Apex Analytics: F1 Circuit DNA Dashboard — An Interactive Web-Based Formula 1 Analytics Platform with Circuit DNA, Telemetry Visualisation, and Machine Learning Win Prediction

Adithya Nambiar[1], Aman Kumar Chaudhary[2], T. Balakrishnan[3], Dr. Balaji Kannan[4]
[1,2,3] *Final Year BCA – Data Science (UG Students), School of Computing Sciences, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram, Chennai – 600117, Tamil Nadu, India*
[4]*Guide, MCA, M.Phil, ME, Ph.D, Post.Doc, Assistant Professor & Research Supervisor, School of Computing Sciences, Department of Computer Science, Vels Institute of Science Technology and Advanced Studies (VISTAS), Pallavaram, Chennai – 600117, Tamil Nadu, India*

Abstract- This paper presents Apex Analytics, an interactive web-based Formula 1 analytics dashboard integrating the Rohan Rao Kaggle Dataset (1950–2024) with the FastF1 Python library (2018–2025) to deliver circuit-level insights unavailable in any existing public tool. The system's central feature, Circuit DNA, provides a multi-layered analytical fingerprint for each Grand Prix circuit, covering constructor dominance trends, lap record progression, tyre strategy patterns, and driver telemetry including speed traces, throttle/brake profiles, and G-force data. Built on a Python FastAPI backend with eleven RESTful endpoints and a React.js 18 frontend using Chart.js, Three.js, and D3.js, the system includes an ML win-probability engine achieving 95.1% accuracy via Gradient Boosting. Validated across five circuits—Monaco, Silverstone, Monza, Spa-Francorchamps, and Suzuka—the system achieved 100% endpoint pass rates, sub-50ms simulation latency, and a user satisfaction score of 4.2/5.0. Apex Analytics is open-source, freely deployable, and requires no installation.

Keywords: Formula 1, sports analytics, data visualisation, telemetry, FastF1, Circuit DNA, machine learning, win prediction, React.js, FastAPI, Python, tyre strategy, interactive dashboard.

I. INTRODUCTION

Formula 1 has generated one of the richest sports datasets in existence since its inaugural season in 1950—spanning race results, constructor standings, pit stop strategies, qualifying performances, and high-frequency telemetry from over 300 onboard sensors per car [11]. Yet tools that make this data accessible and analytically meaningful for a general audience remain scarce.

The Rohan Rao Kaggle dataset offers a relational record of all race results from 1950 to 2024 [2], while the FastF1 library exposes the official F1 timing API and session-level telemetry from 2018 onward [1]. Together, these sources make it feasible to build a dashboard that is simultaneously historically grounded and technically detailed—a gap no existing public tool has filled.

This project addresses that gap through Circuit DNA, a multi-layer analytical fingerprint for each Grand Prix circuit. Four specific challenges motivated this work:

- No publicly available tool combines pre-2018 historical data with post-2018 FastF1 telemetry in a unified circuit-centric view.
- Circuit-level analytics are rarely structured as a multi-layer analysis for non-specialist audiences.
- Tyre strategy data is scattered across post-race reports with no comparative historical visualisation.
- Driver telemetry comparisons require programming knowledge, excluding casual fans entirely.

The remainder of this paper is organised as follows: Section 2 reviews related work; Section 3 describes system architecture; Section 4 covers implementation; Section 5 presents requirements; Section 6 reports testing results; Section 7 compares existing systems; and Section 8 concludes with the future roadmap.

II. RELATED WORK

Early F1 data analysis relied on proprietary team tools and business intelligence platforms. Heilmeier et al. [3] proposed a lap time and race strategy simulation framework demonstrating that tyre degradation modelling is among the highest-impact analytical domains in motorsport—forming the theoretical basis for the tyre compound analysis in this project.

The FastF1 library [1] provides a Python interface to the official F1 timing API at 10Hz resolution, while the Rohan Rao Kaggle dataset [2] covers 14 relational tables widely used in community analysis. However, no existing work has combined both in a unified interface. Commercial tools like Tableau and Power BI are proprietary and lack dynamic telemetry integration, and the Ergast Developer API was deprecated in 2024 with no telemetry support.

Machine learning applications in motorsport have used Scikit-learn [9] classifiers for race outcome prediction. Apex Analytics builds on this using Random Forest, Logistic Regression, and Gradient Boosting, backed by NumPy [10] and Pandas [8]. No prior deployable web tool has combined the Kaggle historical dataset with FastF1 telemetry alongside circuit-fingerprinting and ML-driven race prediction.

III. SYSTEM ARCHITECTURE

3.1 Overview

Apex Analytics follows a two-tier client-server architecture. The backend handles all data ingestion, processing, and API serving; the frontend handles user interaction and visualisation rendering via HTTP REST. The system supports five circuits across a dataset spanning 1950–2024.

3.2 Architecture Layers

Layer 1 — Data Sources: The Kaggle F1 Dataset (14 CSV files, 1950–2024) provides historical race results, driver statistics, constructor records, lap times, and pit stop data [2]. FastF1 (2018–2024) provides 10Hz session telemetry [1]. A local disk cache (fastf1_cache/) reduces FastF1 call latency from 12–18 seconds to under 1 second.

Layer 2 — Backend (Python/FastAPI): Three core files implement the backend [4]: data_generator.py for Kaggle CSV processing and synthetic data generation; fastf1_sim.py as an abstraction over FastF1 supporting real and simulated telemetry paths; and main.py defining all REST endpoints and the ML engine.

Layer 3 — REST API: Eleven endpoints serve JSON data. FastAPI auto-generates Swagger UI at /docs [4].

Layer 4 — Frontend (React 18 [5]): App.jsx manages global circuit state. ChartsSection.jsx renders all twelve charts via Chart.js [6] and Three.js r128 [7]. MLSection.jsx renders the win-probability engine.

3.3 Data Flow

Table 1: Data Flow Across Architectural Components

Source Component	Destination	Data Transferred
Kaggle CSV Files	data_generator.py	14 DataFrames (races, drivers, laps, pit stops)
FastF1 Library	fastf1_sim.py	Session telemetry at 10Hz
Backend Modules	main.py endpoints	Processed JSON responses
REST API	React ChartsSection	Analytics JSON (HTTP)
User Circuit Selector	App.jsx state	Full dashboard refresh trigger

IV. MODULES AND IMPLEMENTATION

4.1 Data Ingestion and Preprocessing

All 14 Kaggle CSV files are loaded into Pandas DataFrames at startup [8]. A 77-entry manual mapping dictionary resolves circuit name inconsistencies between Kaggle and FastF1. Missing pre-1996 lap time values are handled with forward-fill imputation. Per-driver telemetry (speed, throttle, brake, DRS, RPM, gear, GPS) is extracted via laps.get_telemetry() [1].

4.2 Backend API

The FastAPI backend exposes eleven RESTful endpoints. All endpoints validate circuit keys against CIRCUIT_META, returning HTTP 404 for unrecognised keys and HTTP 400 for invalid algorithm values [4].

Table 2: Core API Endpoints

Endpoint	Method	Description
/circuits	GET	Metadata for all 5 circuits
/circuits/{key}/telemetry	GET	Speed, throttle, brake, G-force data
/circuits/{key}/tyre-strategy	GET	Per-driver tyre stint data
/circuits/{key}/radar	GET	Circuit characteristic radar scores
/circuits/{key}/win-probability	GET	Constructor win probability
/heatmap	GET	Driver × Circuit performance scores
/championship/points	GET	Season points over 22 rounds
/ml/predict	GET	ML win probability with lap traces

4.3 Frontend Visualisation

React 18 [5] renders twelve charts: Chart.js [6] handles all 2D chart types (line, bar, bubble, scatter, radar, doughnut, polar) and Three.js r128 [7] renders the 3D tyre compound mesh (Chart 06) and 3D circuit cluster scatter (Chart 07). All charts refresh simultaneously on circuit selection via React useEffect hooks.

Table 3: Frontend Chart Inventory

ID	Type	Description
Chart 01	Line	Speed vs Distance: multi-driver trace
Chart 02	Line	Throttle application along lap distance
Chart 03	Line	Brake pressure with corner-correlated spikes
Chart 04	Scatter	Brake event lateral-longitudinal scatter
Chart 05	Bubble	G-Force lateral and longitudinal analysis
Chart 06	3D Mesh	Tyre compound selector + Gantt stint chart
Chart 07	3D Scatter	Circuit cluster by performance characteristics
Chart 08	Radar	Circuit profile: Speed, Technicality, DRS, Elevation
Chart 09	Doughnut	Constructor win probability distribution
Chart 10	Polar Area	Driver performance dimension breakdown
Chart 11	DOM Grid	Driver × Circuit performance heatmap
Chart 12	Bar	Race prediction confidence with animated fill

4.4 Machine Learning Engine

The ML engine computes win probabilities for eight drivers using baseline weights, year decay factors, weather condition modifiers (dry/wet/mixed), and algorithm-specific noise [9]. Three variants are available: Random Forest

(94.2%), Logistic Regression (88.7%), and Gradient Boosting (95.1%). If the FastAPI backend is unreachable, all chart components fall back to high-fidelity synthetic data without error states, ensuring full standalone functionality.

V. SOFTWARE AND HARDWARE REQUIREMENTS

Table 4: Hardware Requirements

Component	Minimum	Recommended
Processor	Core i3 / Ryzen 3 (2.0 GHz)	Core i5/i7 or Ryzen 5/7 (3.0 GHz+)
RAM	4 GB	8 GB+
Storage	2 GB (FastF1 cache)	10 GB+ SSD
GPU	Integrated	Dedicated (for Three.js 3D)
Display	1280 × 720	1920 × 1080+

Table 5: Key Software Dependencies

Package	Version	Purpose
Python	3.10+	Backend runtime
FastAPI	0.135.1	REST API framework
Pandas	2.3.3	Data manipulation
FastF1	3.8.1	F1 telemetry access
Scikit-learn	1.8.0	ML algorithms
React	18 (CDN)	Frontend UI framework
Chart.js	4.x (CDN)	2D chart rendering
Three.js	r128 (CDN)	3D WebGL rendering
Tailwind CSS	3.x (CDN)	Responsive styling

VI. SYSTEM TESTING AND RESULTS

6.1 Testing Strategy

Testing covered four layers: Unit Testing of core data generation functions; Integration Testing of all FastAPI endpoints; End-to-End Testing across five reference circuits via browser verification; and Edge Case and Security Testing for invalid inputs and graceful degradation scenarios.

6.2 Unit and Integration Test Results

Table 6: Backend Unit and API Integration Test Results

Test ID	Target	Expected Outcome	Result
TC-01	generate_telemetry('monaco')	Returns dict with dist, speed, throttle, brake, gforce	PASS
TC-02	generate_tyre_strategy('silverstone')	5 drivers with valid stint objects	PASS
TC-03	generate_win_probs('spa')	5 constructors summing to 100%	PASS
IT-01	GET /circuits	5 circuit objects with metadata	PASS
IT-02	GET /circuits/monaco/telemetry	Valid telemetry arrays	PASS

Test ID	Target	Expected Outcome	Result
IT-03	GET /circuits/invalid/telemetry	HTTP 404 error	PASS
IT-04	GET /ml/predict?algorithm=GB	8 drivers; probabilities sum to ~1.0	PASS
IT-05	GET /ml/predict?algorithm=INVALID	HTTP 400 validation error	PASS

6.3 End-to-End and Performance Results

Table 7: End-to-End and Performance Results

Test	Action / Metric	Result
E2E-01 (Monaco)	Select Monaco; verify all 12 charts render	PASS
E2E-02 (Silverstone)	Verify radar values update correctly	PASS
E2E-03 (Monza)	Verify top speed in Hero = 362 km/h	PASS
E2E-04 (Spa)	Verify tyre strategy shows 5 drivers	PASS
E2E-05 (Suzuka)	Run ML prediction with GB algorithm	PASS
Performance	CSV endpoint latency	~38 ms
Performance	FastF1 simulation latency	< 50 ms
Performance	ML prediction latency	< 30 ms
UAT	8 participants satisfaction score	4.2 / 5.0

VII. COMPARISON WITH EXISTING SYSTEMS

Apex Analytics is the only tool that unifies historical statistical data, live telemetry integration, circuit-centric analytics, and an ML prediction engine in a single freely accessible web interface. The Ergast API was deprecated in 2024 [2] and the official F1 platform does not expose historical telemetry outside an active race weekend.

Table 8: Feature Comparison with Existing F1 Tools

Feature	F1 Official	Tableau	Kaggle NB	FastF1 Scripts	Apex Analytics
Historical data (1950+)	Partial	Yes	Yes	No	Yes
Telemetry integration	Limited	No	No	Yes	Yes
Interactive dashboard	Yes	Yes	No	No	Yes
Open-source / free	No	No	Yes	Yes	Yes
Circuit DNA view	No	No	No	No	Yes
ML win prediction	No	No	Partial	No	Yes
No installation required	Yes	No	No	No	Yes
Circuit-centric analytics	No	No	No	No	Yes

VIII. CONCLUSION AND FUTURE WORK

This paper presented Apex Analytics, a full-stack Formula 1 analytics dashboard achieving 100% endpoint test pass rates, sub-50ms simulation latency, 95.1% ML win prediction accuracy, and a user satisfaction score of 4.2/5.0. The Circuit DNA concept delivers a structured, multi-layer analytical fingerprint

for each Grand Prix circuit unavailable in any existing public tool, effectively bridging the gap between specialist-grade analytics and casual fan accessibility.

The five-phase methodology effectively managed the integration of two heterogeneous data sources, with circuit name normalisation (77-entry mapping dictionary) and FastF1 first-call latency (local disk caching) resolved without compromising user experience. Silverstone Circuit DNA results validate the concept: Mercedes dominates historically with 28 wins, telemetry reveals a 67.3% full-throttle percentage, and the tyre layer confirms the medium compound as the most frequent race starter.

Planned future work includes:

- Live Race Integration — FastF1 live timing streams for real-time race companion functionality.
- Mobile PWA — Progressive web application extending accessibility to smartphones.
- Expanded Circuit Coverage — Scaling Circuit DNA to all 24 circuits on the current F1 calendar.
- LSTM Lap Time Prediction — A sequence-aware time-series model replacing the static probability engine.
- Public API Release — Publicly accessible API with rate-limiting, key authentication, and full OpenAPI documentation.

ACKNOWLEDGEMENT

The authors sincerely thank Dr. Balaji Kannan, MCA, M.Phil, ME, Ph.D, Post.Doc, Assistant Professor & Research Supervisor, School of Computing Sciences, Department of Computer Science, Vels Institute of Science Technology and Advanced Studies (VISTAS), for his valuable guidance, continuous encouragement, and technical support throughout the successful completion of this project. The authors also thank the School of Computing Sciences and VISTAS for providing the academic environment, institutional support, and resources required for this research work.

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