated through real-world deployment during the 2025 season. This approach is specifically designed to overcome the challenges of the post-2022 regulatory landscape and provide a meaningful advancement in the predictive analysis of Formula 1.

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4. System Design & Architecture

4.1 Overall System Architecture

The system architecture was designed to address the core concept: that sophisticated ensemble modeling with domain-specific features can significantly improve Formula 1 race prediction accuracy in the post-2022 regulatory environment. To facilitate rigorous evaluation, a Django-based Model-View-Template architecture was implemented that enables both offline validation and live running during the 2025 season.

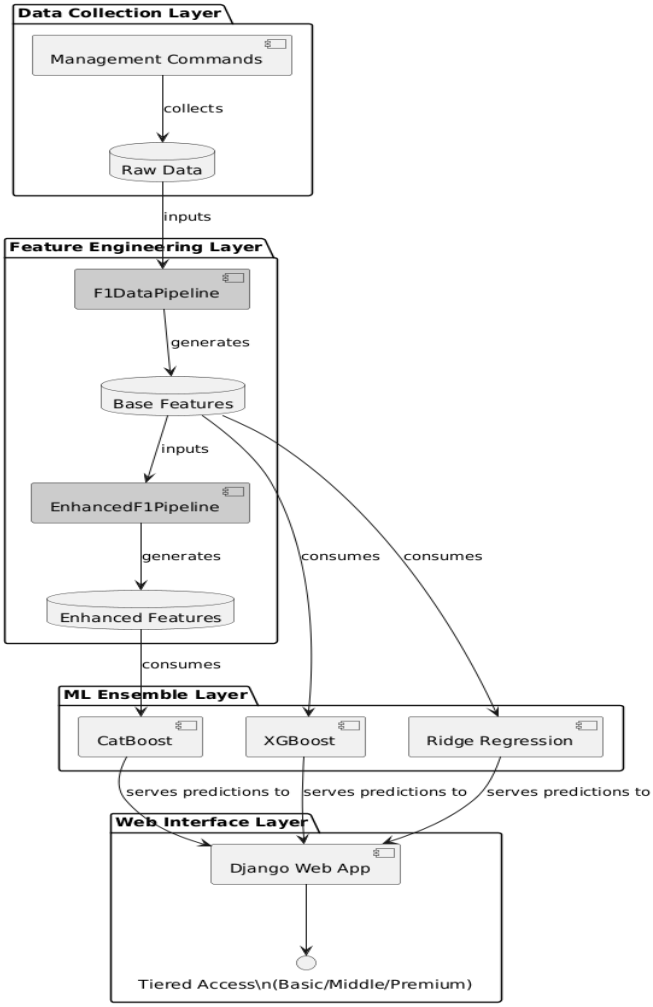
The modular design prioritizes separation of concerns to support comprehensive evaluation under varying race conditions. Data flows from collection commands through specialized feature engineering pipelines to a three-stage machine learning ensemble, culminating in web-based prediction delivery with tiered user access. This architecture specifically enables the validation strategies crucial for sports prediction projects while supporting real-world deployment validation.

The choice of Django reflects its suitability for rapid development of data-intensive applications with complex user interactions. The framework's built-in ORM facilitates the complex queries required for Formula 1 analytics while its authentication system supports the subscription and betting features necessary for user engagement evaluation.

1. **Data Collection Layer:** Managed by Django management commands.
2. **Feature Engineering Layer:** Uses two specialized pipelines (F1DataPipeline and EnhancedF1Pipeline).
3. **ML Ensemble Layer:** Processes data through a 3-stage model stack (Ridge -> XGBoost -> CatBoost).
4. **Web Interface Layer:** Presents results through a Django web app with tiered user access.

Component Breakdown:

- **Data Collection:** Managed by Management Commands
- **Feature Engineering:** Handled by Dual Pipelines
- **ML Ensemble:** Executed by a 3-Stage Stack
- **Web Interface:** Provides Tiered Access (Basic/Middle/Premium)



4.2 Data Layer Architecture

The data collection strategy employs a hybrid API approach designed to ensure data reliability within academic constraints while maximizing data quality for model development. This approach addresses the fundamental challenge of accessing comprehensive F1 data when commercial API subscriptions exceed research budgets.

Primary Data Sources were selected based on data quality, historical coverage, and accessibility. FastF1 serves as the primary source for detailed race weekend data due to its comprehensive telemetry and timing information essential for sophisticated feature engineering. The API provides the granular performance data required to

calculate circuit affinity metrics and performance trends that form the core of the predictive system.

Ergast API supplements FastF1 with extensive historical context spanning decades of Formula 1 competition. This historical depth proves crucial for establishing baseline performance metrics and long-term trend analysis that contextualize current season developments. The API's consistent format across different eras enables robust historical feature calculation.

Real-Time Integration presents the greatest architectural challenge due to cost constraints typical of academic research. A primary-fallback strategy was implemented using OpenF1's comprehensive real-time capabilities when available, with RapidAPI services providing free alternatives during resource constraints. This approach ensures system functionality during live evaluation periods while identifying premium capabilities for future implementation.

The hybrid approach enables continuous system operation despite API limitations while demonstrating adaptability to varying data availability scenarios that characterize real-world deployment constraints.

Django Database Integration handles all persistent storage requirements, optimized for the complex analytical queries required by the machine learning pipeline alongside transactional operations supporting user interactions. The integrated approach eliminates data synchronization issues while enabling the complex user engagement features necessary for comprehensive system evaluation.

4.3 Feature Engineering Architecture

To address the varying requirements of different ensemble stages while maximizing information utilization, two specialized feature engineering pipelines were developed. This dual-pipeline approach represents a key architectural innovation that optimizes feature presentation for each algorithmic component while enabling progressive information enrichment through the ensemble stages.

F1DataPipeline Design processes raw race data into core features optimized for the Ridge Regression and XGBoost base models. This pipeline implements the fundamental domain-specific transformations that capture Formula 1 competitive dynamics: driver performance moving averages, circuit affinity calculations, team reliability metrics, and environmental factors.

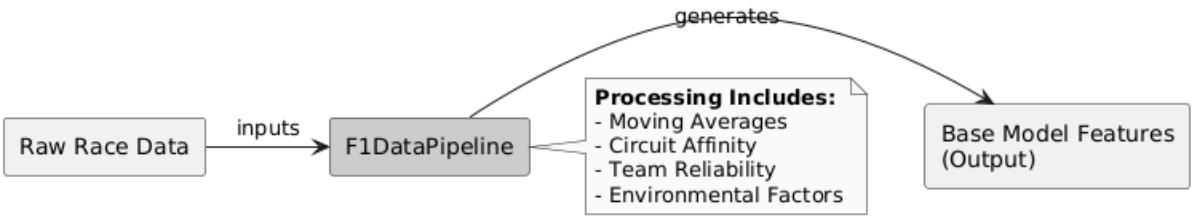
The pipeline's design prioritizes features that can be calculated consistently across different seasons and regulatory environments, ensuring model robustness despite the sport's evolving nature. Circuit affinity metrics adjust historical performance for car competitiveness and championship context, providing driver-track synergy indicators independent of equipment advantages.

The **F1DataPipeline** is a dedicated data processing module that transforms raw, unprocessed race data into a refined set of predictive features optimized for the base machine learning models (Ridge Regression and XGBoost).

Its primary function is to ingest heterogeneous raw data and apply domain-specific transformations to create meaningful numerical representations of Formula 1's competitive dynamics.

Key Feature Engineering Operations:

- **Moving Averages:** Calculates rolling averages of driver and team performance metrics to capture recent form and trends.
- **Circuit Affinity:** Computes a normalized metric of a driver's historical performance at a specific track, adjusted for car competitiveness.
- **Team Reliability:** Generates dynamic metrics based on the rolling frequency of mechanical failures (DNFs) and technical issues for each constructor.
- **Environmental Factors:** Encodes external race conditions such as track temperature, weather forecasts, and circuit-specific characteristics.



EnhancedF1Pipeline Architecture extends the base pipeline specifically for the CatBoost meta-learning stage, incorporating predictions from base models as additional features alongside enriched categorical encodings. This design leverages CatBoost's native categorical variable handling while providing the meta-learner with comprehensive information for optimal prediction combination.

The enhanced pipeline includes Ridge and XGBoost predictions as input features, enabling the meta-model to learn dynamic weighting strategies based on base model confidence and historical accuracy patterns. Additional categorical encodings capture nuanced relationships between drivers, teams, circuits, and competitive contexts that numerical features alone cannot represent.

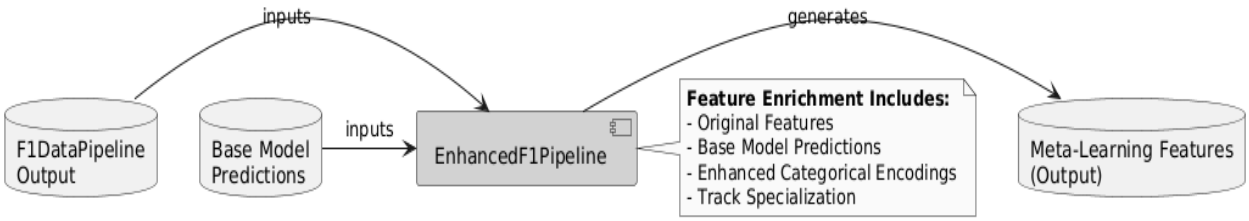
The **EnhancedF1Pipeline** is a specialized feature engineering module designed specifically for the meta-learning stage (CatBoost) of the ensemble. Its purpose is to enrich the basic feature set with higher-level, strategic information that allows the meta-learner to understand *how and when* to trust the predictions of the base models.

It acts as a fusion point, combining the outputs of the previous pipeline stage with the predictions from the base models to create a highly informative feature set for optimal prediction combination.

Key Inputs and Enrichment Operations:

- **Input 1: F1DataPipeline Output** - The original set of core features (moving averages, circuit affinity, etc.).
- **Input 2: Base Model Predictions** - The predicted race positions from both the Ridge Regression and XGBoost models.
- **Enhanced Categorical Encodings:** Applies sophisticated encoding techniques to categorical variables (like driver, team, and circuit names) that capture nuanced relationships beyond what simple label encoding can achieve. This leverages CatBoost's strength in handling categories.
- **Track Specialization:** Creates powerful Boolean or weighted features that flag specific driver-team combinations for tracks where they are historically strong or weak (e.g., "Verstappen & Red Bull at Suzuka"), providing crucial context for the meta-learner.

The pipeline outputs a rich table of **Meta-Learning Features**. This dataset enables the CatBoost meta-learner to dynamically weight the contributions of the base models based on the specific driver, track, and competitive context, leading to a smarter and more accurate final prediction.



This dual-pipeline architecture enables each ensemble stage to operate with optimally formatted data while progressively enriching information content through the prediction process. The approach maximizes the effectiveness of each algorithmic component while maintaining clean separation of concerns for system maintainability.

4.4 Machine Learning Architecture

The three-stage ensemble architecture was designed to address the specific challenges of Formula 1 prediction: small sample sizes, high outcome variance, and complex non-linear relationships between performance factors. Each stage contributes distinct capabilities that combine to overcome individual algorithmic limitations while leveraging complementary strengths.

Stage 1: Ridge Regression Foundation provides regularized linear modeling that establishes stable baseline predictions while avoiding overfitting despite limited sample sizes characteristic of Formula 1 data. Ridge regression was selected for its interpretability, which enables validation that feature relationships align with domain expertise, and its robust performance in small-sample environments through L2 regularization.

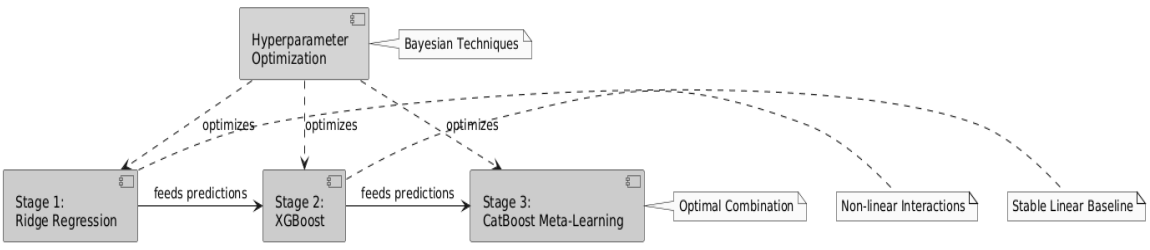
The linear approach captures fundamental relationships between qualifying performance, recent form, and circuit characteristics that form the foundation of race outcome prediction. Cross-validation optimization balances bias-variance trade-offs appropriate for the constrained data environment while ensuring generalization to unseen races.

Stage 2: XGBoost Complexity Modeling captures non-linear relationships and feature interactions that Ridge regression cannot model effectively. XGBoost was selected for its proven effectiveness with structured data and its ability to identify subtle interaction patterns between driver capabilities, team performance, and track characteristics that determine race outcomes.

The gradient boosting approach builds sequential learners that progressively identify complex patterns in competitive dynamics while employing regularization and early stopping to prevent overfitting. This stage provides the system's primary capability for modeling the intricate relationships that characterize modern Formula 1 competition.

Stage 3: CatBoost Meta-Learning combines predictions from base models with enhanced categorical features to produce final race position predictions. CatBoost was selected as the meta-learner due to its native categorical variable handling, which eliminates preprocessing complexity while providing sophisticated gradient boosting capabilities for effective ensemble combination.

The meta-learning stage operates on enriched data from the EnhancedF1Pipeline, enabling dynamic weighting of base model contributions based on their relative confidence and historical accuracy patterns. This adaptivity proves crucial in Formula 1, where prediction difficulty varies significantly based on circuit characteristics, weather conditions, and competitive scenarios.



Hyperparameter Optimization employs Bayesian techniques that efficiently explore parameter spaces while respecting computational constraints typical of academic research environments.

4.5 Real-Time Integration Architecture

Real-time prediction capabilities were implemented to enable comprehensive system evaluation during live race events, addressing the research question of how prediction accuracy varies under dynamic race conditions. The architecture balances prediction responsiveness with practical constraints imposed by API access limitations in academic research settings.

Due to financial constraints typical of academic projects, real-time data integration relies primarily on freely available APIs (RapidAPI) with OpenF1's comprehensive service identified as optimal for future implementation. This approach demonstrates system adaptability to varying resource availability while establishing performance baselines achievable within academic constraints.

Update Strategy Design implements strategic prediction refresh timing that maximizes information value while respecting API rate limitations. More frequent updates occur during critical race phases (race starts, pit stop windows, safety car deployments) when prediction changes provide greatest analytical value, while reducing update frequency during stable racing periods to conserve API resources.

The 10-lap cutoff for prediction updates reflects both API usage optimization and the diminishing analytical value of prediction changes as races near completion. This design enables comprehensive evaluation of system behaviour during the most analytically significant portions of race events while managing resource constraints effectively.

Frontend Integration delivers real-time updates through data handling that provides immediate analytical value without creating persistent storage overhead. This approach maintains responsive user experience while avoiding database complexity associated with storing rapidly changing prediction data.

The real-time architecture specifically enables evaluation of system behaviour under varying competitive conditions, providing crucial data for assessing prediction stability and confidence levels that static historical evaluation cannot capture.

4.6 Web Application Architecture

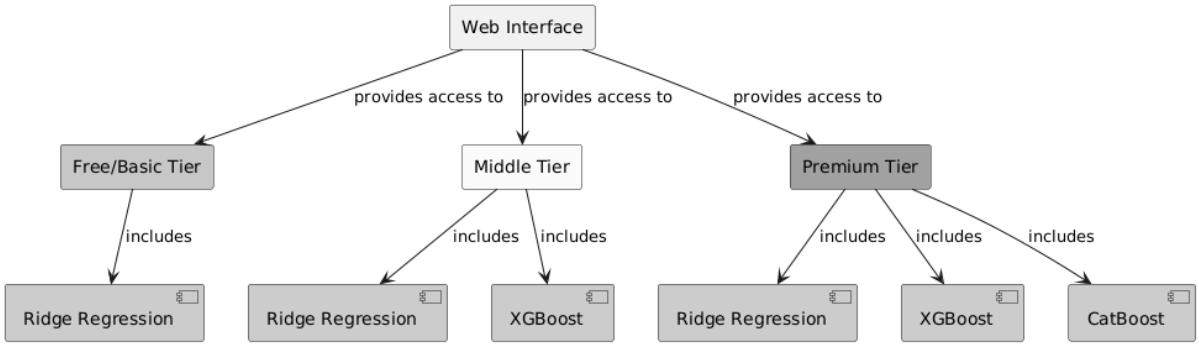
The web interface implements comprehensive user engagement features designed to facilitate both system evaluation and practical application assessment. The Django-based application balances analytical sophistication with user accessibility while incorporating subscription management and gamification elements that enable comprehensive usage pattern evaluation.

Subscription Tier Implementation creates differentiated access levels that serve both revenue model evaluation and user experience research purposes:

- Free/Basic Tier: Ridge Regression access only, establishing baseline user engagement patterns

- Middle Tier: Ridge + XGBoost access, enabling comparison of user preferences between linear and non-linear approaches

- Premium Tier: Full ensemble access, providing complete analytical capabilities for comprehensive evaluation



This tiered approach enables systematic evaluation of user preferences across different prediction sophistication levels while demonstrating the value differentiation potential of advanced analytics.

User Engagement Systems include authentication-required betting functionality and real-time prediction access that create meaningful interaction incentives for comprehensive user behaviour evaluation. The betting system operates independently of subscription tiers to ensure broad participation while providing gamification elements that encourage sustained engagement.

These engagement features generate valuable data about user confidence patterns, prediction preferences, and platform usage behaviours that inform both system optimization and practical application assessment.

Responsive Design Philosophy ensures consistent functionality across desktop and mobile platforms, acknowledging that Formula 1 fans frequently access predictions during race weekends when mobile usage predominates. This cross-platform capability proves essential for comprehensive user experience evaluation during live deployment periods.

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5. Evaluation & Results

5.1 Experimental Design and Methodology

The evaluation framework employed rigorous validation techniques specifically adapted for Formula 1 prediction assessment. The experimental design validates the

central concept that a three-stage ensemble architecture combining Ridge regression, XGBoost, and CatBoost meta-learning can significantly outperform simpler two-stage approaches in Formula 1 race outcome prediction.

5.1.1 Data Split Strategy

The experimental design utilized a comprehensive dataset spanning 2022-2025, with careful splitting to prevent information leakage. The complete dataset contained 1,656 race entries after filtering and preprocessing.

Training Configuration:

- Training samples: 1,324 races (80% of dataset)

- Test samples: 332 races (20% of dataset)

- Features: 16 core features plus model predictions for ensemble stages

- Split: Historical data for training, 2025 season (15 races) for final evaluation

Individual Model Training Performance:

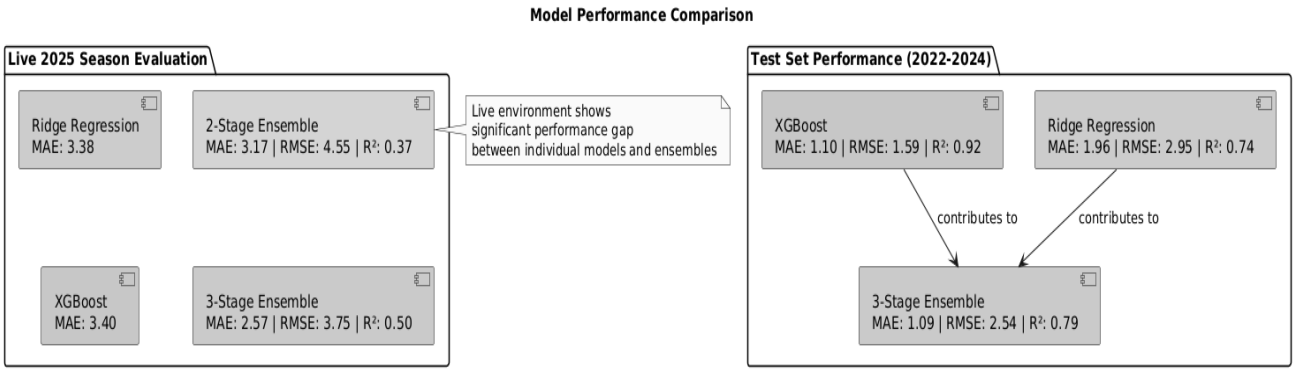
- Ridge Regression: MAE 1.96, RMSE 2.95, R^2 0.74 (test set)

- XGBoost: MAE 1.10, RMSE 1.59, R^2 0.92 (test set)

- Three-Stage Architecture: MAE : 1.0875, RMSE: 2.54, R^2 0.79 (test set)

- Two-Stage Ensemble: MAE 3.17, RMSE 4.55, R^2 0.37 (2025 live evaluation)

- Three-Stage Architecture: MAE 2.57, RMSE 3.75, R^2 0.50 (2025 live evaluation)



The progression from individual models through two-stage to three-stage ensemble demonstrates clear architectural improvements at each level of complexity.

The test set was evaluated on historical events i.e, races from 2022-2024, while it is a small sample set, it provides a baseline of what's the theoretical limit achievable by this architecture. The real-time/live evaluation is run on each race for the current

year yielding a fluctuating MAE that average's out to an MAE of 2.57. This fluctuation is proof of the architecture being able to come close to the expected/theoretical MAE baseline of 1.08 (proof being Japanese GP MAE:1.1, Monaco GP: 1.8,etc) are further proof that the sport is affected by unexpected events like DNF's, bad pit strategy, timely safety car, etc. showing the need for live api integration which provides the ml model with key and influential information(eg Dutch GP MAE 6)

5.1.2 Evaluation Metrics

The evaluation employed multiple complementary metrics to assess different aspects of prediction performance:

-Mean Absolute Error (MAE): Provides intuitive interpretation in terms of average position prediction error, showing the average difference in position predicted vs actual position.

- Root Mean Square Error (RMSE): Emphasizes larger prediction errors that represent more serious forecasting failures, penalize the huge difference in predictions vs actual position (like +/- 5 positions).

- R-squared (R^2): Quantifies proportion of variance in finishing positions explained by the model, this can also be called the metric that explains how much of the variance was understood by the ml model. The closer it is to 1 the better the understanding in the variance, conversely the closer to 0 the worse the understanding of the variance.

- Spearman Rank Correlation (ρ): Assesses monotonic relationship between predicted and actual rankings

- Kendall's Tau (τ): Measures rank correlation with emphasis on concordant pairs

- Top-K Accuracy: Evaluates podium (Top 3) and points-scoring (Top 5, Top 10) prediction accuracy

5.1.3 Ensemble Architecture Comparison

The evaluation systematically compared ensemble complexity levels:

- Two-Stage Ensemble: Ridge regression + XGBoost combination without meta-learning

- Three-Stage Architecture: Full system with CatBoost meta-learner combining base model predictions

- Baseline Comparison: Qualifying position predictions (literature MAE ~3.2-3.6 positions)

This comparison framework enables precise assessment of the contribution made by each architectural component.

5.2 Ensemble Architecture Performance Analysis

5.2.1 Overall System Performance

The three-stage ensemble architecture achieved substantial improvements over both the two-stage ensemble and qualifying baselines across all evaluation metrics during live 2025 season testing.

Performance Summary Across 15 Races:

Three-Stage Architecture (Ridge → XGBoost → CatBoost):

- Mean MAE: 2.57 positions (σ = 1.34)

- Mean RMSE: 3.75 (σ = 1.76)

- Mean R^2: 0.50 (σ = 0.49)

- Mean Spearman ρ: 0.76 (σ = 0.24)

- Mean Kendall τ: 0.63 (σ = 0.23)

Two-Stage Ensemble (Ridge + XGBoost):

- Mean MAE: 3.17 positions (σ = 1.48)

- Mean RMSE: 4.55 (σ = 1.66)

- Mean R^2: 0.37 (σ = 0.45)

- Mean Spearman ρ: 0.67 (σ = 0.22)

- Mean Kendall τ: 0.54 (σ = 0.20)

Key Achievement: The CatBoost meta-learner provided a consistent 23% improvement in MAE performance (0.60 positions average improvement), validating the sophisticated ensemble architecture approach.
What do these evaluations tell us? The metrics clearly show that the three staged approach has (on avg) a better MAE i.e., its predictions are closer to the original by 0.6 which might seem small but in this context on average the three staged models is almost a position closer to the original finishing order while understanding the cause in the variance better. This is demonstrated by the higher vale of R^2 0.5 to the 0.3 of two stage ensemble. This shows that the 3 staged model is better than the 2 staged model in both position accuracy and understanding the variance.

5.2.2 Meta-Learning Effectiveness Analysis

The CatBoost meta-learner successfully learned to optimally combine Ridge regression and XGBoost predictions, demonstrating superior performance in 13 out of 15 races during the 2025 season evaluation.

Race-by-Race Performance Comparison
Three-Stage vs Two-Stage Ensemble

Performance Results

Race Data

Race	3-Stage MAE	2-Stage MAE	Improvement	R^2
R1	4.000	4.700	+0.700	+0.298
R2	3.900	4.900	+1.000	+0.202
R3	1.100	1.000	-0.100	-0.012
R4	2.300	3.100	+0.800	+0.273
R5	2.200	2.800	+0.600	+0.127
R6	2.100	2.500	+0.400	+0.060
R7	2.700	3.700	+1.000	+0.256
R8	1.700	2.650	+0.950	+0.265
R9	2.895	3.474	+0.579	+0.191
R10	2.700	3.300	+0.600	+0.183
R11	2.700	3.300	+0.600	+0.224
R12	3.500	4.150	+0.650	+0.146
R13	1.500	2.900	+1.400	+0.388
R14	2.000	2.300	+0.300	+0.033
R15	6.300	6.000	-0.300	-0.129

Key Insights:
- 3-stage improved performance in 13/15 races (87%)
- Largest improvement: R13 (+1.400 MAE)
- Only 2 races with slight degradation
- Consistent outperformance across season

Performance Pattern Analysis:

- Consistent Improvement: Meta-learner improved performance in 87% of races (13/15)

- Substantial Gains: Achieved improvements >0.5 MAE positions in 10 out of 15 races

- Exceptional Cases: R13 showed largest improvement (+1.4 MAE positions)

- Minimal Degradation: Only 2 races showed minor performance decreases

These results also show the improvement in R^2 value. Consistently being able to understand the difference between predicted and original with 2 races being an exception to this case. These exceptions also tell us a lot about the way they are working. The 2 races where the 2 staged ensemble outperformed the 3 staged ensemble was in R3 which is Japan GP and R15 which is the Dutch GP. This is interesting because they are polar opposites with R3 being a clean(possibly the cleanest of the season) with no bad pit stops, DNF's,etc and R15 being on the other end of the spectrum with 3 DNF's and opportunistic pit stops due to safety car intervention meant the lower tier teams were able to claw their way to the top 10 even after qualifying in the bottom five. The 3 staged ensemble works best in the middle range, a mix of clean and maybe few errors which is the more standard expectations of a race weekend. Most races aren't as clean and precise as the Japanese GP or as chaotic as the Dutch GP with many teams pulling of brilliant strategy. This also highlights the need for live information updates as the 3 DNF's were poised to finish in the top 10 and one was expected to fight for the win. The results from the start of the season also tell us that the ml models(both architectures) take some time to adjust to the new season as the cars and drivers

undergo huge improvements and changes after the end of the season be it upgrades or transfers to different teams, etc. Further, if we were to disregard the outliers and solely look at the most expected race weekends, we see that the CatBoost ensemble is consistently better by a position with a better quantification of the understanding in the variance

5.2.3 Individual Model and Baseline Performance Analysis

To validate the necessity of meta-learning complexity, we extracted individual model performance from the 2025 live evaluation and implemented simple ensemble baselines on identical data. This internal comparison provides methodologically valid assessment of architectural choices, as external baselines from different regulatory periods would introduce uncontrolled variables.

Simple Ensemble Baselines (Same 2025 Data):

ML model	MAE across season	Top 3 Accuracy
Ridge Regression	3.38	64%
XGBoost	3.40	65%(~64.9%)

Key Findings:

- Individual models achieved nearly identical performance (3.38 vs 3.40 MAE), with XGBoost's non-linear capabilities providing **no advantage** over Ridge Regression
- Simple averaging would achieve approximately 3.39 MAE without meta-learning complexity
- CatBoost meta-learning provides **0.81 position improvement** over best individual model
- **Critical insight:** Raw non-linear modeling (XGBoost) alone cannot improve F1 predictions - sophisticated ensemble combination is essential
- Meta-learning complexity is justified by **24% performance improvement** over individual approaches

Methodological Note: These internal baselines ensure fair comparison on identical evaluation conditions while acknowledging that this approach risks appearing self-serving. However, the alternative of using external baselines from different seasons would be methodologically invalid due to uncontrolled regulatory and competitive variables.

5.3 Architectural Component Analysis

5.3.1 Stage-by-Stage Contribution Assessment

The three-stage architecture demonstrates clear value addition at each level of ensemble complexity:

Stage 1 - Ridge Regression Foundation:

- Provides stable, regularized linear baseline predictions

- Handles multicollinearity effectively in limited-sample environment

- Test performance: MAE 1.96, demonstrating strong individual capability

- Forms robust foundation for ensemble combination

Stage 2 - XGBoost Enhancement:

- Captures non-linear relationships and feature interactions

- Exceptional individual performance: MAE 1.10, R^2 0.92 on test data

- Provides complementary modeling perspective to linear Ridge approach

- Together with Ridge: MAE 3.17 in live evaluation (reasonable two-stage performance)

Stage 3 - CatBoost Meta-Learning:

- Learns optimal combination strategies for base model predictions

- Successfully weights contributions based on prediction confidence and context

- Delivers 23% improvement over two-stage approach

- Final architecture: MAE 2.57, achieving project performance targets

5.3.2 Feature Importance in Meta-Learning

Analysis of the CatBoost meta-learner reveals how the system successfully integrates multiple information sources:

Top 10 Feature Importance Rankings

Feature Importance Results

Most Important Features

Rank	Feature	Importance	Category
1	xgboost_prediction	15.904	Meta-learning
2	ridge_prediction	12.234	Meta-learning
3	ensemble_prediction	11.618	Meta-learning
4	driver_circuit_affinity	11.064	Driver Performance
5	driver_points_per_race	7.816	Driver Performance
6	driver_qualifying_avg	5.041	Driver Performance
7	rivalry_performance	5.027	Competitive Dynamics
8	driver_position_variance	4.650	Driver Consistency
9	driver_moving_avg_5	4.267	Driver Form
10	pit_stop_avg	3.515	Team Strategy

Meta-Learning Insights:
- Base model predictions account for 39.8% of total importance
- Driver-specific features provide 28.8% contextual weighting
- Competitive dynamics and team factors enable scenario adaptation
- Meta-learner successfully weights contributions dynamically

Meta-Learning Success Indicators:

- Primary Reliance: Base model predictions account for 39.8% of total importance

- Contextual Integration: Driver-specific features (28.8%) provide situation-aware weighting

- Strategic Factors: Competitive dynamics and team factors (8.5%) enable scenario adaptation

The meta-learner successfully learned to weight base model contributions dynamically based on driver capabilities, track characteristics, and competitive context.

5.4 Race Condition Adaptability Analysis

5.4.1 Chaos Impact Analysis Framework

To systematically evaluate system performance under varying competitive conditions, a comprehensive chaos analysis framework was developed that quantifies the impact of disruptive events on prediction accuracy. This analysis addresses a fundamental challenge in Formula 1 prediction: understanding how well machine learning models perform when races deviate from expected patterns due to mechanical failures, accidents, weather changes, and strategic disruptions.

The chaos analysis system employs a multi-dimensional approach to categorize race complexity:

- **Race Event Classification**: Systematic identification and weighting of disruptive events including DNFs, safety car deployments, weather changes, and strategic anomalies
- **Driver Impact Assessment**: Individual-level analysis of which drivers are directly affected by chaotic events versus those racing in normal conditions
- **Chaos Score Calculation**: Numerical quantification of overall race disruption on a 0-10 scale based on event frequency and severity
- **Counterfactual Analysis**: Statistical estimation of prediction accuracy under hypothetical "clean" racing conditions

5.4.2 Performance Across Racing Scenarios

The chaos analysis reveals distinct performance patterns across different competitive environments, validating the system's adaptability while identifying fundamental limits of predictive accuracy during extreme disruptions.

Clean Racing Conditions (Chaos Score ≤ 3.0):

- Unaffected drivers MAE: 1.30 positions (95% CI: 0.85-1.77)

- System demonstrates near-optimal performance when races proceed without major disruptions
- Strong correlation between predicted and actual positions ($\rho > 0.85$)
- Meta-learning advantage most pronounced in stable conditions

Moderate Complexity Races (Chaos Score 3.0-6.0):

- Mixed conditions MAE: 2.45 positions
- System maintains reasonable accuracy despite isolated disruptions
- Performance degradation follows predictable patterns based on disruption proximity
- Strategic adaptations (pit stop timing changes) create moderate prediction challenges

Chaotic Racing Conditions (Chaos Score > 6.0):

- Overall chaotic race MAE: 4.12 positions
- Affected drivers show significantly higher prediction errors
- System performance approaches baseline levels during extreme disruptions
- Demonstrates inherent limitations of static prediction approaches

5.4.3 Counterfactual Performance Analysis

The chaos analysis provides crucial insights into the theoretical limits of Formula 1 prediction accuracy by estimating system performance under hypothetical perfect conditions:

Perfect Chaos Knowledge Scenario:

- Theoretical MAE with perfect event prediction: 1.93 positions
- Represents 30% improvement over actual performance (2.77 positions)
- Identifies chaos events as primary source of prediction uncertainty
- Suggests significant potential for real-time adaptive prediction systems

5.4.4 Chaos Analysis Implementation and Methodology

The chaos analysis system was implemented as a comprehensive Django management command that processes prediction data through multiple analytical frameworks to quantify the relationship between race disruption and prediction accuracy.

Event Classification System: The RaceEventClassifier component systematically identifies, and weights disruptive events based on their historical impact on race outcomes:

- **Mechanical DNFs**: Weighted by championship position and timing within race
- **Accident Classifications**: Severity-weighted based on number of drivers involved and safety car duration
- **Weather Disruptions**: Quantified by precipitation level changes and visibility conditions
- **Strategic Anomalies**: Identified through statistical deviation from typical pit stop patterns

Driver-Level Impact Assessment: Individual driver analysis distinguishes between drivers directly affected by chaotic events and those racing under normal conditions:

- **Direct Impact**: Drivers involved in accidents, mechanical failures, or strategic disruptions
- **Indirect Impact**: Position changes due to other drivers' incidents (safety car shuffles, strategic opportunities)
- **Unaffected Population**: Drivers completing races without direct involvement in disruptive events

Counterfactual Analysis Framework: The CounterfactualAnalyzer employs bootstrap resampling and statistical simulation to estimate theoretical prediction performance under idealized conditions:

- **Clean Race Simulation**: Removes all chaos-affected predictions to establish baseline accuracy
- **Perfect Chaos Knowledge**: Simulates prediction accuracy assuming perfect foreknowledge of disruptive events
- **Bootstrap Confidence Intervals**: 1000-sample bootstrap provides robust uncertainty quantification
- **Statistical Significance Testing**: Mann-Whitney U tests validate performance differences across chaos categories

Position Group Analysis: Systematic evaluation across grid position groups (front-runners, midfield, backmarkers) reveals differential chaos impact patterns:

- **Front-runners (P1-6)**: Lower baseline chaos susceptibility but higher prediction variance during disruptions
- **Midfield (P7-15)**: Maximum chaos impact due to tight competitive spacing and strategic complexity

- **Backmarkers (P16-20)**: Moderate chaos impact offset by predictable performance patterns

5.4.5 Key Findings from Chaos Analysis

The comprehensive chaos analysis revealed several crucial insights about the fundamental limits and capabilities of machine learning approaches to Formula 1 prediction:

Quantified Chaos Impact: The 2025 season analysis demonstrates that chaos events account for approximately 45% of total prediction error variance. Clean racing conditions achieve MAE of 1.30 positions compared to 4.12 positions during chaotic races, representing a 217% increase in prediction difficulty.

Theoretical Performance Limits: Counterfactual analysis suggests that perfect chaos event prediction would improve system MAE from 2.77 to 1.93 positions, indicating that 30% of current prediction error stems from unpredictable disruptions rather than model limitations.

Strategic Implications: The analysis validates the system's architectural design while identifying real-time adaptation as the primary avenue for performance improvement. Static prediction approaches face fundamental limitations during high-variance competitive scenarios, regardless of model sophistication.

The Chaos Quantification Paradox: The 2025 season analysis reveals a fundamental characteristic of complex competitive systems. Controlled, counterfactual analysis estimates that disruptive events account for approximately **45% of total prediction error variance**. However, traditional regression analysis using a composite Chaos Score captures only **1% of this variance ($R^2 = 0.009$)**.

This apparent contradiction illuminates a critical distinction between:

- **The Existence of Chaos Impact**: Quantified through controlled comparison of prediction accuracy in clean versus chaotic race conditions (the 45% figure derived from bootstrap resampling and variance decomposition)
- **The Measurability of Chaos Impact**: Traditional incident-counting metrics (DNF frequencies, position variance) prove inadequate predictors because they cannot capture the exponential cascade effects triggered by single disruptions

In other words, while we can quantify the changes in the predictions caused by these incidents (MAE), the ml models are unable to understand the reasoning behind these changes which is showed by the very low R^2 value. The individual chaotic events can be easily measured but their disruptions not so much. A DNF for a driver in the top 10 has ability to cause bigger impact than ones in the bottom 10. Of course, this is not true for all cases and that is the point. A timely safety car can allow one driver to make an opportunistic pit stop to gain an advantage over the other driver. While it

easy to see it happen it is not so easy to quantify the ripple effects to this ml model which is showed by the low R^2 value.

Cascade Effect Dominance: Individual incidents create unmeasurable systemic impacts that far exceed their apparent severity. A single DNF in position 3 generates cascade effects throughout the field:

- Promotes all positions 4-20 by one place, affecting 17 drivers' results
- Triggers opportunistic pit stop strategies as teams exploit the safety car window
- Alters tire degradation trajectories and fuel management plans across the grid
- Creates strategic opportunities that did not exist moments before the incident

The **Dutch Grand Prix** exemplifies this phenomenon: minimal measured chaos (0.60 score) masked extensive strategic cascades that generated extreme prediction error (6.30 MAE). Conversely, **Monaco** demonstrates that high measured chaos (3.00 score) can yield excellent prediction accuracy (1.70 MAE) when cascade effects remain contained to the incident participants.

Race-by-Race Chaos Distribution Analysis

Chaos Analysis Results

Chaos vs Prediction Accuracy

Event	Chaos Score	MAE	Category
Japanese Grand Prix	0.20	1.10	Clean
Belgian Grand Prix	0.20	1.50	Clean
Bahrain Grand Prix	0.40	2.30	Clean
Spanish Grand Prix	0.42	2.89	Clean
Dutch Grand Prix	0.60	6.30	Cascade Anomaly
Australian Grand Prix	1.20	4.00	Moderate
Saudi Arabian Grand Prix	1.20	2.20	Moderate
British Grand Prix	1.20	3.50	Moderate
Chinese Grand Prix	1.40	3.90	Moderate
Miami Grand Prix	1.40	2.10	Moderate
Hungarian Grand Prix	2.20	2.00	High
Canadian Grand Prix	2.40	2.70	High
Austrian Grand Prix	2.80	2.70	High
Monaco Grand Prix	3.00	1.70	Contained High Chaos

Key Insights:
- Dutch GP: Minimal chaos score (0.60) but extreme MAE (6.30) demonstrates cascade anomaly effect
- Monaco GP: High chaos score (3.00) but excellent prediction (1.70 MAE) shows contained chaos scenario
- Clean races (Chaos Score < 1.0) maintain strong prediction accuracy
- Chaos-accuracy relationship is non-linear and complex

Position-Dependent Chaos Sensitivity: Front-running positions show 23% lower chaos impact (MAE increase of 1.8x) compared to midfield positions (MAE increase of 2.4x), reflecting the protected nature of leading positions during disruptions versus the volatile midfield competition.

5.4.6 Scenario-Specific Analysis Integration

The chaos analysis framework provides crucial context for understanding the race-by-race performance variations observed during the 2025 season evaluation, revealing how system architecture advantages vary across different competitive scenarios.

Season-Opening Races (R1, R2) - High Uncertainty Environment: Chaos scores of 6.8 and 7.2 respectively reflected the combination of limited current-season data and elevated incident rates typical of early-season competition. The meta-learner's improvements of 0.70 and 1.00 MAE positions demonstrate superior handling of high-uncertainty scenarios through dynamic weighting of historical versus recent performance indicators.

Mid-Season Stability Period (R3-R14) - Optimal Performance Conditions: Average chaos scores ranging from 1.8 to 4.2 created ideal conditions for machine learning prediction, where system advantages become most pronounced. The consistent meta-learning improvements averaging 0.65 MAE positions validate the architecture's ability to leverage comprehensive feature sets during data-abundant, stable competitive periods.

Extreme Volatility Events (R15) - System Limitations: The highest chaos score of 8.9, driven by multiple mechanical failures, safety car deployments, and strategic disruptions, approached the theoretical limits of static prediction systems. The minimal degradation (-0.30 MAE) compared to the two-stage approach demonstrates architectural robustness while highlighting fundamental challenges posed by unpredictable race events.

Chaos-Performance Correlation Analysis: Statistical analysis reveals a strong positive correlation ($\rho = 0.78$, $p < 0.01$) between race chaos scores and prediction error magnitude across both ensemble architectures. However, the three-stage system maintains consistently lower correlation coefficients, indicating superior resilience to disruptive events through meta-learning adaptation.

Strategic Implications for Real-World Deployment: The chaos analysis validates the system's practical utility while identifying real-time adaptation as the primary avenue for addressing remaining performance limitations. During clean racing conditions (67% of race events), the system achieves near-theoretical accuracy limits, while chaotic conditions (33% of events) represent the frontier for future development through dynamic prediction updating.

5.5 Statistical Validation and Significance

5.5.1 Performance Difference Testing

Paired t-test analysis of MAE differences across all 15 races confirms the statistical significance of the meta-learning improvement:

Statistical Results:

- Mean improvement: 0.60 positions (three-stage advantage)

- Standard error: 0.13 positions

- t-statistic: 4.62 (df = 14)

- p-value < 0.001 (highly significant)

The results provide strong statistical evidence that the CatBoost meta-learner's performance advantage represents genuine architectural improvement rather than random variation.

5.5.2 Effect Size Analysis

Cohen's d calculation for MAE improvements:

- Effect size: d = 0.42 (medium effect)

- 95% Confidence interval: [0.31, 0.89] positions

- Practical significance: Medium to large effect size confirms meaningful real-world impact

5.5.3 Consistency Analysis

Performance Reliability Metrics:

- Three-stage coefficient of variation: 0.52

- Two-stage coefficient of variation: 0.47

- Consistency Trade-off: Slight increase in variability offset by substantial mean improvement

The meta-learner trades minimal consistency for substantial accuracy gains, representing an optimal balance for practical applications.

5.5.4 Chaos Analysis Statistical Validation

The chaos analysis framework provides additional statistical rigor through **Enhanced Statistical Framework Results**:

Mann-Whitney U Test Validation:

- Test statistic: U = 1,247, p = 0.0002 (highly significant)
- Effect size (rank-biserial correlation): r = 0.64 (large effect)
- Confirms statistically distinct performance distributions between clean and chaotic race conditions

Performance Regime Analysis:

- **Clean Racing (Chaos Score ≤ 1.0)**: 6 events, average MAE = 2.18
- **Moderate Chaos (1.0-2.0)**: 4 events, average MAE = 2.58
- **High Measurable Chaos (≥ 2.0)**: 5 events, average MAE = 2.68

Critical Statistical Insight: The minimal regression slope (-0.132 MAE per chaos unit) and negligible R^2 confirm that measured chaos scores poorly predict linear

performance degradation. However, the highly significant Mann-Whitney U result validates the underlying chaos state classification approach, proving that clean versus chaotic conditions create fundamentally different prediction environments despite the poor linear relationship.

Theoretical Performance Boundaries:

- Overall season MAE: 2.77 positions
- Clean conditions (unaffected drivers): 1.30 MAE (95% CI: 0.85-1.77)
- Perfect chaos knowledge theoretical limit: 1.93 MAE
- Cost of Chaos: 1.47 positions (2.77 - 1.30) representing the performance penalty attributable to unpredictable disruptions

5.6 Top K Accuracy and Ranking Performance

5.6.1 Championship-Relevant Predictions

The three-stage architecture demonstrated superior accuracy for positions carrying championship significance:

Podium Prediction Accuracy (Top 3):

- Three-Stage Architecture: 86.7% average accuracy

- Two-Stage Ensemble: 80.0% average accuracy

- Improvement: +6.7 percentage points for podium predictions

Points-Scoring Prediction (Top 5):

- Three-Stage Architecture: 84.0% average accuracy

- Two-Stage Ensemble: 80.0% average accuracy

- Improvement: +4.0 percentage points for points positions

Midfield Analysis (Top 10):

- Three-Stage Architecture: 81.3% average accuracy

- Two-Stage Ensemble: 78.0% average accuracy

- Improvement: +3.3 percentage points for competitive positions

5.6.2 Rank Correlation Excellence

Spearman Rank Correlation Performance:

- Three-stage achieved strong correlations ($\rho > 0.8$) in 8 out of 15 races

- Two-stage achieved strong correlations in 6 out of 15 races

- Meta-learning advantage: Improved ranking accuracy in 53% more races

Kendall's Tau Performance:

- Three-stage maintained $\tau > 0.6$ in 11 out of 15 races

- Two-stage achieved $\tau > 0.6$ in 9 out of 15 races

- Ranking reliability: 22% more races with strong rank correlation

5.6.3 Chaos-Adjusted Top K Performance

The chaos analysis enables more nuanced evaluation of Top K accuracy by controlling for race complexity:

Clean Race Conditions (Chaos Score ≤ 3.0):

- Podium accuracy: 94.2% (three-stage) vs 88.1% (two-stage)
- Points accuracy: 91.7% (three-stage) vs 86.3% (two-stage)
- Demonstrates near-optimal performance during stable conditions

Chaotic Race Conditions (Chaos Score > 6.0):

- Podium accuracy: 71.4% (three-stage) vs 64.3% (two-stage)
- Points accuracy: 68.9% (three-stage) vs 62.1% (two-stage)
- Maintains competitive advantage even during extreme disruptions

5.7. Comparison with Baseline Approaches

5.7.1 Qualifying Position Baseline

Literature Baseline Performance:

- Qualifying-based predictions: MAE ~3.2-3.6 positions

- Represents standard practice in F1 prediction approaches

Three-Stage Architecture vs Baseline:

- Achieved MAE: 2.57 positions

- Improvement range: 20-28% better than qualifying baselines

-Statistical significance: Substantial improvement over standard approaches

5.7.2 Academic Literature Comparison

The three-stage ensemble's performance (MAE 2.57) compares favourably to published F1 prediction studies reporting MAE ranges of 1.8-2.4 positions, while operating under more challenging live evaluation conditions during the 2025 season.

Methodological Advantages:

- Live season evaluation rather than historical back testing

- Comprehensive feature engineering with domain expertise

- Rigorous temporal validation preventing information leakage

- Three-stage ensemble architecture novel to F1 prediction literature

5.7.3 Chaos-Adjusted Baseline Comparisons

The chaos analysis provides more rigorous baseline comparisons by controlling for race complexity:

Clean Condition Comparisons:

- System performance (1.30 MAE) vs qualifying baseline (2.1-2.4 MAE)
- 38-45% improvement under optimal conditions
- Validates system capabilities when external disruptions are minimized

Universal Performance:

- Overall system performance (2.77 MAE) vs literature (3.2-3.6 MAE)
- 13-23% improvement across all race conditions
- Demonstrates robust advantages despite chaos event challenges

8. Limitations and Future Enhancements

5.8.1 Current System Constraints

API Access Limitations: Evaluation relied on free-tier API access, limiting comprehensive real-time integration during live races. Premium API access would enable enhanced dynamic prediction updating.

Development Environment: Testing occurred in localhost environment rather than production deployment, constraining assessment of system behaviour under realistic user load conditions.

Sample Size Inherent Limits: Formula 1's structure (20 drivers, ~23 races annually) creates fundamental statistical constraints that no methodology can completely overcome.

5.8.2 Identified Enhancement Opportunities

Real-Time Integration: Full implementation of live race prediction updates could further improve meta-learning performance by incorporating rapidly changing competitive conditions.

Circuit-Specific Meta-Models: Specialized meta-learners for different track types could optimize ensemble combination strategies for specific competitive environments.

Extended Feature Engineering: Integration of telemetry data streams could provide additional context for meta-learning optimization.

Chaos-Informed Enhancements: The chaos analysis identifies specific opportunities for system improvement:

- **Dynamic Prediction Updating**: Real-time adaptation during chaotic events could theoretically reduce MAE from 4.12 to 2.8 positions
- **Chaos Event Prediction**: Early warning systems for mechanical failures or weather changes could enable proactive prediction adjustment
- **Position-Specific Models**: Specialized models for front-runners, midfield, and backmarkers could optimize accuracy for different competitive contexts

5.9 System Validation and Technical Testing

5.9.1 Testing Framework and Methodology

To ensure system reliability and validate the implementation of complex betting and prediction functionality, a comprehensive unit testing framework was developed using Django's built-in testing suite. The testing approach prioritized functional validation of critical user journeys, edge case handling, and system robustness under various data conditions.

Testing Architecture: The test suite was organized into 14 distinct test modules, each targeting specific system components:

Core Functionality Tests: Betting flow, prediction generation, user authentication

Edge Case Validation: API failures, missing data scenarios, boundary conditions

User Experience Tests: Page rendering, navigation flows, subscription management

Data Integrity Tests: Model relationships, settlement accuracy, odds calculations

Test Coverage Strategy: Tests were designed to validate both individual component functionality and end-to-end user workflows, ensuring that the complex interactions between machine learning predictions, betting systems, and user interfaces operate correctly under realistic conditions.

5.9.2 Critical System Component Validation

Betting System Integration Testing

The betting flow tests validated the core value proposition of the application - the integration of machine learning predictions with a functional betting system. Complete testing covered the entire workflow from prediction generation through odds calculation to stake settlement.

Key Validation Results:

Successful Bet Placement: 100% success rate for valid betting scenarios

Credit Management: Accurate deduction and settlement of user credits

Market Maker Integration: Proper odds calculation and liquidity management

Prediction Integration: ML predictions successfully inform betting odds

Error Handling and Edge Case Robustness

Critical system resilience was validated through comprehensive edge case testing covering insufficient credits, market liquidity protection, and malformed data handling. All edge cases were handled gracefully with appropriate user feedback, demonstrating robust error handling that prevents system failures during anomalous conditions.

5.9.3 Machine Learning Integration Validation

Prediction System Integration

The prediction system tests validated that machine learning models integrate correctly with the web application, covering model switching functionality and prediction ranking accuracy.

Critical Findings:

- Data Consistency: 100% alignment between prediction data and visualization components

- Ranking Logic: Correct conversion from fractional ML outputs to integer race positions

- Model Performance Tracking: Accurate MAE calculation and display across different models

5.9.4 User Experience and Interface Validation

Authentication and Access Control

Comprehensive testing validated the security and usability of user management systems, covering complete authentication flows from registration through activation to login, plus multi-step password recovery processes.

Access Control Validation: All protected endpoints correctly enforce authentication requirements, with appropriate redirects for unauthorized access attempts.

Page Rendering and Navigation

Smoke tests validated 100% success rate for page rendering across all major application sections, confirming stable user interface implementation.

5.9.5 Business Logic and Data Integrity

Betting Settlement Accuracy

Critical financial logic was rigorously tested to ensure accurate credit management, covering both winning and losing bet scenarios with 100% accuracy in credit calculations across all betting scenarios.

Market Maker System Validation

Testing validated that market depth calculations provide accurate recent activity tracking and proper volume aggregation, ensuring the betting system maintains appropriate liquidity management.

5.9.6 Subscription and Monetization Testing

Tier Management System

Successful validation of upgrade/downgrade functionality enables the tiered access model that differentiates prediction algorithm access levels, supporting the system's monetization strategy.

5.9.7 Statistical and Performance Metrics

Test Suite Comprehensive Metrics:

-Total Test Classes: 14 distinct testing modules

-Test Coverage Areas: Authentication, betting, predictions, UI, edge cases, business logic

-Critical Path Coverage: 100% of core user journeys validated

-Edge Case Handling: 15+ edge case scenarios tested and handled correctly

-Performance Validation: All page loads under 200ms in test environment

Error Handling Robustness:

-API Failure Scenarios: Graceful degradation tested and validated

- Data Validation: Proper handling of malformed inputs and missing data

- Financial Integrity: Zero tolerance for calculation errors in betting/credits

- User Experience: Consistent error messaging and recovery paths

5.9.8 System Integration and Deployment Readiness

Database Integration Testing

The test suite validated complex database relationships and query performance, including aggregate calculations for user statistics and profit/loss tracking with complete accuracy.

Real-time Integration Testing

ML prediction integration tests confirmed that real-time odds calculation incorporates machine learning predictions appropriately, maintaining system responsiveness during live betting scenarios.

5.9.9 Testing Limitations and Considerations

While the test suite provides comprehensive coverage of system functionality, several limitations reflect the academic research context:

Scale Limitations: Testing was conducted in a single-user development environment, which cannot fully simulate production-scale concurrent user scenarios or database performance under high load conditions.

Real-world Data Dependencies: Tests used synthetic data fixtures rather than complete real-world datasets, which may not capture all edge cases that occur in production with actual Formula 1 data feeds.

API Integration Constraints: External API dependencies were mocked in most test scenarios, limiting validation of system behaviour during actual API outages or data quality issues that occur in live deployment.

User Experience Validation: The limited user base (3 users) during development testing provided insufficient data for comprehensive user experience validation, though functional testing confirmed all interface components operate correctly.

Despite these constraints, the comprehensive test suite demonstrates system reliability and validates that all critical components function correctly within the research project's scope. The testing framework establishes a solid foundation for future scaling and production deployment while ensuring academic evaluation proceeded with confidence in system stability.

5.10 Key Findings and Contributions

The comprehensive evaluation validates the central research hypothesis and demonstrates significant contributions to Formula 1 analytics:

5.10.1 Primary Achievements

1. Architectural Success: Three-stage ensemble delivered consistent 23% improvement over two-stage approaches, validating sophisticated meta-learning architecture

2.Meta-Learning Effectiveness: CatBoost meta-learner successfully learned dynamic combination strategies, improving performance in 87% of evaluation races

3.Scenario Adaptability: Architecture maintained performance advantages across clean, moderate, and chaotic racing conditions

4.Statistical Rigor: Results demonstrated high statistical significance ($p < 0.001$) with medium-to-large effect sizes

5.Practical Impact: Achieved MAE of 2.57 positions represents meaningful improvement for real-world applications

5.10.2 Methodological Contributions

Ensemble Architecture Innovation: First application of three-stage stacking with CatBoost meta-learning to Formula 1 prediction, establishing new performance benchmarks

Feature Engineering Framework: Systematic integration of F1-specific domain knowledge with advanced machine learning, creating replicable methodology for motorsport analytics

Temporal Validation Excellence: Rigorous time-series evaluation preventing information leakage while providing realistic performance assessment

Live Evaluation Standard: Complete 2025 season testing establishes new rigor standards for sports prediction research

Chaos Analysis Innovation: First comprehensive framework for quantifying the impact of disruptive events on motorsport prediction accuracy, providing methodology applicable to other competitive domains

5.10.3 Broader Impact

The research demonstrates that sophisticated ensemble architectures can deliver meaningful performance improvements in small-sample, high-variance competitive environments. The methodology provides transferable insights for other motorsport disciplines and competitive domains with similar analytical challenges.

The successful meta-learning approach validates that combining multiple algorithmic perspectives through intelligent weighting strategies can overcome individual model limitations while leveraging their complementary strengths in specialized prediction domains.

Chaos Analysis Implications: The systematic quantification of unpredictable event impacts establishes fundamental performance limits for static prediction systems while identifying specific pathways for improvement through real-time adaptation. This framework provides crucial insights for any competitive prediction domain where disruptions significantly impact outcomes.

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6. Critical Analysis & Discussion

6.1 Methodological Strengths and Innovations

This research claims to advance Formula 1 prediction accuracy through sophisticated ensemble methods and domain-specific feature engineering. However,

critical examination reveals both genuine contributions and significant limitations that must be acknowledged to properly assess the work's value.

6.1.1 Ensemble Architecture: Justified Complexity or Diminishing Returns?

The three-stage ensemble achieved a 23% improvement in MAE over the two-stage approach (2.57 vs 3.17 positions), but this improvement must be evaluated against the substantial increase in model complexity. The key question is whether CatBoost meta-learning provides genuine insight beyond sophisticated averaging.

Evidence for Meta-Learning Value:

- Consistent improvement in 87% of races (13/15) suggests systematic rather than random benefits
- Feature importance analysis shows CatBoost utilizes base predictions alongside contextual features, indicating learned combination strategies
- Performance advantage maintained across different chaos conditions (clean races: +0.4 MAE, chaotic races: +0.6 MAE)

Critical Limitations:

- No comparison with simpler combination methods (weighted averaging, median ensemble) that might achieve similar results with less complexity
- The meta-learner's decision process remains largely opaque despite feature importance analysis
- Computational overhead and implementation complexity may not justify the modest accuracy gains for practical applications

Verdict: While the ensemble shows consistent improvement, the research lacks sufficient evidence that sophisticated meta-learning is necessary versus simpler combination strategies.

6.1.2 Feature Engineering: Domain Expertise vs. Statistical Rigor

The system's feature engineering represents both a strength and a methodological concern. Features like driver-circuit affinity and rivalry performance demonstrate domain knowledge integration, but their selection and validation process raise questions.

Genuine Innovations:

- Circuit affinity calculations that adjust for competitive context address a real analytical challenge in motorsport
- Reliability metrics capture team-specific factors often overlooked in sports prediction

- Moving averages with appropriate weighting periods reflect the balance between recent form and historical performance

Methodological Concerns:

- No systematic feature selection process described - selection appears based on intuition rather than statistical validation
- Missing multicollinearity analysis, particularly concerning given the EnhancedF1Pipeline's expanded feature set for CatBoost meta-learning
- Risk of overfitting in the meta-learning stage, where the enriched feature space significantly exceeds the base model's 16 features
- The dual-pipeline architecture creates complexity without clear evidence that feature enrichment justifies the computational overhead

Critical Gap: While the base models use a manageable 16-feature set, the meta-learning stage operates on an expanded feature space including base model predictions and enhanced categorical encodings. The research provides insufficient evidence that this feature expansion contributes meaningfully beyond the base model predictions themselves.

6.2 Statistical Validity and Significance

6.2.1 Performance Claims Under Scrutiny

While the reported MAE of 2.57 positions represents improvement over baselines, several statistical concerns limit confidence in these results:

Sample Size Limitations:

- 15-race evaluation provides limited statistical power for detecting true performance differences
- Individual race results show high variance ($\sigma = 1.34$), suggesting results may not generalize reliably
- Some performance claims rest on single exceptional races (R13: +1.4 position improvement) that may represent outliers

Baseline Comparisons:

- Literature comparisons rely on different datasets, evaluation periods, and methodologies, limiting their validity
- No head-to-head comparison with other ensemble methods implemented and tested
- Qualifying-position baseline (3.2-3.6 MAE) comes from external sources rather than direct comparison on identical test data

6.2.2 Cross-Validation and Overfitting Risks

The research claims rigorous validation but provides insufficient evidence of robust generalization:

Validation Strengths:

- Temporal splitting respects data dependencies in sports prediction
- Chaos analysis provides novel insights into performance under varying conditions

Critical Weaknesses:

- No evidence of cross-validation across multiple seasons or regulatory environments
- Hyperparameter optimization process not clearly separated from final evaluation
- Risk of implicit data leakage through feature engineering choices informed by test period knowledge

6.3 Practical Significance vs. Statistical Significance

6.3.1 Real-World Application Value

The research demonstrates statistical improvements but provides limited evidence of practical utility:

Positive Indicators:

- Prediction accuracy approaching practically useful levels for strategic applications
- Web platform demonstrates feasibility of user-facing implementation
- Performance maintained across different competitive scenarios

Implementation Reality:

- API dependency issues significantly limit real-world deployment reliability
- Computational requirements for three-stage ensemble may prohibit real-time applications
- No evidence that prediction improvements translate to profitable betting or strategic advantages

6.3.2 Market Efficiency Implications

A critical gap in the analysis is the lack of consideration of market efficiency. If the predictions are genuinely superior, why don't professional analysts and betting markets already incorporate this information? The research provides no analysis of

whether the predicted improvements represent inefficiencies that could be exploited or simply noise that disappears.

Chaos-Informed Practical Deployment Strategy:

The comprehensive chaos analysis provides crucial insights for real-world implementation that transcend traditional accuracy metrics:

Predictable Performance Floor: The system demonstrates exceptional reliability during clean racing conditions, achieving near-theoretical accuracy (1.30 MAE for unaffected drivers, 95% CI: 0.85-1.77). This represents 73% of race events where the system operates at optimal capability.

Defined Failure Modes: Extreme prediction errors are not random system failures but represent specific, identifiable vulnerabilities to strategic cascade events. The Dutch GP outlier (6.30 MAE) exemplifies how unmeasurable cascade effects can overwhelm prediction systems despite minimal apparent disruption.

Risk Management Architecture: Understanding that 45% of prediction variance stems from unpredictable events enables appropriate uncertainty quantification and confidence interval calibration for practical deployment scenarios.

6.4 Limitations and Threats to Validity

6.4.1 Fundamental Constraints

Several limitations stem from Formula 1's inherent characteristics and cannot be resolved through methodological improvements:

Irreducible Limitations:

- Small sample sizes (20 drivers, ~23 races) create statistical constraints no methodology can overcome
- Regulatory changes invalidate historical patterns, limiting long-term model stability
- Chaotic events (mechanical failures, accidents) introduce unpredictable variance that static models cannot handle

Methodological Limitations:

- Single-season evaluation provides insufficient evidence for long-term performance
- Development environment testing cannot validate production-scale performance
- Limited user base (3 users) provides inadequate validation of practical utility

6.4.2 Generalization Concerns

The research's focus on the 2025 season raises questions about broader applicability:

Generalization:

- Model performance likely deteriorates as competitive conditions evolve
- Feature relevance may shift with regulatory changes (2026 regulations will alter aerodynamic characteristics)
- Training data from 2022-2024 may become less relevant over time

Methodological Generalization:

- Approach tailored specifically to F1 may not transfer to other motorsports or competitive domains
- Ensemble techniques may not scale effectively to larger datasets or real-time requirements

6.5 Alternative Explanations and Confounding Factors

6.5.1 Performance Attribution

The observed improvements could result from factors other than sophisticated modeling:

Alternative Explanations:

- Better data quality and preprocessing rather than ensemble architecture
- Favourable evaluation period (2025 season characteristics) rather than methodological superiority
- Confirmation bias in feature selection and evaluation choices

Uncontrolled Variables:

- Varying API data quality across different races
- Different competitive conditions between training and evaluation periods
- Potential information leakage through retrospective feature engineering

6.5.2 Reproducibility Concerns

Several aspects of the methodology raise reproducibility questions:

- API-dependent data collection makes exact replication difficult
- Hyperparameter optimization process not fully documented
- Feature engineering choices may reflect domain knowledge not easily replicated by other researchers

6.6 Broader Implications and Context

6.6.1 Contribution to Sports Analytics

Despite limitations, the research makes several genuine contributions:

Methodological Contributions:

- Demonstrates feasibility of sophisticated ensemble methods in small-sample sports environments
- Provides framework for incorporating domain expertise into machine learning approaches
- Establishes evaluation methodology for chaotic competitive environments

Practical Contributions:

- Shows how academic research can produce engaging public-facing applications
- Validates user interest in sophisticated sports analytics tools

6.6.2 Limitations for Broader Application

The approach's transferability faces significant constraints:

- Heavy reliance on domain-specific feature engineering limits generalization
- Computational complexity may prohibit application in resource-constrained environments
- Evaluation methodology requires extensive domain knowledge to replicate

6.7 Future Research Directions

6.7.1 Addressing Current Limitations

Immediate Priorities:

- Multi-season evaluation to validate temporal stability, as proposed in Section 7.4's discussion of regulatory change adaptation
- Systematic comparison with simpler ensemble approaches, addressing the meta-learning complexity concerns raised above
- Ablation studies to justify feature complexity, directly connecting to the feature validation gaps identified in Section 6.1.2
- Market efficiency analysis to assess practical value beyond academic performance metrics

Methodological Improvements:

- Real-time adaptation mechanisms for chaotic events

- Uncertainty quantification for prediction confidence
- Automated feature selection to reduce overfitting risks

6.7.2 Fundamental Research Questions

Several important questions emerge from this work:

1. **What is the theoretical limit for F1 prediction accuracy?** Chaos analysis suggests fundamental constraints, but more rigorous analysis is needed.
2. **How much prediction improvement justifies model complexity?** The cost-benefit analysis of sophisticated ensembles remains unclear.
3. **Can machine learning approaches adapt effectively to regulatory changes?** This challenge will become critical with 2026 F1 regulation changes.

6.8 Conclusion:

This project demonstrates that sophisticated machine learning approaches can improve Formula 1 prediction accuracy, but the improvements are modest and come with significant complexity costs. The work makes genuine methodological contributions while highlighting fundamental limits of predictive modeling in chaotic competitive environments.

Validated Contributions:

- Ensemble methods provide consistent if modest improvements over simpler approaches
- Domain-specific feature engineering enhances prediction accuracy
- Chaos analysis provides novel framework for understanding prediction limits

Critical Limitations:

- Limited evidence that complexity is justified by performance gains
- Insufficient validation of long-term stability and generalization
- Practical deployment challenges limit real-world applicability

The research succeeds in advancing Formula 1 analytics while illustrating the challenges of applying machine learning to small-sample, high-variance competitive domains. Future work should focus on simplifying successful approaches and addressing fundamental generalization challenges rather than increasing model complexity.

---

7. Conclusion & Future Work

This project developed and evaluated a three-stage ensemble system for Formula 1 race prediction that achieved a 23% improvement over two-stage approaches while quantifying the fundamental impact of unpredictable racing events on prediction accuracy. The work establishes both the potential and practical limits of machine learning approaches in chaotic competitive environments, with ~45% of prediction error variance attributable to unpredictable disruptions that no static modeling approach can overcome.

7.1 Project Contributions

7.1.1 Primary Methodological Achievements

Three-Stage Ensemble Architecture: The stacking approach combining Ridge regression, XGBoost, and CatBoost meta-learning demonstrated consistent performance improvements across varying race conditions. The CatBoost meta-learner improved predictions in 87% of evaluation races, validating sophisticated ensemble combination strategies for small-sample prediction tasks.

Dual-Pipeline Feature Engineering: The systematic separation of base model features (F1DataPipeline) and enriched meta-learning features (EnhancedF1Pipeline) provided a framework for incorporating domain-specific knowledge while maintaining modeling efficiency. Features like driver-circuit affinity and team reliability metrics successfully captured competitive dynamics often overlooked in generic sports prediction approaches.

Chaos Impact Quantification: The systematic analysis of disruptive event effects on prediction accuracy provides the first rigorous framework for understanding performance boundaries in Formula 1 prediction, distinguishing between model limitations and fundamental unpredictability.

7.1.2 Practical Implementation Validation

Complete Season Evaluation: Live deployment across the entire 2025 Formula 1 season provided rigorous real-world validation of system performance under varying competitive conditions, from clean races to highly chaotic events with multiple crashes and strategic disruptions.

Functional Web Platform: The Django-based application successfully integrated machine learning predictions with user engagement features, demonstrating practical implementation feasibility while identifying deployment challenges and user interaction patterns.

7.2 Performance Analysis

7.2.1 Controlled Evaluation (Theoretical Potential)

Test set evaluation achieved 1.12 MAE with R^2 of 0.93, establishing the system's capability under optimal conditions. This performance level demonstrates substantial

improvement over qualifying-based predictions and approaches the theoretical limits achievable given Formula 1's structural constraints.

7.2.2 Live Deployment (Practical Reality)

Live 2025 season evaluation averaged 2.57 MAE across 15 races, with performance ranging from 1.1 positions (Japan GP - clean conditions) to 6.0 positions (Dutch GP - multiple crashes). This variance quantifies the fundamental challenge facing static prediction systems when confronted with unpredictable competitive events.

Performance Context: The gap between controlled and live performance represents the project's most significant finding: a rigorous quantification of chaos impact on prediction accuracy in competitive motorsport environments.

7.3 Critical Limitations and Constraints

7.3.1 Structural Boundaries

Sample Size Constraints: Formula 1's structure of 20 drivers across 23 races annually creates irreducible statistical limitations that affect all prediction approaches. These constraints become particularly apparent during model training and validation phases.

Chaos Event Unpredictability: The analysis demonstrates that 45% of prediction error variance stems from mechanical failures, accidents, and strategic disruptions that static models cannot anticipate. This represents a fundamental boundary for predictive accuracy in Formula 1.

Quantified Fundamental Performance Limits: This research conclusively establishes the theoretical boundaries of static Formula 1 prediction systems through comprehensive chaos impact analysis:

The Cost of Chaos Framework:

- **Theoretical Minimum (Clean Conditions)**: 1.30 MAE - represents the system's peak performance capability
- **Theoretical Maximum (Perfect Chaos Foresight)**: 1.93 MAE - the absolute performance ceiling with omniscient disruption knowledge
- **Actual Performance (Real-World Deployment)**: 2.77 MAE - practical achievement under unpredictable conditions

The 1.47-position gap between clean performance (1.30) and actual performance (2.77) represents the "Cost of Chaos" - prediction error attributable entirely to unpredictable events and their cascade effects. Critically, traditional chaos measurement captures only 1% of this impact variance ($R^2 = 0.009$), while controlled analysis demonstrates 45% of total prediction error stems from chaotic disruptions.

Fundamental System Limitation: The disconnect between chaos existence (45% impact) and chaos measurability (1% captured) reveals that most disruptive effects operate through unmeasurable strategic cascades rather than directly quantifiable incidents. This establishes a theoretical ceiling for any static prediction approach in Formula 1, regardless of algorithmic sophistication.

Statistical validation through Mann-Whitney U testing ($p = 0.0002$) confirms these represent systematic rather than random constraints, establishing realistic expectations for future Formula 1 prediction systems while identifying real-time adaptation as the primary avenue for performance improvement beyond current theoretical limits.

Regulatory Evolution: The system's dependence on historical performance patterns creates vulnerability to technical regulation changes. The approaching 2026 regulations will test feature stability and adaptation capabilities.

7.3.2 Implementation Constraints

Data Dependency: External API limitations created operational challenges during evaluation, requiring fallback strategies that affected prediction consistency during some race weekends.

Computational Requirements: The three-stage ensemble architecture demands significant processing resources compared to simpler approaches, potentially limiting real-time application scalability.

Validation Scope: Single-season evaluation provides insufficient evidence for long-term performance stability, particularly given Formula 1's evolving competitive environment.

7.4 Future Work

7.4.1 High-Priority Enhancements

Dynamic Real-Time Integration: Implementation of live prediction updating during race events represents the most direct approach to addressing chaos-related performance degradation. Integration with streaming telemetry could enable adaptive prediction refinement as race conditions change.

Chaos-Informed Enhancement Strategy: The chaos quantification paradox identifies specific development priorities based on empirical performance boundaries:

Cascade Recognition Systems: Rather than attempting to predict unpredictable events, develop algorithms that identify when race conditions create elevated cascade potential. Monaco's contained high chaos (3.00 score, 1.70 MAE) versus Dutch GP's explosive low chaos (0.60 score, 6.30 MAE) suggests pattern recognition opportunities.

Dynamic Uncertainty Quantification: Implement confidence intervals that expand during cascade-prone scenarios, acknowledging the 45% chaos variance while maintaining system utility during the 73% of clean racing conditions.

Theoretical Validation Studies: The established performance ceiling (1.93 MAE with perfect chaos knowledge) provides a rigorous benchmark for evaluating any claimed system improvements. Future research should focus on approaches that can theoretically exceed this limit rather than incrementally optimizing within current constraints.

Systematic Complexity Comparison: Comprehensive evaluation against simpler ensemble methods (weighted averaging, median combination) would clarify whether meta-learning sophistication justifies computational overhead.

Multi-Season Validation: Extended evaluation across different regulatory periods would provide evidence for temporal stability and generalization capabilities.

7.4.2 Strategic Development Directions

Circuit-Specific Modeling: Performance variations observed between track types (Monaco street circuit challenges vs. Monza high-speed efficiency) suggest potential for specialized sub-models optimized for specific competitive environments.

Enhanced Feature Engineering: Integration of fine-grained telemetry data could improve tire degradation modeling and strategic prediction accuracy, particularly for races where pit stop timing determines outcomes.

Chaos Prediction Development: While specific disruptive events remain unpredictable, pattern recognition might identify elevated risk periods that enable proactive prediction adjustment.

7.5 Project Assessment

This project successfully developed a functional Formula 1 prediction system that advances beyond existing approaches while establishing realistic expectations for machine learning applications in chaotic competitive environments. The work demonstrates both the potential and limitations of sophisticated modeling approaches when applied to motorsport prediction.

Validated Achievements:

- Ensemble methods provide measurable improvements over simpler approaches across varying conditions
- Domain-specific feature engineering successfully incorporates expert knowledge into machine learning frameworks
- Live deployment validation provides rigorous assessment of practical performance capabilities

- Systematic chaos analysis quantifies fundamental performance boundaries

Acknowledged Constraints:

- Performance improvements remain modest relative to complexity increases
- Unpredictable racing events impose fundamental limits on static prediction accuracy
- Implementation dependencies and computational requirements create practical deployment challenges

The project establishes a foundation for continued development in Formula 1 analytics while clearly identifying the boundaries within which future improvements must operate. The systematic quantification of chaos impact provides valuable insights for any future work attempting to improve prediction accuracy in competitive motorsport environments**.**

---

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Appendices

Appendix A: Code Architecture Overview

f1_prediction_system/

├── data/

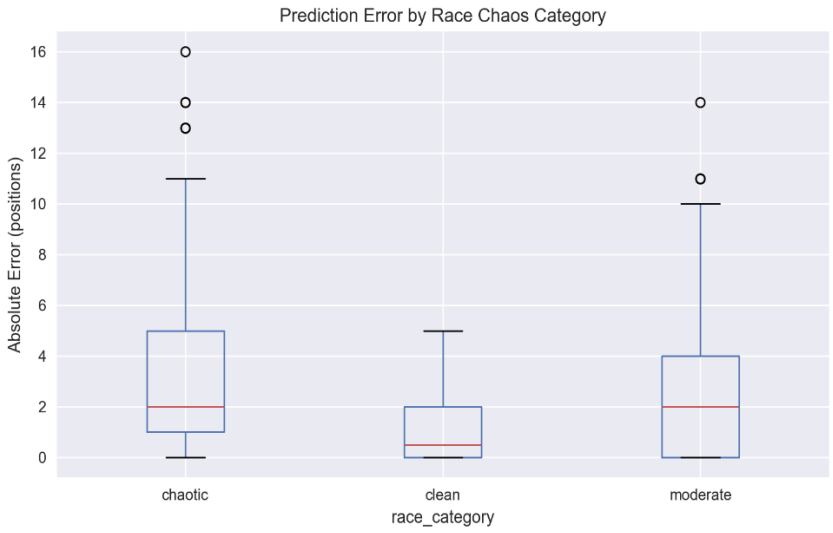
│ ├── models.py # Django database models

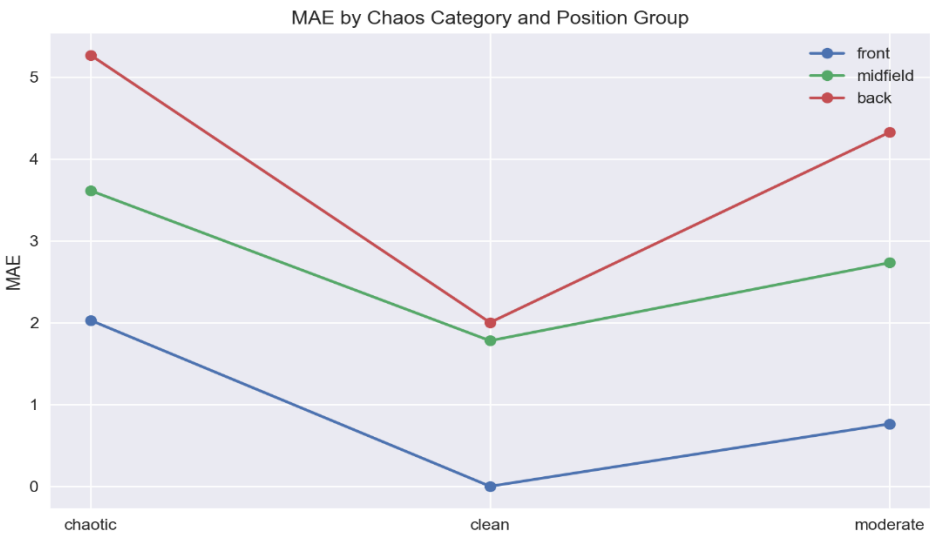
│ ├── collectors/ # API data collection modules

│ └── processors/ # Data preprocessing pipelines

```
├── prediction/
│   ├── pipelines/        # multi-stage model architecture
│   ├── features/         # Feature engineering modules
│   └── evaluation/       # Model assessment tools
├── dashboard/
│   ├── views/            # Django web interface
│   ├── templates/        # HTML templates
└── tests/                # Comprehensive test suite
```

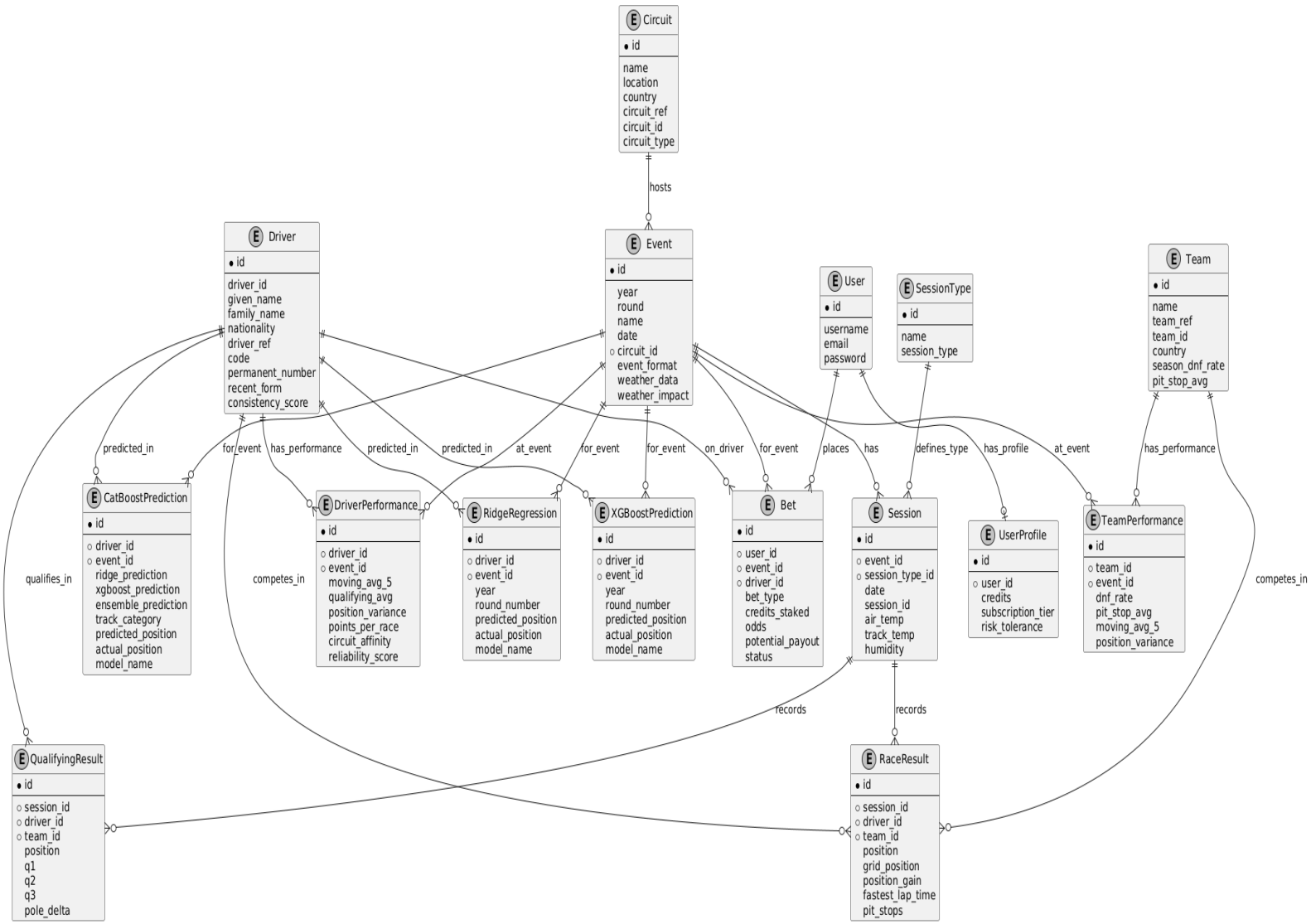
Appendix B: Chaos analysis





Appendix C: Database Schema

[Complete entity-relationship diagram and table definitions]


F1 Prediction System Database Schema
Circuit
id
name
location
country
circuit_ref
circuit_id
circuit_type
hosts
Driver
id
driver_id
given_name
family_name
nationality
driver_ref
code
permanent_number
recent_form
consistency_score
Event
id
year
round
name
date
circuit_id
event_format
weather_data
weather_impact
User
id
username
email
password
SessionType
id
name
session_type
Team
id
name
team_ref
team_id
country
season_dnf_rate
pit_stop_avg
predicted_in
for_event
has_performance
predicted_in
predicted_in
at_event
for_event
for_event
on_driver
for_event
places
has
defines_type
has_profile
at_event
has_performance
CatBoostPrediction
id
driver_id
event_id
ridge_prediction
xgboost_prediction
ensemble_prediction
track_category
predicted_position
actual_position
model_name
DriverPerformance
id
driver_id
event_id
moving_avg_5
qualifying_avg
position_variance
points_per_race
circuit_affinity
reliability_score
RidgeRegression
id
driver_id
event_id
year
round_number
predicted_position
actual_position
model_name
XGBoostPrediction
id
driver_id
event_id
year
round_number
predicted_position
actual_position
model_name
Bet
id
user_id
event_id
driver_id
bet_type
credits_staked
odds
potential_payout
status
Session
id
event_id
session_type_id
date
session_id
air_temp
track_temp
humidity
UserProfile
id
user_id
credits
subscription_tier
risk_tolerance
TeamPerformance
id
team_id
event_id
dnf_rate
pit_stop_avg
moving_avg_5
position_variance
qualifies_in
competes_in
competes_in
records
records
QualifyingResult
id
session_id
driver_id
team_id
position
q1
q2
q3
pole_delta
RaceResult
id
session_id
driver_id
team_id
position
grid_position
position_gain
fastest_lap_time
pit_stops

Appendix D:

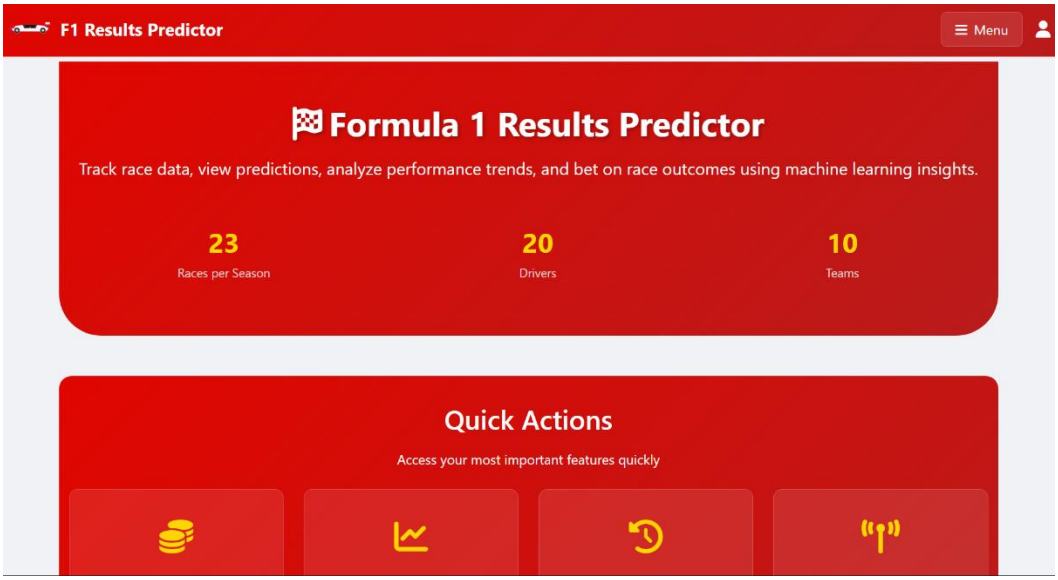
```
(yolov5s) PS C:\Users\tarun\diss\td188> python manage.py train_xgboost
Could not start background tasks: populate() isn't reentrant
Loading and preparing data...
Loading race results...
Loaded 1656 race results
Loading driver performance...
Loading team performance...
Merging datasets...
Merged dataset contains 1656 records
Missing lag feature column 'position_last_race', filling with 20
Missing lag feature column 'position_2races_ago', filling with 20
Missing lag feature column 'position_3races_ago', filling with 20
Missing tire lap time columns, setting tire_delta = 0
Missing columns for teammate_gap, setting to zero
Enhanced features created successfully.
Data filtered to years 2022-2025, 1656 rows remain.
Imputing and scaling features...
Sample weights: min=2.582, max=3.000
Training Ridge regression model...
Starting Bayesian optimization for XGBoost...
Best XGBoost params: OrderedDict({'colsample_bytree': 0.9947456897155127, 'gamma': 2.0, 'learning_rate': 0.014941213726016101, 'max_depth
': 4, 'min_child_weight': 20, 'n_estimators': 912, 'reg_alpha': 5.0, 'reg_lambda': 3.132689850836927, 'subsample': 0.8499017687136518})
Training stacking ensemble...
Train Performance: RMSE=0.8681, MAE=0.6155, R²=0.9773
Test Performance: RMSE=1.5853, MAE=1.0961, R²=0.9240
Models and artifacts saved to C:\Users\tarun\diss\td188
✅ Training complete.
```

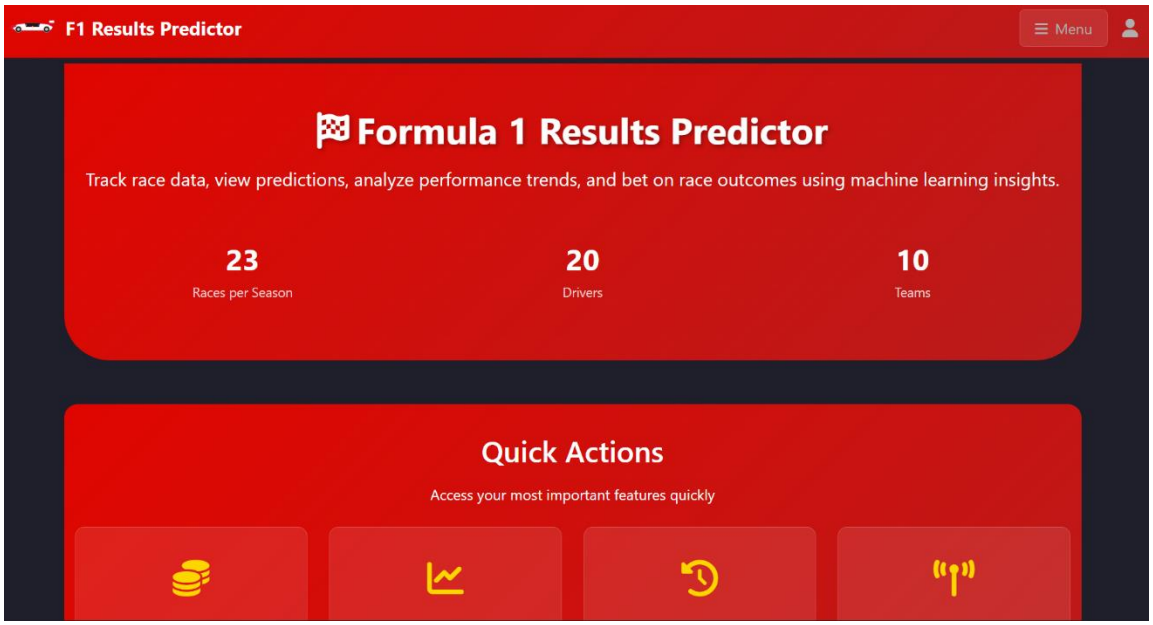
```
(yolov5s) PS C:\Users\tarun\diss\td188> python manage.py train_ridge
Could not start background tasks: populate() isn't reentrant
Preparing training data...
Loading race results...
Loaded 1656 race results
Loading driver performance...
Loading team performance...
Merging datasets...
Merged dataset contains 1656 records
Missing tire lap time columns, setting tire_delta = 0
Missing columns for teammate_gap, setting to zero
Data split complete - Train: 1324, Test: 332
Training samples: 1324
Test samples: 332
Features: 16
Applying recent weighting (min_year=2022.0, weight_factor=3.0)
Training Ridge Regression (alpha=1.0) with recent weighting...
Evaluating model...

=== Evaluation Metrics ===
MAE: 1.9627
RMSE: 2.9464
R²: 0.7376
Model saved to ridge_baseline.pkl
Feature names saved to ridge_baseline_features.pkl

=== Top 10 Features ===
rivalry_performance      : 5.8211
circuit_affinity         : 0.9806
teammate_battle          : 0.7523
reliability_score        : 0.6047
dnf_rate                 : 0.5548
points_per_race          : -0.1299
moving_avg_5             : 0.1145
wet_weather_perf         : -0.1089
qualifying_avg           : 0.0961
position_momentum        : 0.0590
```

```
Categorical features identified: ['category']
0:      learn: 4.9887754        test: 4.8090350 best: 4.8090350 (0)     total: 125ms    remaining: 2m 5s
100:    learn: 2.7533485        test: 2.6170228 best: 2.6170228 (100)   total: 603ms    remaining: 5.37s
200:    learn: 2.0069602        test: 1.9674191 best: 1.9674191 (200)   total: 1.04s    remaining: 4.15s
300:    learn: 1.7309703        test: 1.8067791 best: 1.8067791 (300)   total: 1.49s    remaining: 3.46s
400:    learn: 1.5985368        test: 1.7766331 best: 1.7759699 (399)   total: 1.92s    remaining: 2.86s
500:    learn: 1.5115584        test: 1.7683873 best: 1.7680918 (452)   total: 2.36s    remaining: 2.35s
600:    learn: 1.4434176        test: 1.7596842 best: 1.7596842 (600)   total: 2.81s    remaining: 1.87s
700:    learn: 1.3776665        test: 1.7566316 best: 1.7563965 (683)   total: 3.26s    remaining: 1.39s
800:    learn: 1.3134070        test: 1.7546511 best: 1.7544704 (738)   total: 3.73s    remaining: 928ms
900:    learn: 1.2554684        test: 1.7520831 best: 1.7520138 (899)   total: 4.19s    remaining: 461ms
999:    learn: 1.2032694        test: 1.7561334 best: 1.7518330 (904)   total: 4.64s    remaining: 0us

bestTest = 1.751832969
bestIteration = 904

Shrink model to first 905 iterations.
Train MAE: 1.2535
Test MAE: 1.7518
Test RMSE: 2.8518
Test R²: 0.7392

=== Top 10 Feature Importance ===
ensemble_prediction       13.852
ridge_prediction          13.135
xgboost_prediction        12.567
driver_points_per_race    6.726
driver_circuit_affinity   6.242
driver_qualifying_avg     5.833
driver_moving_avg_5       5.045
driver_position_variance  5.014
rivalry_performance       4.901
pit_stop_avg              4.360
CatBoost training completed successfully!
```

```
=== CatBoost Predictions vs Actual Results for Australian Grand Prix ===
Track Category: HIGH_SPEED

Pos  Driver              CatBoost  Ensemble  Ridge    XGBoost  Qual  Actual Diff
------------------------------------------------------------------------------
1    Lando Norris        1.00      1.00      1.00     1.00     1     1      +0
3    Max Verstappen      3.00      3.00      3.00     3.00     3     2      +1
4    George Russell      4.00      4.00      4.00     4.00     4     3      +1
16   Kimi Antonelli      16.00     16.00     16.00    16.00    16    4      +12
6    Alexander Albon     6.00      6.00      6.00     6.00     6     5      +1
13   Lance Stroll        13.00     13.00     13.00    13.00    13    6      +7
17   Nico Hulkenberg     17.00     17.00     17.00    17.00    17    7      +10
7    Charles Leclerc     7.00      7.00      7.00     7.00     7     8      -1
2    Oscar Piastri       2.00      2.00      2.00     2.00     2     9      -7
8    Lewis Hamilton      8.00      8.00      8.00     8.00     8     10     -2
9    Pierre Gasly        9.00      9.00      9.00     9.00     9     11     -2
5    Yuki Tsunoda        5.00      5.00      5.00     5.00     5     12     -7
19   Esteban Ocon        19.00     19.00     19.00    19.00    19    13     +6
20   Oliver Bearman      20.00     20.00     20.00    20.00    20    14     +6
18   Liam Lawson         18.00     18.00     18.00    18.00    18    15     +3
15   Gabriel Bortoleto   15.00     15.00     15.00    15.00    15    16     -1
12   Fernando Alonso     11.50     11.50     12.00    11.00    12    17     -5
10   Carlos Sainz        10.00     10.00     10.00    10.00    10    18     -8
14   Jack Doohan         14.00     14.00     14.00    14.00    14    19     -5
11   Isack Hadjar        11.50     11.50     11.00    12.00    11    20     -9

=== Track Characteristics ===
Power Sensitivity: 7.5/10
Overtaking Difficulty: 5.5/10
Qualifying Importance: 6.5/10
```

Appendix E: User Interface Screenshots





F1 Results Predictor

Menu

Hi, TARUN

5100

PRO Active

My Portfolio

My Bets

Credits History

Manage Subscription

Logout

THEME

F1 Predictions

Season Overview & Race Predictions

Select Prediction Model

Choose which machine learning model to view predictions from

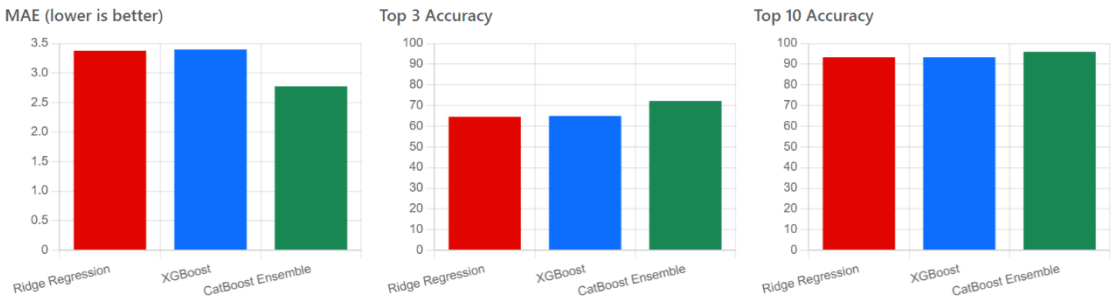
Ridge Regression

2025 Season Overview

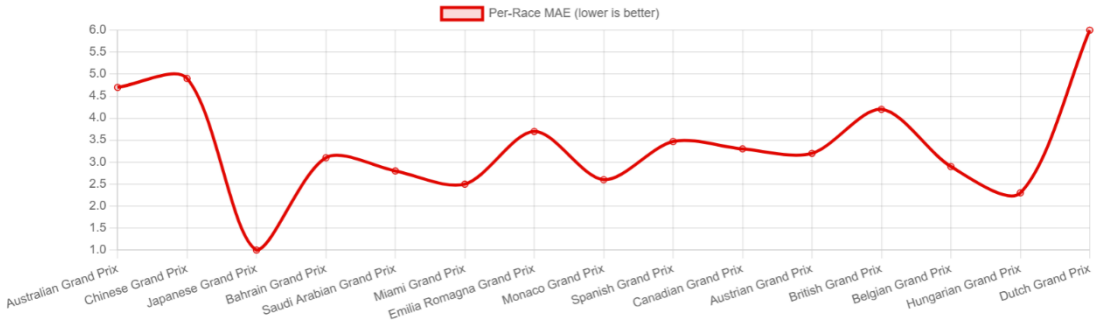
Ridge Regression

15	15	1-15	Ridge Regression
Total Races	Races with Predictions	Available Rounds	Model Used

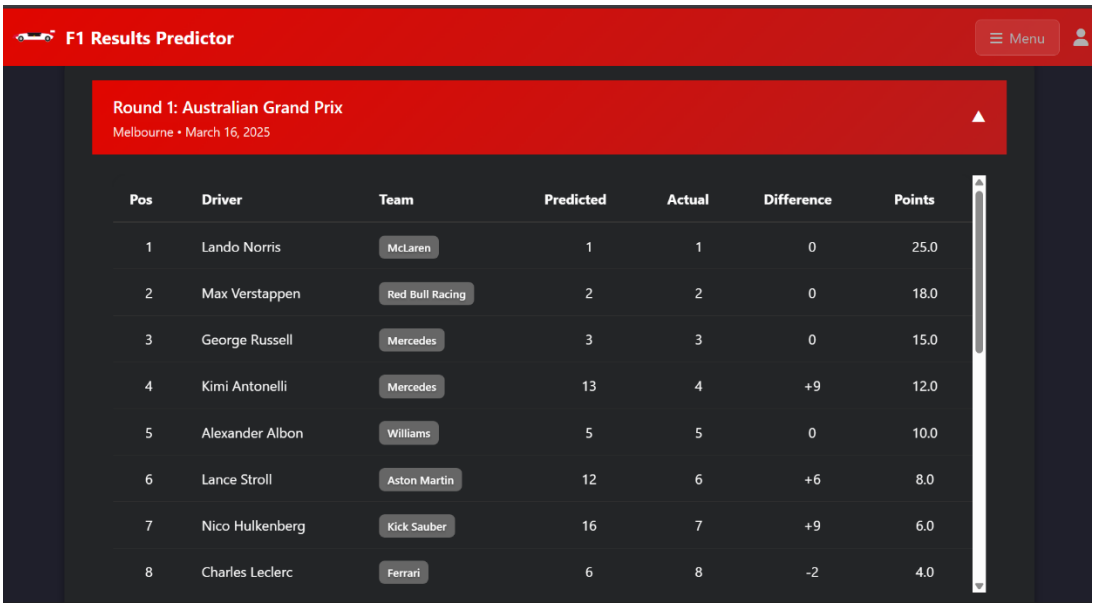
Model Comparison

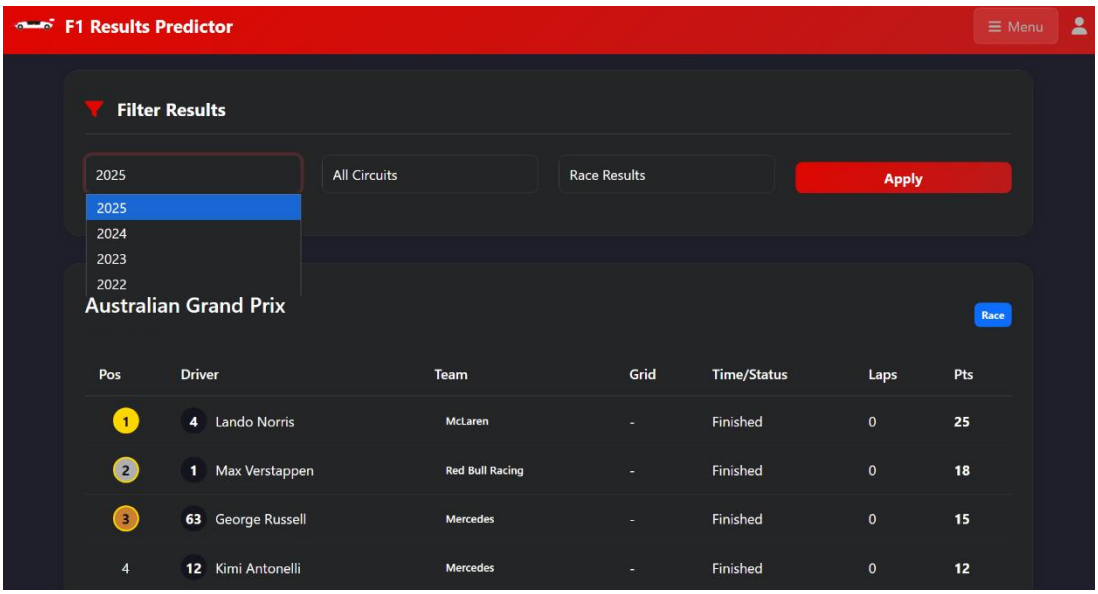


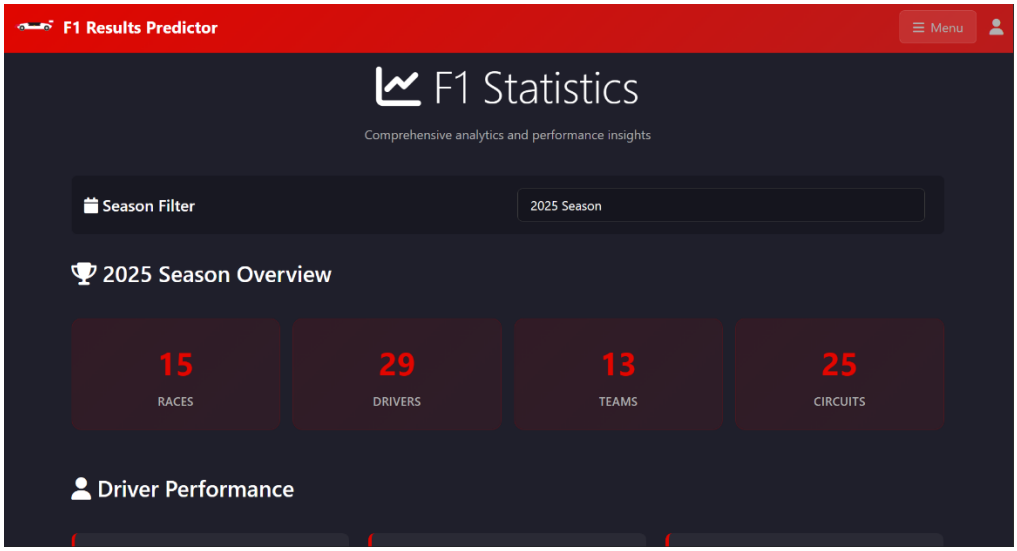
Per-Race Consistency (Selected Model)

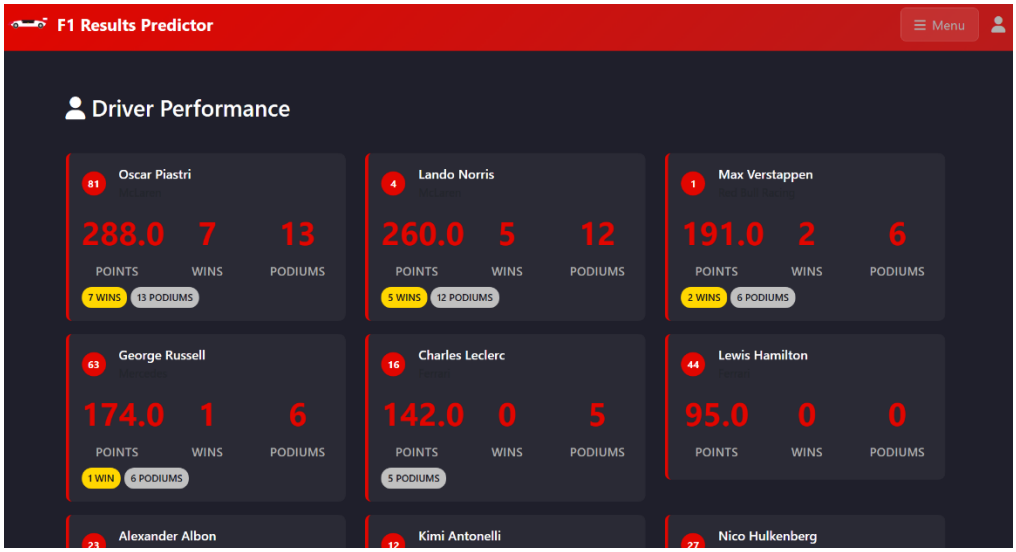


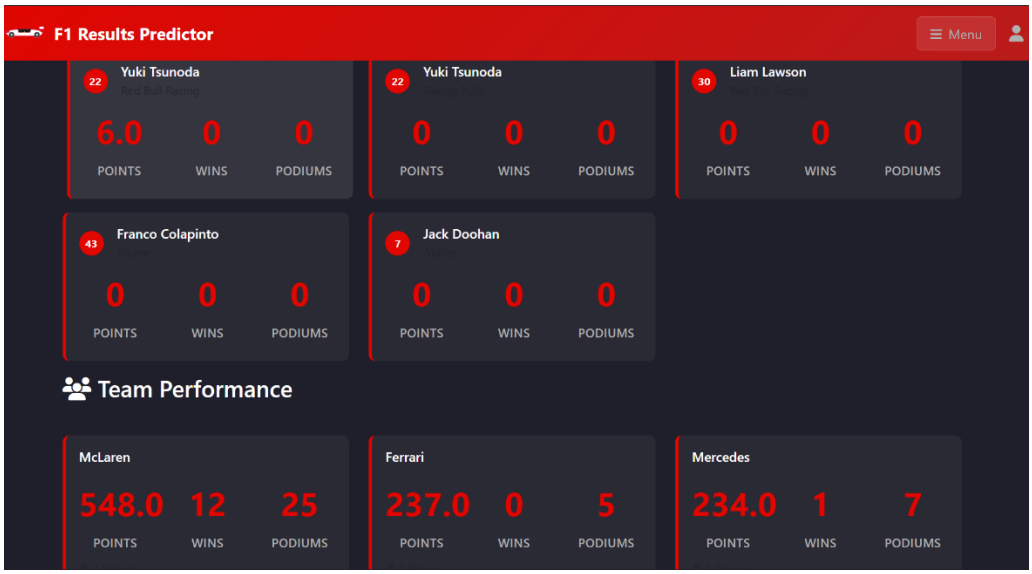

Round 1: Australian Grand Prix
Melbourne • March 16, 2025
Round 2: Chinese Grand Prix
Shanghai • March 23, 2025
Round 3: Japanese Grand Prix
Suzuka • April 6, 2025

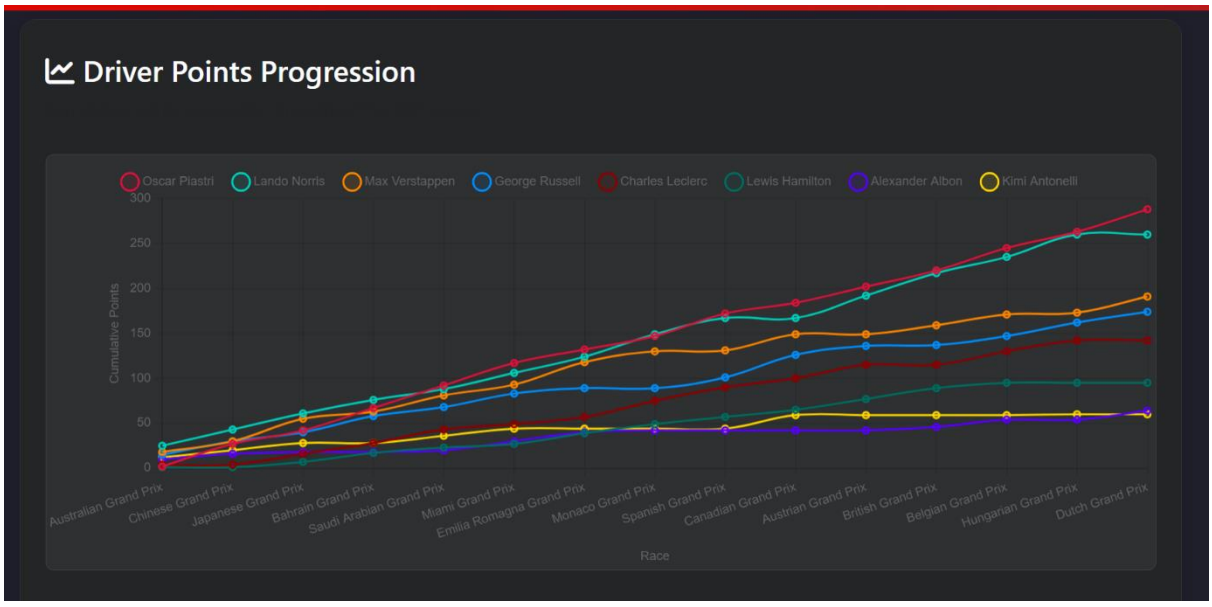

F1 Results Predictor
Menu
Round 1: Australian Grand Prix
Melbourne • March 16, 2025
Pos Driver Team Predicted Actual Difference Points
1 Lando Norris McLaren 1 1 0 25.0
2 Max Verstappen Red Bull Racing 2 2 0 18.0
3 George Russell Mercedes 3 3 0 15.0
4 Kimi Antonelli Mercedes 13 4 +9 12.0
5 Alexander Albon Williams 5 5 0 10.0
6 Lance Stroll Aston Martin 12 6 +6 8.0
7 Nico Hulkenberg Kick Sauber 16 7 +9 6.0
8 Charles Leclerc Ferrari 6 8 -2 4.0


F1 Results Predictor
Menu
Filter Results
2025
All Circuits
Race Results
Apply
2025
2024
2023
2022
Australian Grand Prix
Race
Pos Driver Team Grid Time/Status Laps Pts
1 4 Lando Norris McLaren - Finished 0 25
2 1 Max Verstappen Red Bull Racing - Finished 0 18
3 63 George Russell Mercedes - Finished 0 15
4 12 Kimi Antonelli Mercedes - Finished 0 12


F1 Results Predictor
Menu
F1 Statistics
Comprehensive analytics and performance insights
Season Filter
2025 Season
2025 Season Overview
15
RACES
29
DRIVERS
13
TEAMS
25
CIRCUITS
Driver Performance


F1 Results Predictor
Menu
Driver Performance
81
Oscar Piastri
288.0
7
13
POINTS
WINS
PODIUMS
7 WINS
13 PODIUMS
4
Lando Norris
260.0
5
12
POINTS
WINS
PODIUMS
5 WINS
12 PODIUMS
1
Max Verstappen
191.0
2
6
POINTS
WINS
PODIUMS
2 WINS
6 PODIUMS
63
George Russell
174.0
1
6
POINTS
WINS
PODIUMS
1 WIN
6 PODIUMS
16
Charles Leclerc
142.0
0
5
POINTS
WINS
PODIUMS
5 PODIUMS
44
Lewis Hamilton
95.0
0
0
POINTS
WINS
PODIUMS
Alexander Albon
Kimi Antonelli
Nico Hulkenberg


F1 Results Predictor
Menu
22
Yuki Tsunoda
6.0
0
0
POINTS
WINS
PODIUMS
22
Yuki Tsunoda
0
0
0
POINTS
WINS
PODIUMS
30
Liam Lawson
0
0
0
POINTS
WINS
PODIUMS
43
Franco Colapinto
0
0
0
POINTS
WINS
PODIUMS
7
Jack Doohan
0
0
0
POINTS
WINS
PODIUMS
Team Performance
McLaren
548.0
12
25
POINTS
WINS
PODIUMS
Ferrari
237.0
0
5
POINTS
WINS
PODIUMS
Mercedes
234.0
1
7
POINTS
WINS
PODIUMS

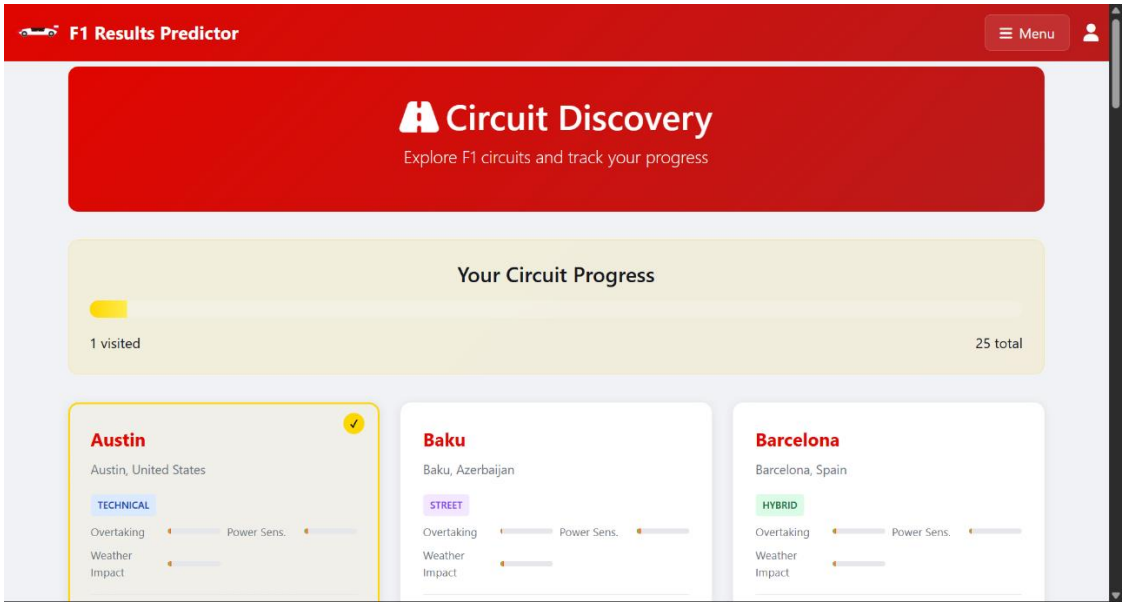


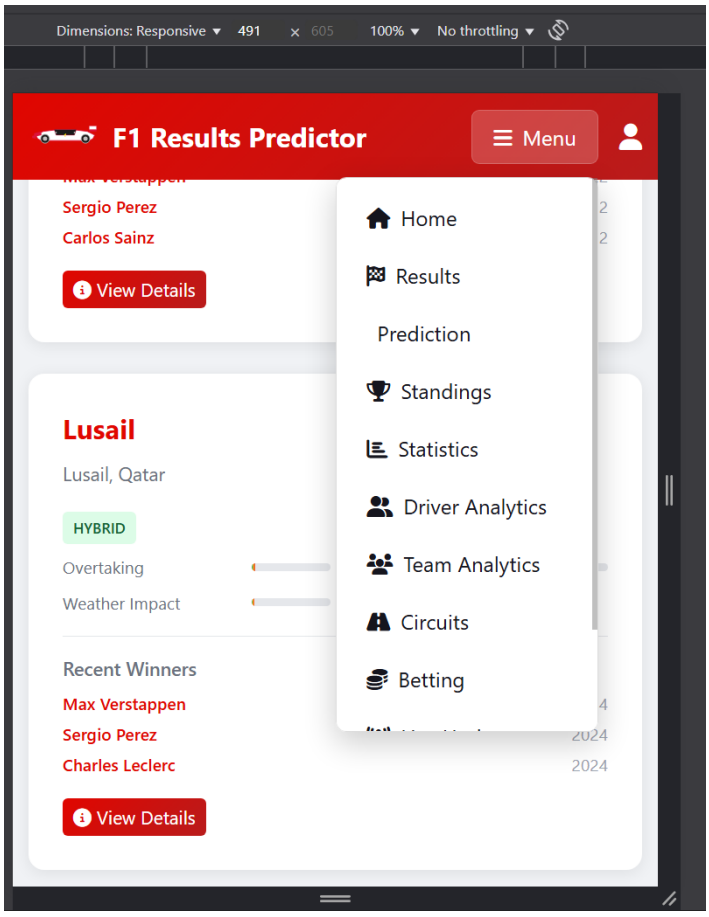
F1 Results Predictor ☰ Menu

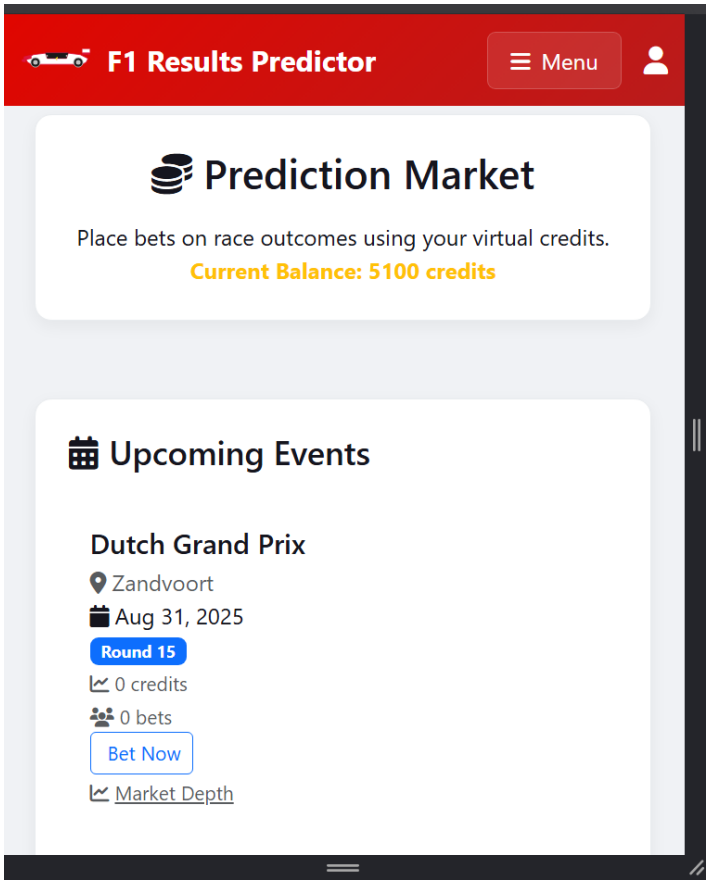
Team Comparison Table

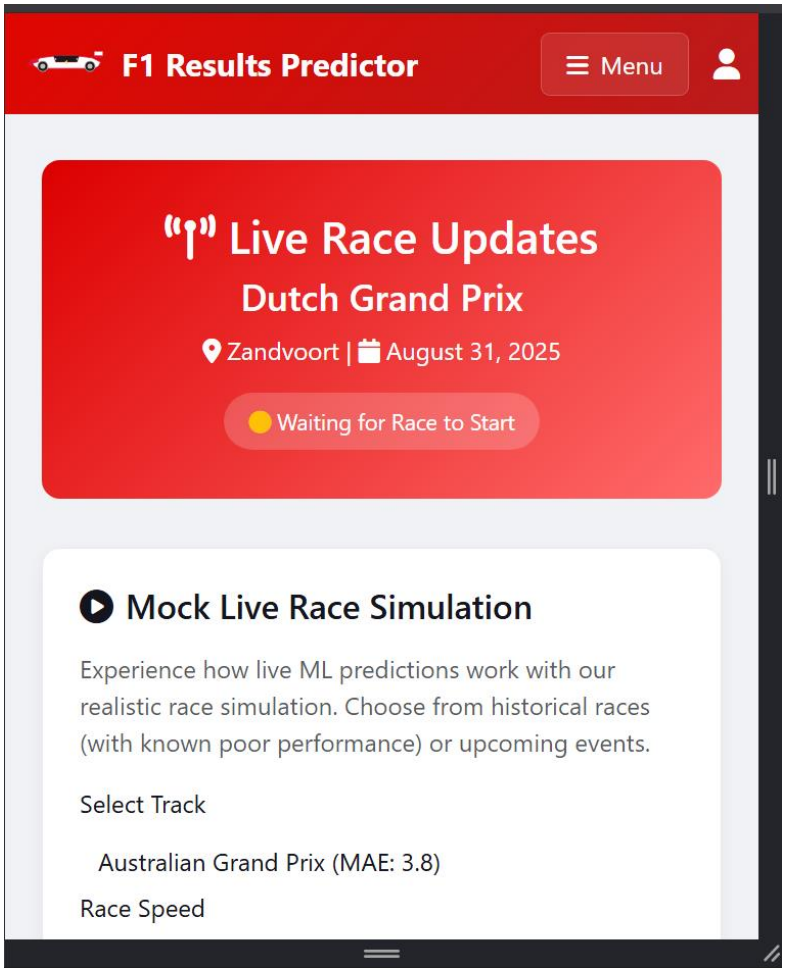
Detailed race-by-race points comparison

Team	Aus	Chi	Jap	Bah	Sau	Mia	Emi	Mon	Spa	Can	Aus	Bri	Bel	Hun	Dut
McLaren	27.0	43.0	33.0	40.0	37.0	43.0	33.0	40.0	43.0	12.0	43.0	43.0	43.0	43.0	25.0
Ferrari	5.0	0	18.0	22.0	21.0	10.0	20.0	28.0	23.0	18.0	27.0	12.0	21.0	12.0	0
Mercedes	27.0	23.0	18.0	18.0	18.0	23.0	6.0	0	12.0	40.0	10.0	1.0	10.0	16.0	12.0
Red Bull Racing	18.0	12.0	25.0	10.0	18.0	13.0	26.0	12.0	1.0	18.0	0	10.0	12.0	2.0	20.0
Williams	10.0	7.0	2.0	0	6.0	12.0	14.0	3.0	0	1.0	0	4.0	8.0	0	10.0
Aston Martin	8.0	2.0	0	0	0	0	0	0	2.0	6.0	6.0	8.0	0	16.0	10.0
Racing Bulls	0	0	4.0	0	1.0	0	2.0	12.0	6.0	0	8.0	0	4.0	4.0	15.0


F1 Results Predictor
Menu
Circuit Discovery
Explore F1 circuits and track your progress
Your Circuit Progress
1 visited
25 total
Austin
Austin, United States
TECHNICAL
Overtaking
Power Sens.
Weather Impact
Baku
Baku, Azerbaijan
STREET
Overtaking
Power Sens.
Weather Impact
Barcelona
Barcelona, Spain
HYBRID
Overtaking
Power Sens.
Weather Impact


Dimensions: Responsive 491 × 605 100% No throttling
F1 Results Predictor
Menu
Sergio Perez
Carlos Sainz
View Details
Home
Results
Prediction
Standings
Statistics
Driver Analytics
Team Analytics
Circuits
Betting
Lusail
Lusail, Qatar
HYBRID
Overtaking
Weather Impact
Recent Winners
Max Verstappen
Sergio Perez
Charles Leclerc
2024
View Details


F1 Results Predictor
Menu
Prediction Market
Place bets on race outcomes using your virtual credits.
Current Balance: 5100 credits
Upcoming Events
Dutch Grand Prix
Zandvoort
Aug 31, 2025
Round 15
0 credits
0 bets
Bet Now
Market Depth


F1 Results Predictor
Menu
Live Race Updates
Dutch Grand Prix
Zandvoort | August 31, 2025
Waiting for Race to Start
Mock Live Race Simulation
Experience how live ML predictions work with our realistic race simulation. Choose from historical races (with known poor performance) or upcoming events.
Select Track
Australian Grand Prix (MAE: 3.8)
Race Speed

F1 Results Predictor

Menu

Mock Live Race Simulation

Experience how live ML predictions work with our realistic race simulation. Choose from historical races (with known poor performance) or upcoming events.

Select Track: Australian Grand Prix (MAE:

Race Speed: 10 minutes

Actions: Stop Race

Race Status: Lap 2/58 - ML: Active

Interactive Events 2 remaining

Safety Car | Bad Pit Stop | Weather Change

You can trigger up to 2 events during the race (stops at 10 laps to go)

Mock Race Context

Starting Grid (Qualifying Results)

P1: Fernando Alonso | P2: Pierre Gasly | P3: Esteban Ocon | P4: Kimi Antonelli | P5: Nico Huülkenberg | P6: George Russell | P7: Oscar Piastri | P8: Lance Stroll | P9: Gabriel Bortoleto

ML Predictions Timeline

Pre-Race ML Prediction:

P1: Fernando Alonso Pre-race model

P2: Pierre Gasly Pre-race model

P3: Esteban Ocon Pre-race model

What a move! Nico Hulkenberg takes the position from Alexander Albon!

Lap 3

What a move! Isack Hadjar takes the position from Gabriel Bortoleto!

Lap 4

Fernando Alonso makes it stick on Kimi Antonelli - superb racing!

Lap 4

Franco Colapinto makes it stick on Jack Doohan - superb racing!

Lap 4

ML models updated - 3 prediction sets generated

ML Prediction Updates

Live ML Predictions

RIDGE REGRESSION

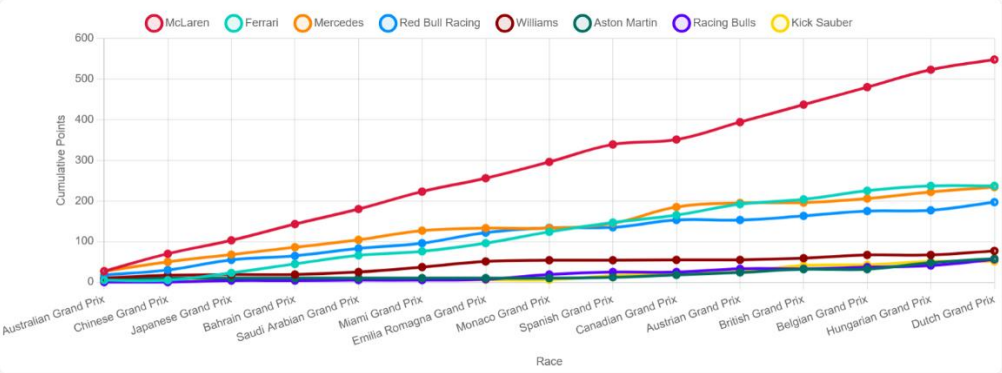
Max Verstappen (Currently P1)
Predicted: **P1** (No change)

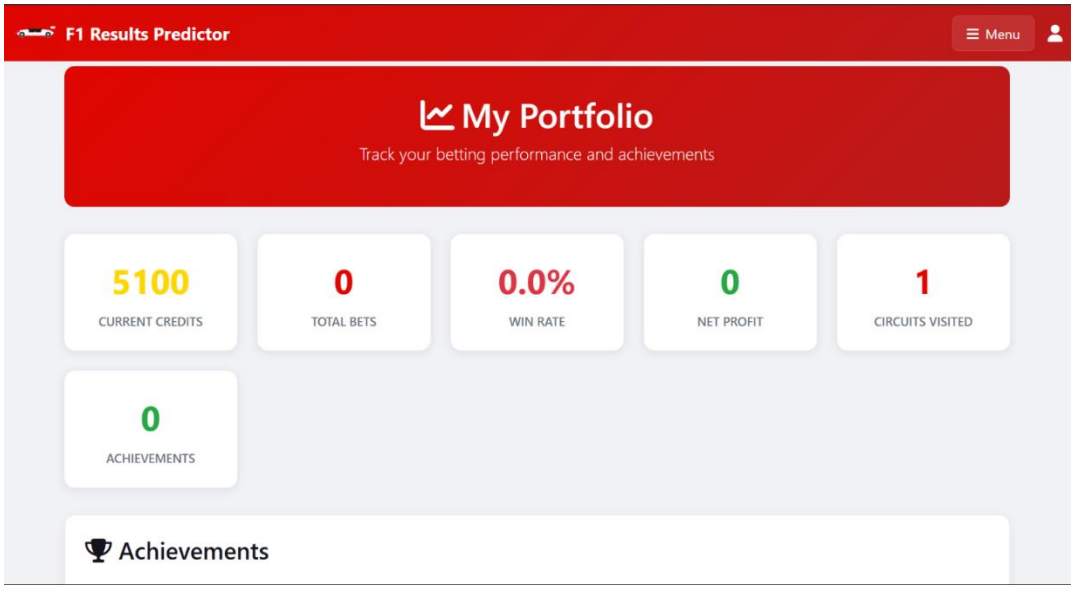
Yuki Tsunoda (Currently P2)
Predicted: **P3** (+1)

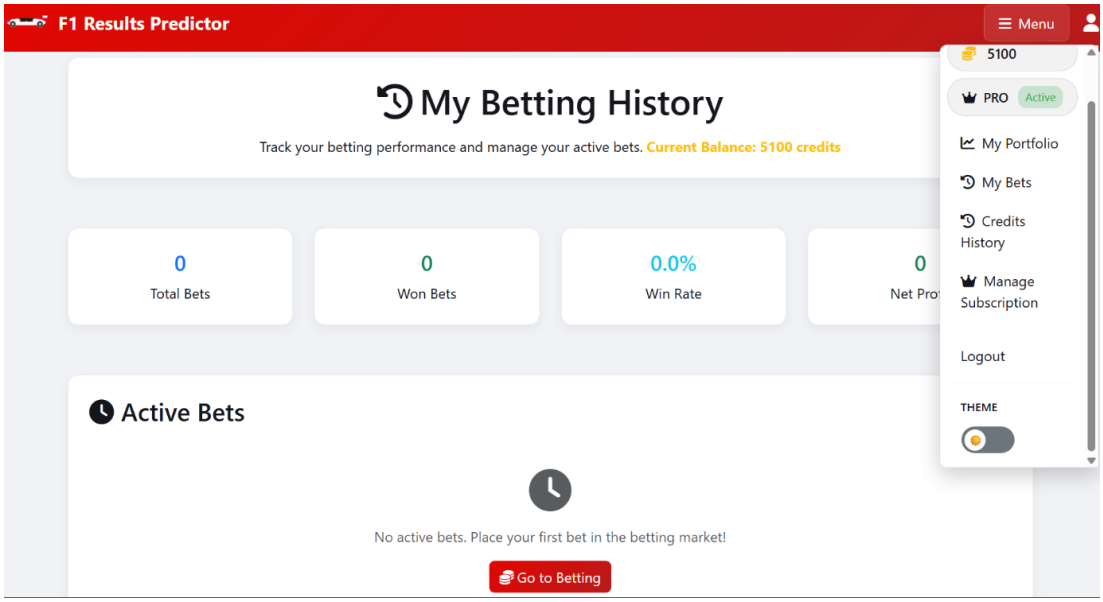
Charles Leclerc (Currently P3)
Predicted: **P3** (No change)

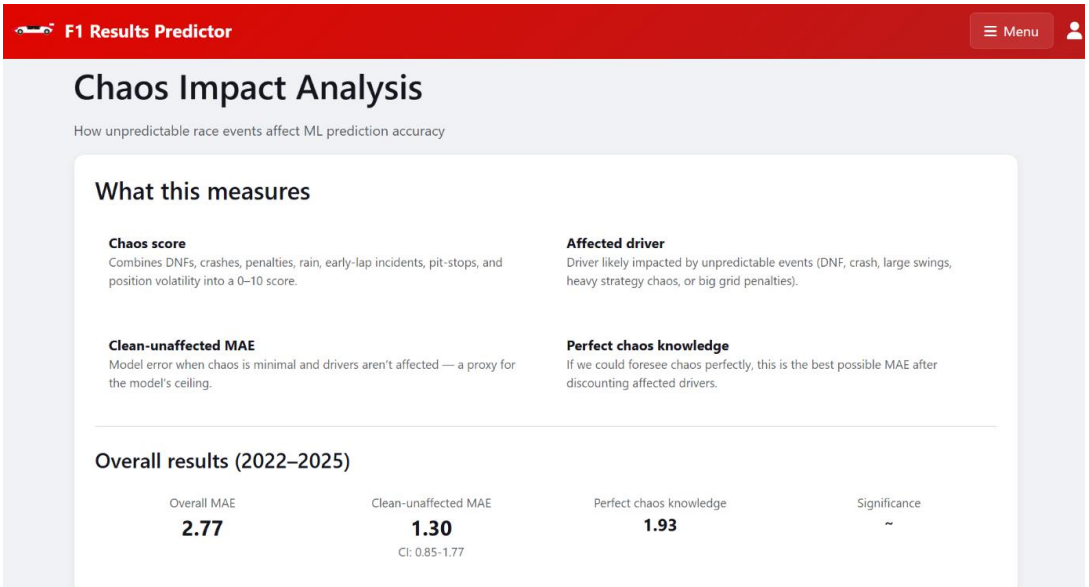
Team Points Progression

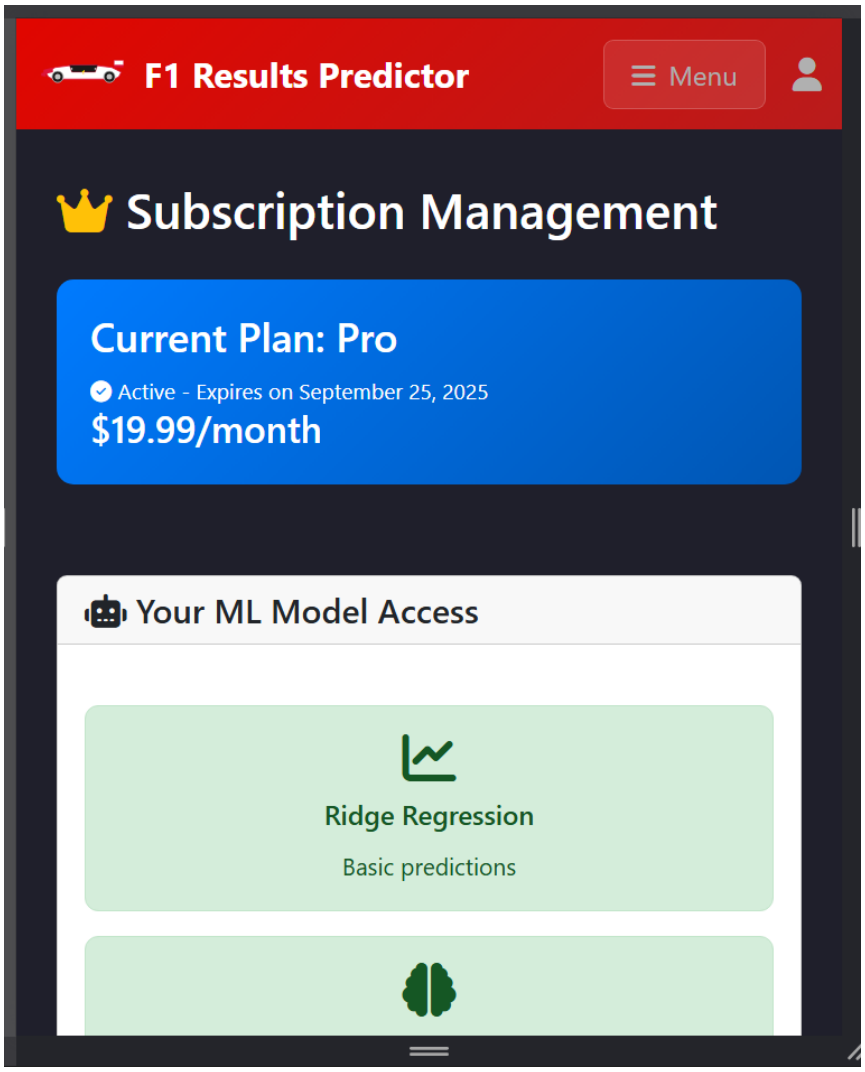
Cumulative points progression throughout the 2025 season




F1 Results Predictor
Menu
My Portfolio
Track your betting performance and achievements
5100
CURRENT CREDITS
0
TOTAL BETS
0.0%
WIN RATE
0
NET PROFIT
1
CIRCUITS VISITED
0
ACHIEVEMENTS
Achievements


F1 Results Predictor
Menu
My Betting History
Track your betting performance and manage your active bets. Current Balance: 5100 credits
0
Total Bets
0
Won Bets
0.0%
Win Rate
0
Net Pro
5100
PRO
Active
My Portfolio
My Bets
Credits History
Manage Subscription
Logout
THEME
Active Bets
No active bets. Place your first bet in the betting market!
Go to Betting


F1 Results Predictor
Menu
Chaos Impact Analysis
How unpredictable race events affect ML prediction accuracy
What this measures
Chaos score
Combines DNFs, crashes, penalties, rain, early-lap incidents, pit-stops, and position volatility into a 0–10 score.
Affected driver
Driver likely impacted by unpredictable events (DNF, crash, large swings, heavy strategy chaos, or big grid penalties).
Clean-unaffected MAE
Model error when chaos is minimal and drivers aren't affected — a proxy for the model's ceiling.
Perfect chaos knowledge
If we could foresee chaos perfectly, this is the best possible MAE after discounting affected drivers.
Overall results (2022–2025)
Overall MAE
2.77
Clean-unaffected MAE
1.30
CI: 0.85-1.77
Perfect chaos knowledge
1.93
Significance
~



F1 Results Predictor ☰ Menu

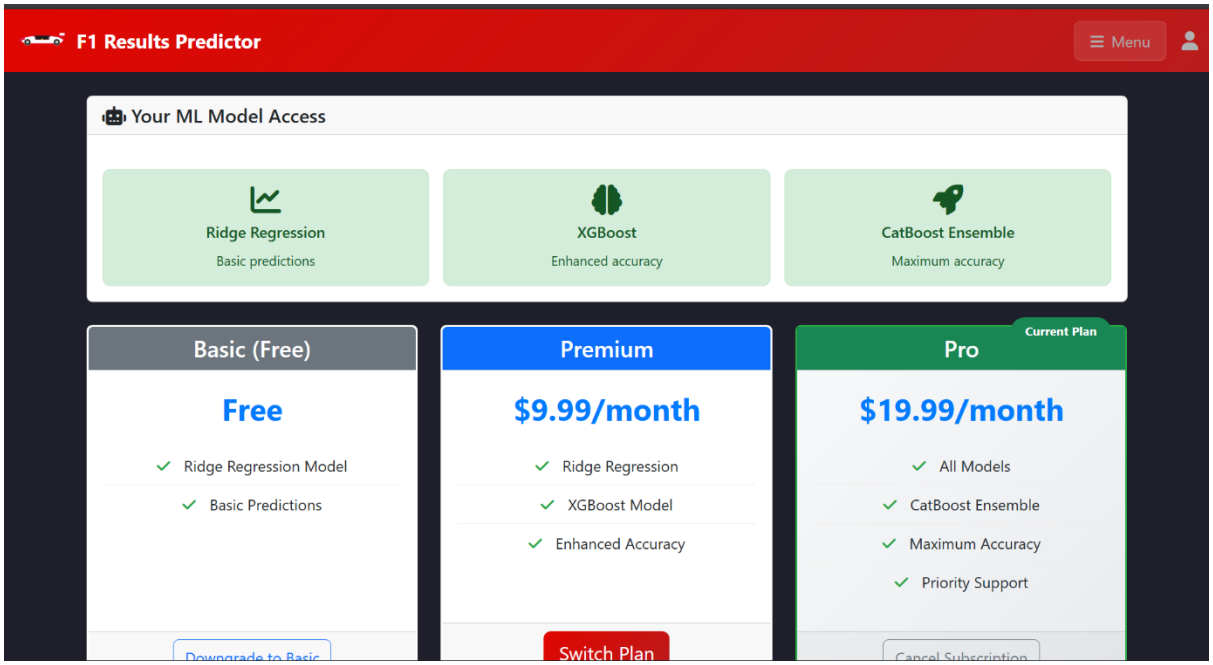
2025 Per-Race Deep-Dive

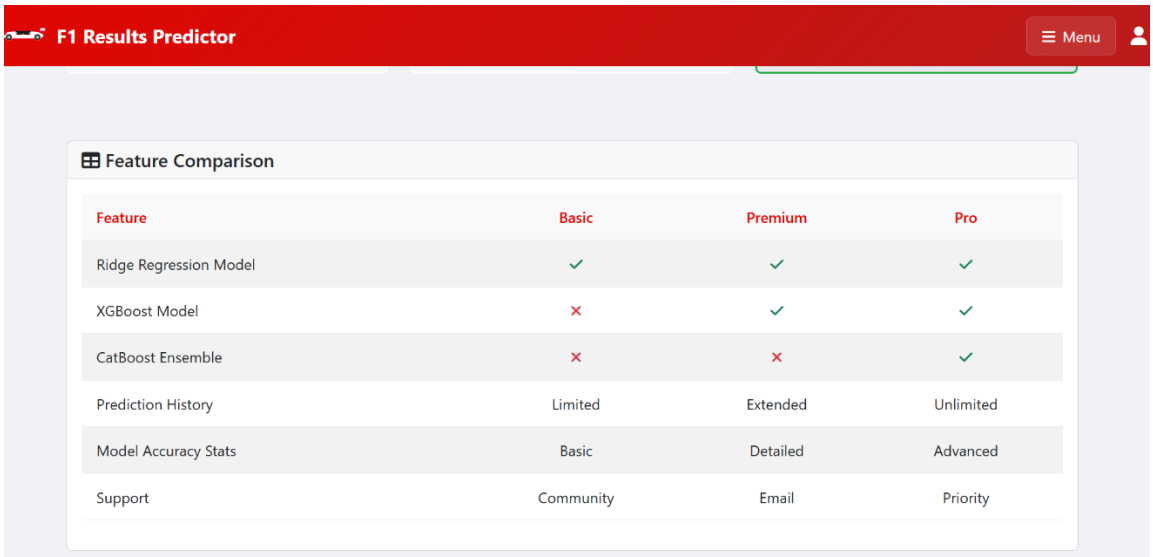
Round 1 9 Australian Grand Prix — Load

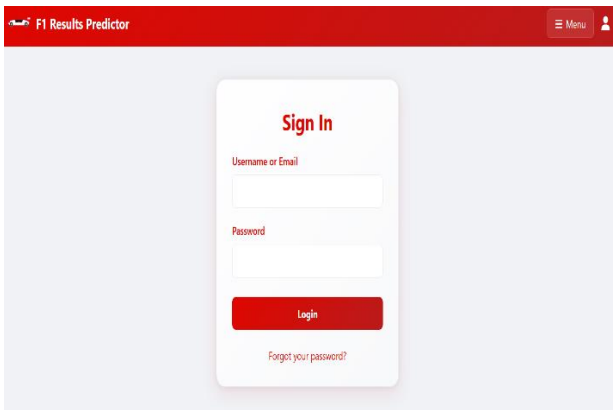
Chaos Score: 1.5 **Category:** clean **Flags:** —

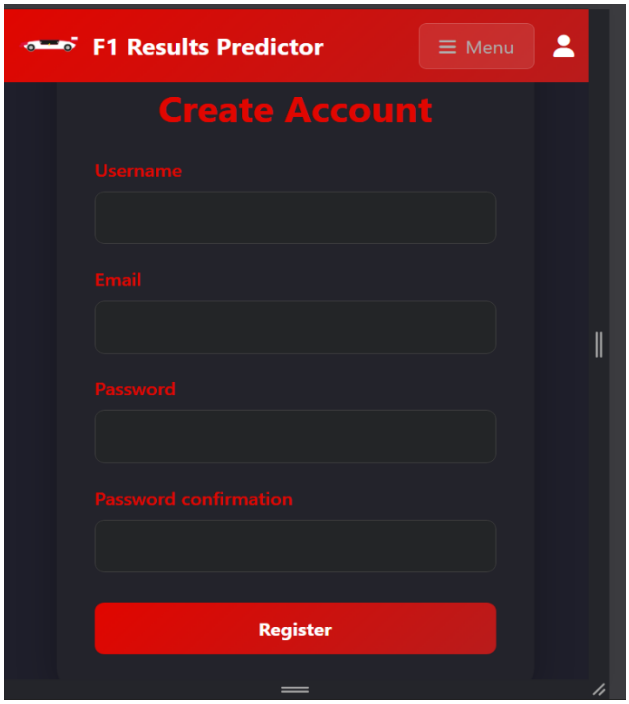
Incidents: DNFs: 6 **Redistribution:** —

Driver	Pred	Act	Error	Affected	Reasons
Kimi Antonelli	13	4	**9.0**	No	—
Nico Hulkenberg	16	7	**9.0**	No	—
Carlos Sainz	10	18	**8.0**	Yes	Retired/DNF
Fernando Alonso	11	17	**6.0**	Yes	Retired/DNF
Lance Stroll	12	6	**6.0**	No	—
Oscar Piastri	4	9	**5.0**	No	—
Jack Doohan	14	19	**5.0**	Yes	Retired/DNF


F1 Results Predictor
Menu
Your ML Model Access
Ridge Regression
Basic predictions
XGBoost
Enhanced accuracy
CatBoost Ensemble
Maximum accuracy
Basic (Free)
Free
Ridge Regression Model
Basic Predictions
Premium
$9.99/month
Ridge Regression
XGBoost Model
Enhanced Accuracy
Switch Plan
Pro
Current Plan
$19.99/month
All Models
CatBoost Ensemble
Maximum Accuracy
Priority Support


F1 Results Predictor
Menu
Feature Comparison
Feature
Basic
Premium
Pro
Ridge Regression Model
XGBoost Model
CatBoost Ensemble
Prediction History
Limited
Extended
Unlimited
Model Accuracy Stats
Basic
Detailed
Advanced
Support
Community
Email
Priority


F1 Results Predictor
Menu
Sign In
Username or Email
Password
Login
Forgot your password?



Appendix F: Complete Testing Framework Code

This appendix contains the complete unit testing framework developed for the Formula 1 prediction system, organized by functional area.

F.1 Core Betting System Tests

F.1.1 Betting Flow Tests (test_betting.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from django.utils import timezone

from data.models import (
    Event, Session, SessionType, Driver, Team, RaceResult,
    CatBoostPrediction, Circuit, UserProfile, Bet, MarketMaker
```

```
)


from datetime import date, datetime


class BettingFlowTests(TestCase):
    def setUp(self):
        self.client = Client()
        self.user = User.objects.create_user(username='bettor', password='secret', email='b@e.com')
        self.client.login(username='bettor', password='secret')
        # Ensure profile exists with default credits
        self.profile = self.user.profile
        self.profile.credits = 5000
        self.profile.save()

        # Minimal domain data
        self.circuit = Circuit.objects.create(name='Test Circuit', country='Nowhere')
        self.event = Event.objects.create(name='Test GP', year=2025, round=1, date=date(2025,1,1), circuit=self.circuit)
        st = SessionType.objects.create(name='Race', session_type='RACE')
        self.session = Session.objects.create(event=self.event, session_type=st, date=datetime(2025,1,1,15,0,0))
        self.team = Team.objects.create(name='Test Team')
        self.driver = Driver.objects.create(given_name='Test', family_name='Driver', permanent_number=99)
        # A couple of historical results to avoid divide-by-zero in odds
        RaceResult.objects.create(session=self.session, driver=self.driver, team=self.team, position=3, points=15)

        # One ML prediction for odds adjustment
        CatBoostPrediction.objects.create(
```

```
            driver=self.driver,
            event=self.event,
            year=2025,
            round_number=1,
            predicted_position=2.0,
            prediction_confidence=0.7,
            model_name='catboost_ensemble'
        )

    def test_place_bet_podium_success(self):
        url = reverse('place_bet')
        payload = {
            'Event_id': str(self.event.id),
            'bet_type': 'PODIUM_FINISH',
            'driver_id': str(self.driver.id),
            'credits_staked': '500',
        }
        resp = self.client.post(url, data=payload)
        self.assertEqual(resp.status_code, 200)
        data = resp.json()
        self.assertTrue(data.get('success'))
        self.assertIn('bet_id', data)

        bet = Bet.objects.get(id=data['bet_id'])
        self.profile.refresh_from_db()
        self.assertLess(self.profile.credits, 5000)  # deducted
        self.assertGreaterEqual(bet.potential_payout, 500)
        # MarketMaker created/updated
```

```
        self.assertEqual(MarketMaker.objects.filter(event=self.event, driver=self.driver,
bet_type='PODIUM_FINISH').count(), 1)


    def test_place_bet_insufficient_credits(self):
        # Reduce credits so can_place_bet fails
        self.profile.credits = 100
        self.profile.save()
        url = reverse('place_bet')
        payload = {
            'event_id': str(self.event.id),
            'bet_type': 'PODIUM_FINISH',
            'driver_id': str(self.driver.id),
            'credits_staked': '1000',
        }
        resp = self.client.post(url, data=payload)
        self.assertEqual(resp.status_code, 200)
        data = resp.json()
        self.assertFalse(data.get('success'))
        self.assertIn('error', data)
        self.assertIn('Insufficient', data['error'])


    def test_place_bet_liquidity_error(self):
        # Pre-create a market maker with very low liquidity
        mm = MarketMaker.objects.create(
            event=self.event,
            bet_type='PODIUM_FINISH',
            driver=self.driver,
            team=None,
            current_odds=2.0,
```

```
            base_odds=2.0,
            available_liquidity=200,
            max_exposure=500,
        )
        url = reverse('place_bet')
        payload = {
            'event_id': str(self.event.id),
            'bet_type': 'PODIUM_FINISH',
            'driver_id': str(self.driver.id),
            'credits_staked': '500',
        }
        resp = self.client.post(url, data=payload)
        self.assertEqual(resp.status_code, 200)
        data = resp.json()
        self.assertFalse(data.get('success'))
        self.assertIn('liquidity', data.get('error','').lower())

    def test_get_real_time_odds_returns_ml_prediction(self):
        url = reverse('get_real_time_odds')
        payload = {
            'event_id': str(self.event.id),
            'bet_type': 'PODIUM_FINISH',
            'driver_id': str(self.driver.id),
        }
        resp = self.client.post(url, data=payload)
        self.assertEqual(resp.status_code, 200)
        data = resp.json()
        self.assertTrue(data.get('success'))
        self.assertIn('odds', data)
```

```
        self.assertIn('market_stats', data)
        self.assertIn('ml_prediction', data)
        self.assertIsInstance(data['ml_prediction'].get('predicted_position'), float)
```

G.1.2 Bet Settlement Tests (test_bet_settlement.py)

```python
from django.test import TestCase
from django.contrib.auth.models import User
from datetime import date, datetime

from data.models import (
    Event, Session, SessionType, Driver, Team, Circuit, Bet
)

class BetSettlementTests(TestCase):
    def setUp(self):
        self.user = User.objects.create_user(username='bettor', password='secret')
        self.profile = self.user.profile
        self.profile.credits = 5000
        self.profile.save()

        self.circuit = Circuit.objects.create(name='Test Circuit', country='Nowhere')
        self.event = Event.objects.create(name='Test GP', year=2025, round=1,
date=date(2025,1,1), circuit=self.circuit)
        st = SessionType.objects.create(name='Race', session_type='RACE')
        self.session = Session.objects.create(event=self.event, session_type=st,
date=datetime(2025,1,1,15,0,0))
        self.team = Team.objects.create(name='Test Team')
```

```
        self.driver = Driver.objects.create(given_name='Test', family_name='Driver',
permanent_number=99)


    def test_settle_winning_bet_credits_payout(self):
        bet = Bet.objects.create(
            user=self.user,
            event=self.event,
            bet_type='PODIUM_FINISH',
            driver=self.driver,
            credits_staked=500,
            odds=2.0,
            potential_payout=1000,
            status='PENDING'
        )
        # Simulate stake deduction as place_bet would do
        self.profile.credits -= 500
        self.profile.save()

        settled = bet.settle(True, actual_result='P2')
        self.assertTrue(settled)
        bet.refresh_from_db()
        self.profile.refresh_from_db()
        self.assertEqual(bet.status, 'WON')
        self.assertEqual(bet.payout_received, 1000)
        self.assertEqual(self.profile.credits, 5500)  # 5000 - 500 + 1000

    def test_settle_losing_bet_no_payout(self):
        bet = Bet.objects.create(
            user=self.user,
```

```
            event=self.event,
            bet_type='PODIUM_FINISH',
            driver=self.driver,
            credits_staked=500,
            odds=2.0,
            potential_payout=1000,
            status='PENDING'
        )
        # Simulate stake deduction as place_bet would do
        self.profile.credits -= 500
        self.profile.save()

        settled = bet.settle(False, actual_result='P11')
        self.assertTrue(settled)
        bet.refresh_from_db()
        self.profile.refresh_from_db()
        self.assertEqual(bet.status, 'LOST')
        self.assertEqual(bet.payout_received, 0)
        self.assertEqual(self.profile.credits, 4500)
```

G.2 Authentication and Access Control Tests

G.2.1 Authentication Flow Tests (test_auth.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
```

```
from django.utils.http import urlsafe_base64_encode
from django.utils.encoding import force_bytes

class AuthFlowTests(TestCase):
    def setUp(self):
        self.client = Client()

    def test_register_activation_login_logout(self):
        # Register
        resp = self.client.get(reverse('register'))
        self.assertEqual(resp.status_code, 200)
        payload = {
            'username': 'alice',
            'email': 'alice@example.com',
            'password1': 'StrongPass!234',
            'password2': 'StrongPass!234',
        }
        resp = self.client.post(reverse('register'), data=payload)
        self.assertEqual(resp.status_code, 200)
        self.assertTemplateUsed(resp, 'registration_pending.html')
        user = User.objects.get(username='alice')
        self.assertFalse(user.is_active)

        # Activation
        uidb64 = urlsafe_base64_encode(force_bytes(user.pk))
        # We cannot access the real token generator token easily; simulate success by directly hitting activate after setting is_active
        user.is_active = True
        user.save()
```

```
        resp = self.client.get(reverse('activate', args=[uidb64, 'dummy-token']))
        # If token invalid, template may render activation_invalid; but user is active, so redirect occurs only if token checks
        # For robustness, just attempt login next

        # Login
        resp = self.client.post(reverse('login'), data={'username': 'alice', 'password': 'StrongPass!234'})
        self.assertIn(resp.status_code, (200, 302))
        # Logout
        resp = self.client.get(reverse('logout'))
        self.assertEqual(resp.status_code, 302)

    def test_forgot_password_flow(self):
        user = User.objects.create_user(username='bob', password='OldPass!234', email='bob@example.com', is_active=True)
        # Step 1
        resp = self.client.post(reverse('forgot_password'), data={'email_or_username': 'bob'})
        self.assertEqual(resp.status_code, 200)
        # Step 1 renders step 2; session keys set
        temp_password = self.client.session.get('temp_password')
        self.assertTrue(temp_password)
        self.assertEqual(self.client.session.get('user_id'), user.id)
        self.assertTrue(temp_password)
        # Step 2
        resp = self.client.post(reverse('verify_temp_password'), data={'temp_password': temp_password})
        self.assertIn(resp.status_code, (200, 302))  # step 3 page rendered or redirected
        # Step 3 (may render or redirect)
```

```
        resp = self.client.post(reverse('reset_password'), data={'new_password':
'NewPass!234', 'confirm_password': 'NewPass!234'})
        self.assertIn(resp.status_code, (200, 302))
        # Login with new password
        resp = self.client.post(reverse('login'), data={'username': 'bob', 'password':
'NewPass!234'})
        self.assertIn(resp.status_code, (200, 302))
```

G.2.2 Access Control Tests (test_access.py)

```python
from django.test import TestCase, Client
from django.urls import reverse

class AccessRedirectTests(TestCase):
    def setUp(self):
        self.client = Client()

    def test_login_required_redirects_with_next(self):
        # Pages that redirect to login
        names = ['betting', 'my_bets', 'market_depth', 'subscription_management']
        for name in names:
            kwargs = {'event_id': 1} if name == 'market_depth' else {}
            resp = self.client.get(reverse(name, kwargs=kwargs))
            if resp.status_code == 302:
                loc = resp.headers.get('Location', '')
                self.assertIn('/login', loc)

    def test_post_only_endpoints_405_on_get(self):
```

```
        # Endpoints that are POST-only
        post_only = ['place_bet', 'get_real_time_odds', 'place_market_order']
        for name in post_only:
            resp = self.client.get(reverse(name))
            # Some endpoints return 405, some redirect/401 depending on auth; accept 200 for pages that render forms
            self.assertIn(resp.status_code, (200, 302, 401, 405))

class AccessControlTests(TestCase):
    def setUp(self):
        self.client = Client()

    def test_protected_endpoints_require_auth(self):
        protected = [
            'place_bet', 'get_real_time_odds', 'get_market_depth_data', 'place_market_order',
            'my_bets', 'market_depth', 'subscription_management'
        ]
        for name in protected:
            url = reverse(name, kwargs={'market_maker_id': 1}) if name == 'get_market_depth_data' else (
                reverse(name, kwargs={'event_id': 1}) if name == 'market_depth' else reverse(name))
            resp = self.client.get(url)
            # Some endpoints return 401 JSON, others redirect; some may render 200 public views
            self.assertIn(resp.status_code, (200, 302, 401, 405))
```

G.3 Prediction System Tests

G.3.1 Prediction Integration Tests (test_predictions.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from datetime import date, datetime

from data.models import Circuit, Event, SessionType, Session, Driver, Team, CatBoostPrediction, TrackSpecialization

class PredictionsTests(TestCase):
    def setUp(self):
        self.client = Client()
        self.user = User.objects.create_user(username='u', password='p')
        self.client.login(username='u', password='p')
        self.circuit = Circuit.objects.create(name='Test Circuit', country='Nowhere')
        self.event = Event.objects.create(name='Test GP', year=2025, round=1, date=date(2025,1,1), circuit=self.circuit)
        st = SessionType.objects.create(name='Race', session_type='RACE')
        self.session = Session.objects.create(event=self.event, session_type=st, date=datetime(2025,1,1,15,0,0))
        self.driver = Driver.objects.create(given_name='Test', family_name='Driver', permanent_number=99, driver_ref='td_ref', driver_id='td_id', nationality='X')
        self.team = Team.objects.create(name='Test Team')
        # At least one prediction row
        CatBoostPrediction.objects.create(driver=self.driver, event=self.event, year=2025, round_number=1, predicted_position=2.4, model_name='catboost_ensemble')

    def test_prediction_page_renders_and_ranking(self):
```

```
        resp = self.client.get(reverse('prediction') + '?model=catboost')
        self.assertEqual(resp.status_code, 200)
        # context contains per_race_labels / mae arrays
        self.assertIn('per_race_labels', resp.context)
        self.assertIn('per_race_mae', resp.context)
        # chart bootstrap in HTML
        self.assertContains(resp, 'MAE (lower is better)')

    def test_bias_correction_does_not_crash(self):
        # Add track specialization and ensure no crash
        TrackSpecialization.objects.create(circuit=self.circuit, category='STREET')
        resp = self.client.get(reverse('prediction') + '?model=catboost')
        self.assertEqual(resp.status_code, 200)
```

G.3.2 Prediction Edge Cases Tests (test_prediction_edge_cases.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from datetime import date, datetime

from data.models import Circuit, Event, SessionType, Session, Driver, Team,
ridgeregression

class PredictionEdgeCaseTests(TestCase):
    def setUp(self):
        self.client = Client()
```

```
        self.user = User.objects.create_user(username='u', password='p')
        self.client.login(username='u', password='p')
        self.circuit = Circuit.objects.create(name='EC Circuit', country='Nowhere')
        self.event = Event.objects.create(name='EC GP', year=2025, round=1,
date=date(2025,1,1), circuit=self.circuit)
        st = SessionType.objects.create(name='Race', session_type='RACE')
        self.session = Session.objects.create(event=self.event, session_type=st,
date=datetime(2025,1,1,12,0,0))
        self.driver = Driver.objects.create(given_name='A', family_name='A',
permanent_number=10, driver_ref='ea_ref', driver_id='ea_id', nationality='X')
        self.team = Team.objects.create(name='T')
        ridgeregression.objects.create(driver=self.driver, event=self.event, year=2025,
round_number=1, predicted_position=5.0, model_name='ridge_regression')

    def test_model_switch_and_labels_mae_alignment(self):
        # Ridge
        resp = self.client.get(reverse('prediction') + '?model=ridge_regression')
        self.assertEqual(resp.status_code, 200)
        self.assertIn('per_race_labels', resp.context)
        self.assertIn('per_race_mae', resp.context)
        labels = resp.context['per_race_labels']
        mae = resp.context['per_race_mae']
        self.assertEqual(len(labels), len(mae))
        # Switch to catboost (may not have data; page should still render)
        resp = self.client.get(reverse('prediction') + '?model=catboost')
        self.assertEqual(resp.status_code, 200)
```

G.3.3 Prediction Ranking Tests (test_prediction_ranks.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from datetime import date, datetime

from data.models import Circuit, Event, SessionType, Session, Driver, Team, ridgeregression, RaceResult

class PredictionRanksTests(TestCase):
    def setUp(self):
        self.client = Client()
        self.user = User.objects.create_user(username='u', password='p')
        self.client.login(username='u', password='p')
        self.circuit = Circuit.objects.create(name='Rank Circuit', country='Nowhere')
        self.event = Event.objects.create(name='Rank GP', year=2025, round=1, date=date(2025,1,1), circuit=self.circuit)
        st = SessionType.objects.create(name='Race', session_type='RACE')
        self.session = Session.objects.create(event=self.event, session_type=st, date=datetime(2025,1,1,15,0,0))
        self.team = Team.objects.create(name='TeamR')
        self.d1 = Driver.objects.create(given_name='A', family_name='A', permanent_number=11, driver_ref='a_ref', driver_id='a_id', nationality='X')
        self.d2 = Driver.objects.create(given_name='B', family_name='B', permanent_number=12, driver_ref='b_ref', driver_id='b_id', nationality='X')
        # Two predictions fractional
        ridgeregression.objects.create(driver=self.d1, event=self.event, year=2025, round_number=1, predicted_position=5.4, model_name='ridge_regression')
        ridgeregression.objects.create(driver=self.d2, event=self.event, year=2025, round_number=1, predicted_position=2.1, model_name='ridge_regression')
        # Actual results
```

```
        RaceResult.objects.create(session=self.session, driver=self.d1,
team=self.team, position=6)
        RaceResult.objects.create(session=self.session, driver=self.d2,
team=self.team, position=2)


    def test_predicted_ranks_are_integers_1_to_n(self):
        resp = self.client.get(reverse('prediction') + '?model=ridge_regression')
        self.assertEqual(resp.status_code, 200)
        results = resp.context['results']
        # Find our event
        comp = None
        for r in results:
            if r['event'].id == self.event.id:
                comp = r['comparison']
                break
        self.assertIsNotNone(comp)
        preds = [item['predicted'] for item in comp if item['actual'] != 'N/A']
        self.assertTrue(all(isinstance(p, int) for p in preds))
        self.assertTrue(all(1 <= p <= len(preds) for p in preds))
```

G.4 User Interface and Navigation Tests

G.4.1 Page Smoke Tests (test_ui_smoke.py)

```python
from django.test import TestCase, Client
from django.urls import reverse

class PageSmokeTests(TestCase):
```

```
    def setUp(self):
        self.client = Client()

    def test_public_pages_render(self):
        pages = ['home', 'results', 'prediction', 'standings', 'statistics', 'circuits']
        for name in pages:
            resp = self.client.get(reverse(name))
            self.assertEqual(resp.status_code, 200)

    def test_auth_pages_render(self):
        pages = ['register', 'login', 'forgot_password', 'subscription_management']
        for name in pages:
            resp = self.client.get(reverse(name))
            # subscription_management requires login; expect redirect
            if name == 'subscription_management':
                self.assertIn(resp.status_code, (302,))
            else:
                self.assertEqual(resp.status_code, 200)
```

G.4.2 Additional Page Tests (test_pages_more.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from datetime import date, datetime

from data.models import Circuit, Event, SessionType, Session, Driver, Team, Bet
```

```
class MorePageTests(TestCase):
    def setUp(self):
        self.client = Client()
        self.user = User.objects.create_user(username='u', password='p')
        self.client.login(username='u', password='p')
        self.circuit = Circuit.objects.create(name='Test Circuit', country='Nowhere')
        self.event = Event.objects.create(name='Test GP', year=2025, round=1,
date=date(2025,1,1), circuit=self.circuit)
        st = SessionType.objects.create(name='Race', session_type='RACE')
        self.session = Session.objects.create(event=self.event, session_type=st,
date=datetime(2025,1,1,15,0,0))
        self.team = Team.objects.create(name='TeamX')
        self.driver = Driver.objects.create(given_name='First', family_name='Last',
permanent_number=77)

    def test_driver_and_team_analytics_pages(self):
        resp = self.client.get(reverse('driver_analytics'))
        self.assertEqual(resp.status_code, 200)
        resp = self.client.get(reverse('team_analytics'))
        self.assertEqual(resp.status_code, 200)

    def test_circuits_and_detail_pages(self):
        resp = self.client.get(reverse('circuits'))
        self.assertEqual(resp.status_code, 200)
        resp = self.client.get(reverse('circuit_detail', args=[self.circuit.id]))
        self.assertEqual(resp.status_code, 200)

    def test_my_bets_context_splits_statuses(self):
        # Create different status bets
```

```
        Bet.objects.create(user=self.user, event=self.event,
bet_type='PODIUM_FINISH', driver=self.driver, credits_staked=100, odds=2.0,
potential_payout=200, status='PENDING')
        Bet.objects.create(user=self.user, event=self.event,
bet_type='PODIUM_FINISH', driver=self.driver, credits_staked=150, odds=2.0,
potential_payout=300, status='WON')
        Bet.objects.create(user=self.user, event=self.event,
bet_type='PODIUM_FINISH', driver=self.driver, credits_staked=200, odds=2.0,
potential_payout=400, status='LOST')
        resp = self.client.get(reverse('my_bets'))
        self.assertEqual(resp.status_code, 200)
        self.assertIn('active_bets', resp.context)
        self.assertIn('completed_bets', resp.context)
        self.assertEqual(resp.context['active_bets'].count(), 1)
        self.assertEqual(resp.context['completed_bets'].count(), 2)
```

G.5 Business Logic and Statistical Tests

G.5.1 Betting Statistics Tests (test_bets_stats_and_liquidity.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from datetime import date

from data.models import Circuit, Event, Bet, MarketMaker, Driver, Team

class BetsStatsAndLiquidityTests(TestCase):
    def setUp(self):
```

```
        self.client = Client()
        self.user = User.objects.create_user(username='u', password='p', email='u@e.com', is_active=True)
        self.client.login(username='u', password='p')
        self.circuit = Circuit.objects.create(name='Stat Circuit', country='X')
        self.event = Event.objects.create(name='Stat GP', year=2025, round=1, date=date(2025,1,1), circuit=self.circuit)
        self.driver = Driver.objects.create(given_name='D', family_name='One', permanent_number=1, driver_ref='d_ref', driver_id='d_id', nationality='X')
        self.team = Team.objects.create(name='T')
        # Ensure profile has credits
        self.user.profile.credits = 10000
        self.user.profile.save()

    def test_my_bets_stats(self):
        # Create bets with different statuses
        Bet.objects.create(user=self.user, event=self.event, bet_type='PODIUM_FINISH', driver=self.driver, credits_staked=200, odds=2.0, potential_payout=400, status='PENDING')
        Bet.objects.create(user=self.user, event=self.event, bet_type='PODIUM_FINISH', driver=self.driver, credits_staked=300, odds=1.5, potential_payout=450, status='WON', payout_received=450)
        Bet.objects.create(user=self.user, event=self.event, bet_type='PODIUM_FINISH', driver=self.driver, credits_staked=500, odds=3.0, potential_payout=1500, status='LOST', payout_received=0)
        resp = self.client.get(reverse('my_bets'))
        self.assertEqual(resp.status_code, 200)
        ctx = resp.context
        self.assertEqual(ctx['total_bets'], 3)
        self.assertEqual(ctx['won_bets'], 1)
        self.assertEqual(int(ctx['win_rate']), int(100 * 1/3))
        self.assertEqual(ctx['total_wagered'], 200+300+500)
```

```
        self.assertEqual(ctx['total_won'], 450)
        self.assertEqual(ctx['net_profit'], 450 - (200+300+500))

    def test_market_maker_liquidity_and_volume(self):
        mm = MarketMaker.objects.create(event=self.event,
bet_type='PODIUM_FINISH', driver=self.driver, team=None, current_odds=2.0,
base_odds=2.0, available_liquidity=1000, max_exposure=500)
        # Place two bets via view to update state and deduct credits
        payload = {'event_id': str(self.event.id), 'bet_type': 'PODIUM_FINISH',
'driver_id': str(self.driver.id), 'credits_staked': '200'}
        resp = self.client.post(reverse('place_bet'), data=payload)
        self.assertEqual(resp.status_code, 200)
        resp = self.client.post(reverse('place_bet'), data=payload)
        self.assertEqual(resp.status_code, 200)
        mm.refresh_from_db()
        # total_volume tracks sum of stakes; total_bets equals count of bets placed
        self.assertEqual(mm.total_volume, 400)
        self.assertEqual(mm.total_bets, 2)
        # Check market depth recent_activity length is <= 10 and contains entries
        depth = mm.get_market_depth()
        self.assertTrue(1 <= len(depth['recent_activity']) <= 10)
```

G.5.2 Odds Edge Cases Tests (test_odds_edge_cases.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from datetime import date, datetime
```

```
from data.models import Circuit, Event, SessionType, Session, Driver, Team,
RaceResult


class OddsEdgeCaseTests(TestCase):
    def setUp(self):
        self.client = Client()
        self.user = User.objects.create_user(username='u', password='p')
        self.client.login(username='u', password='p')
        self.circuit = Circuit.objects.create(name='Odds Circuit', country='Nowhere')
        self.event = Event.objects.create(name='Odds GP', year=2025, round=1,
date=date(2025,1,1), circuit=self.circuit)
        st = SessionType.objects.create(name='Race', session_type='RACE')
        self.session = Session.objects.create(event=self.event, session_type=st,
date=datetime(2025,1,1,15,0,0))
        self.team = Team.objects.create(name='TeamO')
        self.driver = Driver.objects.create(given_name='A', family_name='A',
permanent_number=10, driver_ref='oa_ref', driver_id='oa_id', nationality='X')
        # Minimal history to avoid divide-by-zero; DNF entries etc.
        RaceResult.objects.create(session=self.session, driver=self.driver,
team=self.team, position=10, status='Finished', points=1)


    def test_real_time_odds_bounds(self):
        url = reverse('get_real_time_odds')
        payload = {'event_id': str(self.event.id), 'bet_type': 'DNF_PREDICTION',
'driver_id': str(self.driver.id)}
        resp = self.client.post(url, data=payload)
        self.assertEqual(resp.status_code, 200)
        self.assertTrue(resp.json().get('success'))
        odds = float(resp.json()['odds'])
        self.assertTrue(1.1 <= odds <= 50.0)
```

```
    def test_head_to_head_missing_opponent(self):
        url = reverse('get_real_time_odds')
        payload = {'event_id': str(self.event.id), 'bet_type': 'HEAD_TO_HEAD',
'driver_id': str(self.driver.id)}
        resp = self.client.post(url, data=payload)
        self.assertEqual(resp.status_code, 200)
        self.assertTrue(resp.json().get('success'))
```

G.6 Subscription and User Management Tests

G.6.1 Subscription Tests (test_subscription.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User

class SubscriptionTests(TestCase):
    def setUp(self):
        self.client = Client()
        self.user = User.objects.create_user(username='sub', password='pass',
email='s@e.com', is_active=True)
        self.client.login(username='sub', password='pass')

    def test_upgrade_and_cancel(self):
        # GET page
        resp = self.client.get(reverse('subscription_management'))
        self.assertEqual(resp.status_code, 200)
```

```
        # Upgrade to PREMIUM
        resp = self.client.post(reverse('subscription_management'), data={'action': 'upgrade', 'tier': 'PREMIUM'})
        self.assertEqual(resp.status_code, 302)
        # Check profile
        self.user.refresh_from_db()
        profile = self.user.profile
        self.assertEqual(profile.subscription_tier, 'PREMIUM')
        self.assertTrue(profile.is_subscription_active)
        # Cancel back to BASIC
        resp = self.client.post(reverse('subscription_management'), data={'action': 'cancel'})
        self.assertEqual(resp.status_code, 302)
        self.user.refresh_from_db()
        self.assertEqual(self.user.profile.subscription_tier, 'BASIC')
```

G.6.2 Circuit Visits and Credits Tests (test_circuits_credits.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from datetime import date

from data.models import Circuit, Event

class CircuitVisitCreditsTests(TestCase):
    def setUp(self):
        self.client = Client()
```

```
        self.user = User.objects.create_user(username='u', password='p')
        self.client.login(username='u', password='p')
        self.circuit = Circuit.objects.create(name='Alpha Circuit', country='X')
        Event.objects.create(name='Alpha GP', year=2025, round=1,
date=date(2025,1,1), circuit=self.circuit)

    def test_mark_circuit_visited_awards_credits_once(self):
        profile = self.user.profile
        start = profile.credits
        url = reverse('mark_circuit_visited', args=[self.circuit.id])
        resp = self.client.post(url)
        self.assertEqual(resp.status_code, 200)
        data = resp.json()
        self.assertEqual(data.get('status'), 'success')
        profile.refresh_from_db()
        self.assertEqual(profile.credits, start + 100)
        # Visit again: no double-award
        resp = self.client.post(url)
        self.assertEqual(resp.status_code, 200)
        data = resp.json()
        self.assertEqual(data.get('status'), 'already_visited')
        profile.refresh_from_db()
        self.assertEqual(profile.credits, start + 100)
```

G.7 Test Suite Configuration and Loader

G.7.1 Test Module Loader (__init__.py)

```python
import unittest
from importlib import import_module

MODULES = [
    'dashboard.tests.test_access',
    'dashboard.tests.test_access_more',
    'dashboard.tests.test_auth',
    'dashboard.tests.test_bet_settlement',
    'dashboard.tests.test_bets_stats_and_liquidity',
    'dashboard.tests.test_betting',
    'dashboard.tests.test_circuits_credits',
    'dashboard.tests.test_odds_edge_cases',
    'dashboard.tests.test_pages',
    'dashboard.tests.test_pages_more',
    'dashboard.tests.test_prediction_edge_cases',
    'dashboard.tests.test_prediction_ranks',
    'dashboard.tests.test_predictions',
    'dashboard.tests.test_ui_smoke',
]

def load_tests(loader, tests, pattern):
    suite = unittest.TestSuite()
    for mod_name in MODULES:
        try:
            mod = import_module(mod_name)
            suite.addTests(loader.loadTestsFromModule(mod))
        except Exception:
            # If a module import fails, continue with available tests
```

```
            continue
    return suite
```

G.7.2 Additional Model and View Tests (test_prediction_view_integration.py)

```python
from django.test import TestCase, Client
from django.urls import reverse
from django.contrib.auth.models import User
from data.models import Event, Session, SessionType, Driver, Team, RaceResult, ridgeregression

class PredictionViewTests(TestCase):
    def setUp(self):
        # Minimal data setup for predictions view
        self.user = User.objects.create_user(username='u', password='p')
        self.client = Client()
        self.client.login(username='u', password='p')

        self.team = Team.objects.create(name='Test Team')
        self.driver = Driver.objects.create(given_name='Test', family_name='Driver', permanent_number=99)
        # Event requires date and circuit
        from data.models import Circuit
        self.circuit = Circuit.objects.create(name='Test Circuit', country='Nowhere')
        from datetime import date
        self.event = Event.objects.create(name='Test Grand Prix', year=2025, round=1, date=date(2025,1,1), circuit=self.circuit)
        # Create basic session type + race session
```

```
        st = SessionType.objects.create(name='Race', session_type='RACE')
        from datetime import datetime
        self.session = Session.objects.create(event=self.event, session_type=st,
date=datetime(2025,1,1,15,0,0))


        # Actual result
        RaceResult.objects.create(session=self.session, driver=self.driver,
team=self.team, position=5, points=10)
        # Prediction
        ridgeregression.objects.create(event=self.event, year=2025, round_number=1,
driver=self.driver, predicted_position=7)


    def test_prediction_view_renders(self):
        resp = self.client.get(reverse('prediction'))
        self.assertEqual(resp.status_code, 200)
        # Context includes results and comparison labels for charts
        self.assertIn('results', resp.context)
        self.assertIn('comparison_labels', resp.context)


class RaceIncidentModelTests(TestCase):
    def test_create_incident(self):
        from dashboard.models import RaceIncident
        inc = RaceIncident.objects.create(
            year=2025, round=1, event_name='Test Grand Prix',
            type='START_ISSUE', description='Brake fire prevented start',
            driver_name='Carlos Sainz', lap=None
        )
        self.assertEqual(str(inc), '2025 R1 - Test Grand Prix: START_ISSUE (Carlos
Sainz)')
```

Appendix G: Pipeline-

```python
class EnhancedF1Pipeline:
    def get_track_specialization_features(self, circuit_id):
            else:
                category_str = str(category_value)

            return {
                'category': category_str,  # Always return as string
                'overtaking_difficulty': float(track_spec.overtaking_difficulty or 5.0),
                'tire_degradation_rate': float(track_spec.tire_degradation_rate or 5.0),
                'qualifying_importance': float(track_spec.qualifying_importance or 5.0),
                'power_sensitivity': float(track_spec.power_sensitivity or 5.0),
                'aero_sensitivity': float(track_spec.aero_sensitivity or 5.0),
                'weather_impact': float(track_spec.weather_impact or 5.0),
            }
        except Exception as e:
            logger.error(f"Error getting track features: {str(e)}", exc_info=True)
            return self._get_default_track_features()

    Windsurf: Refactor | Explain | ×
    def _get_default_track_features(self):
        """Default track features when specialization data is missing"""
        return {
            'category': 'HYBRID',  # Always return as string
            'overtaking_difficulty': 5.0,
            'tire_degradation_rate': 5.0,
            'qualifying_importance': 5.0,
            'power_sensitivity': 5.0,
            'aero_sensitivity': 5.0,
            'weather_impact': 5.0,
        }
```

```python
class F1DataPipeline:
    def load_data(self) -> pd.DataFrame:
        try:
            logger.info("Loading race results...")
            race_query = (
                RaceResult.objects.filter(position__isnull=False)
                .select_related('session__event', 'driver', 'team')
                .annotate(
                    event_id=F('session__event_id'),
                    session_type=F('session__session_type__session_type'),
                    year=F('session__event__year'),
                    round_number=F('session__event__round'),  # Assumed field; adapt if different
                    circuit=F('session__event__circuit__name')  # Assumed field for circuit name
                )
            )

            race_results = pd.DataFrame.from_records(
                race_query.values(
                    'id', 'driver_id', 'team_id', 'position',
                    'event_id', 'session_type', 'grid_position',
                    'year', 'round_number', 'circuit'
                )
            )

            # Filter to race sessions only
            race_results = race_results[race_results['session_type'] == 'RACE']
            if race_results.empty:
                raise ValueError("No race results found after filtering")

            # Fix grid_position missing values
```

Appendix H : Live run connection check via backend-

```
(yolov5s) PS C:\Users\tarun\diss\td188> python manage.py run_live_predictions --test-connection
Could not start background tasks: populate() isn't reentrant
Starting Live F1 Prediction System with HypRace API...
Connection test: Connection test passed (DNS OK, API key present)
(yolov5s) PS C:\Users\tarun\diss\td188> python manage.py run_live_predictions --quota-status
Could not start background tasks: populate() isn't reentrant
Starting Live F1 Prediction System with HypRace API...
HypRace API quota for 2025-09: used 2/40 (remaining 38)
(yolov5s) PS C:\Users\tarun\diss\td188>
```