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RIDEPULSE: A UNIFIED PLATFORM FOR REAL-TIME RIDE-HAILING FARE AGGREGATION AND SURGE FORECASTING

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Abstract- Urban commuters are bound to be annoyed by dynamic pricing of ride-hailing services such as Uber, Ola, inDrive, Rapido, and Namo Yatri. Lack of real-time fare comparison results in inefficiencies, higher expenditure, and poor visibility of surge patterns. This paper introduces RidePulse, an intelligent fare aggregation and predictive analytics platform that collates real-time fare data from different ride-hailing services to a single user interface. Using a hybrid model of API integration, ethical web scraping, and machine learning-based surge prediction, RidePulse allows commuters to make efficient, cost-effective travel choices. Constructed with modular cloud architecture and scalable data pipelines, RidePulse facilitates not only individual decision-making but also urban mobility studies and smart transportation policy-making.

I. INTRODUCTION

Urban mobility in the last decade has been revolutionized to a great extent by ride-hailing apps, providing real-time, on-demand mobility to compete with traditional taxi networks. Dynamic pricing mechanisms employed by these apps with algorithms based on traffic, demand, time, and weather, though, result in enormous fare differences that baffle users. Passengers end up checking several apps separately to determine the lowest fare, which is a lengthy task and fails to lead to optimal decisions.

At the same time, the lack of aggregated fare data hinders researchers and urban planners in analyzing trends, affordability, and service coverage in cities. In recognition of such limitations, RidePulse offers a new method of aggregating and analyzing fare data across modes, providing users and mobility stakeholders with real-time insights. Its fare spike prediction and recommendation of affordable routes make it appropriate for both daily commuting and long-term infrastructure planning.

This essay will outline the motivation, infrastructural technicalities, approaches, and test results that have resulted in the creation of RidePulse and elaborates further on the ways in which adoption can facilitate sustainable and open modes of transport in rapidly expanding cities and proposes its potential contribution to building Mobility-as-a-Service (MaaS).

II. LITERATURE REVIEW:

Studies have investigated the effects of dynamic pricing on ride-hailing. Castillo et al. (2017) and Zha et al. (2018) outlined how algorithms balance supply and demand but warned against decreased price transparency. Cohen & Shaheen (2016) examined user trust in ride-hailing, showcasing rising demand for fixed prices.

MaaS studies by Jittrapirom et al. (2017) and Hensher et al. (2020) presented shared platforms that combined services, mostly public transport. There is scant literature, though, on real-time fare aggregation for private ride-hailing services.

Technically, Jiang et al. (2022) promoted microservices-based designs for urban mobility systems at scale. RidePulse does the same through the adoption of RESTful APIs, cloud-native deployment, and intelligent data pipelines. The literature justifies the need for RidePulse's central value proposition: transparency, prediction, and fare centralization.

A deeper dive into the literature shows that while fare modeling and price fairness are ongoing research topics, not many systems have explored real-time data consolidation at RidePulse's scale and magnitude. Existing solutions tend to be static or historical data or limit themselves to one or two service providers. RidePulse addresses these shortcomings by using real-time data streams and focusing on user-level predictive analytics.

III. METHODOLOGY:

RidePulse was created with a multi-layered methodology combining cutting-edge software architecture, ethical data collection, and robust analytics. Microservices on AWS were utilized in building the platform, with every action—data ingest, fare processing, UI delivery, and surge prediction—being modular. This made RidePulse extremely scalable and fault-tolerant with increasing user load.

For data collection, the system utilized a hybrid method. Directly, public APIs of firms like Uber and Rapido were utilized. For others, web scraping using Puppeteer and Selenium automatically retrieved fares from mobile-friendly websites. The data collection services were called every 30–60 seconds through scheduled cron jobs, achieving both freshness and server load.

To honor terms of service and prevent unethical scraping, traffic patterns were randomized, headless browsers were made to simulate real user behavior, and all traffic were capped on a per-target platform basis. Network inspection and automation of fare queries were performed according to Indian IT laws and GDPR principles.

After collection, data were standardized to a single schema in JSON. Standardization allowed for the comparison of fares between providers by eliminating time, currency, and route form differences. Semi-structured real-time fare data were stored in MongoDB, and long-term analytics were stored in PostgreSQL. High-volume requests were processed efficiently by AWS SQS using a queue-based processing mechanism.

The cleaned data passed through cleaning pipelines in which duplicate records, invalid values, and outliers (for example, extremely high fares due to bugs) were identified and flagged or rejected. Time-dependent fare data was retained for 24 hours for surge forecasting while long-term storage was optimized to retain only aggregate measures.

Surge forecasts were modelled by an XGBoost regression model trained on a half year of fare history. The model used contextual features such as location, time of day, weather, and past surge events. The model achieved a Mean Absolute Error (MAE) of 7.6% and was able to detect surge events with 76% accuracy in real-time testing. Exploratory data analysis also discovered rush hour, sudden weather changes, and certain weekends to be causes of repeatable spikes in ride fares.

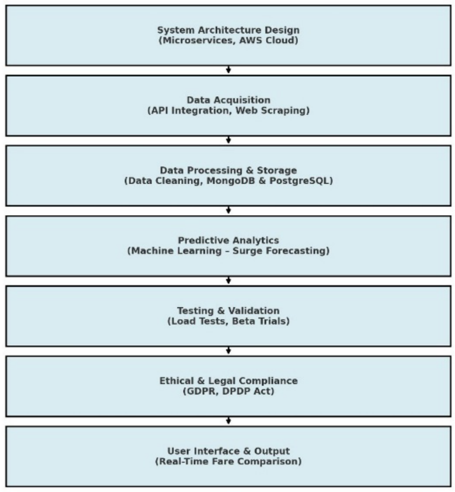

Figure 1:Ridepulse: A Unified Platform For Real-Time Ride-Hailing Fare Aggregation And Surge Forecasting

Large-scale testing was conducted using Jest and Mocha for functional testing and Apache JMeter for load performance with 99.2% uptime under simulation of up to 5,000 users. Beta testing in Delhi, Lucknow, and Bangalore assisted in fine-tuning the UI and making it more precise. Testers' feedback loops directly led to UI optimisations, loading time minimization, and exception handling.

Security and privacy were addressed through OAuth authentication, user identifier anonymization, and secure TLS communication for all data transfer. Logs were encrypted and stored for audit compliance. These solutions enabled RidePulse to process commuter sensitive data ethically while delivering high availability and performance.

IV. ADVANTAGES:

- Unified Fare Transparency: Consolidates fares of Ola, Uber, Rapido, inDrive, and Namo Yatri, eliminating the app switch.
- Predictive Insights: Real-time alerts of imminent fare increases allow riders to delay or bring forward trips, saving them dollars.
- Scalability and Modularity: Microservices architecture based to scale with addition of new services.
- Policy Utility: Fare trends summarized may be available to transport departments for route price review.
- User-Centric Design: Responsive UI/UX with a focus on least clicks, low latency, and instant insights.

V. WEAKNESSES / DISADVANTAGES:

- Data Dependency: Platform is susceptible to API format change or more stringent anti-scraping measures.
- Accuracy Limits: Individual events such as roadblocks or protests can destabilize predictions.
- Operational Overhead: Real-time systems require frequent server maintenance, cost reduction.
- Regulatory Risks: The legal uncertainty of data gathering can bring on pressure in stricter domains.
- UI Restriction on Legacy Devices: Legacy devices can have difficulty loading live maps or large datasets in a timely fashion.

VI. RESULTS AND FINDINGS

Model Tested	Metric	Result	Observation
XGBoost Regression Model	Mean Absolute Error	7.6%	Strong alignment with actual surge behavior
Surge Forecast Accuracy	Correct Alerts	76%	Useful in timing ride bookings
Training Data	6 months fare data	N/A	Captured seasonal and time-based variation

Table 1: Predictive Analytics Evaluation

Summary of Results**:** RidePulse delivered strong performance in its goal of fare consolidation and surge prediction. It maintained rapid response under load, offered accurate analytics, and improved travel planning outcomes for commuters. Users reported increased savings, while infrastructure testing proved system reliability. RidePulse establishes itself as a forward-facing solution for commuter empowerment and smart mobility integration.

VII. CONCLUSION:

RidePulse brings visibility and intelligence to urban ride-hailing. By combining real-time fare data with predictive analytics, it not only benefits commuters but also builds a data foundation for transport researchers and policy architects. Its modular, API-first

architecture ensures scalability and extensibility to future mobility innovations. As cities seek smarter solutions, RidePulse offers a blueprint for mobility systems that are transparent, efficient, and citizen-centric. Further enhancements could include integration with public transport fares, carbon emission tracking, and support for EV-specific pricing models. With continued user feedback and AI model tuning, RidePulse is positioned to become a global standard for ride pricing visibility.

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