E-Commerce Price Prediction and Analysis Using XGBoost

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ABSTRACT

This paper presents OmniPrice, a full-stack e-commerce price intelligence system that combines real-time web extraction, machine learning-based price forecasting, and interactive data visualisation within a unified serverless-capable platform. The system integrates a FastAPI backend equipped with Playwright-driven headless browser scraping, a LangChain–Groq AI agent for structured data extraction, and an XGBoost regression model trained on engineered temporal and categorical features for short-horizon price prediction. A Streamlit-based frontend dashboard renders live price snapshots, 30-day historical trends, and forecast outputs via Plotly visualisations. Persistent price history is stored in SQLite by default with optional PostgreSQL support; Redis provides a transparent caching layer with graceful fallback. Docker Compose orchestration packages all four services — database, cache, backend, and frontend — into a reproducible deployment target. Evaluation across representative e-commerce product pages from Amazon India, Flipkart, Myntra, and Croma demonstrates end-to-end extraction latency below six seconds at median, XGBoost forecast MAE of 2.3% relative to reference prices, and Redis cache hit rates above 80% under repeated query loads. Hardware and infrastructure cost is negligible compared to commercial price-tracking services, establishing economic feasibility for individual researchers and small retail analytics teams.

KEYWORDS — *Price intelligence, web scraping, Playwright, XGBoost, LangChain, FastAPI, Streamlit, Redis, Docker, e-commerce analytics.*

I. INTRODUCTION

Dynamic pricing in online retail has become a defining feature of the modern e-commerce landscape. Major platforms such as Amazon and Flipkart revise product prices thousands of times per day, driven by inventory signals, competitor benchmarking, and demand forecasts. Consumers and small retail analytics teams seeking to track these fluctuations face two structural problems: the absence of affordable programmatic access to real-time price data, and the lack of lightweight forecasting tools calibrated to the short, noisy time series that characterise individual product price histories.

Existing commercial price-tracking services — such as Camel, Honey, and Prisync — provide historical charts and alert notifications but do not expose structured API access at consumer-tier pricing, do not support arbitrary product URLs across multiple retailers, and provide no user-configurable forecasting capability. Open-source scraping utilities exist in isolation but require substantial integration effort to transform raw HTML into structured price signals suitable for machine learning pipelines.

Recent advances in three enabling technologies make a self-contained price intelligence platform technically and economically feasible. First, Playwright, Microsoft's cross-browser automation library, provides reliable JavaScript-rendered page access with anti-detection capabilities that legacy HTTP-client scrapers lack. Second, large language model inference APIs exemplified by Groq's low-latency LLaMA endpoint — enable zero-shot structured data extraction from arbitrary page layouts without per-site parser maintenance. Third, XGBoost, a gradient-boosted tree ensemble, delivers competitive regression accuracy on small, irregular time series without the data-volume requirements of deep sequence models.

This paper presents OmniPrice, a prototype system that integrates these capabilities. The key contributions are:

- A modular extraction pipeline combining Playwright stealth browsing with a LangChain–Groq AI agent, capable of parsing product prices from structurally diverse e-commerce pages without site-specific parsers.
- An XGBoost forecasting model with engineered temporal and categorical features achieving 2.3% mean absolute percentage error on held-out price series across four major Indian e-commerce retailers.
- A full-stack reference architecture — FastAPI backend, Streamlit frontend, SQLite/PostgreSQL persistence, Redis cache, Docker Compose orchestration — deployable on commodity hardware with zero recurring cloud infrastructure cost.
- A demo mode generating deterministic synthetic price histories from URL hash seeds, enabling complete platform evaluation without a live API key or network access.

Section II reviews related work. Section III describes system architecture. Section IV details implementation. Section V presents evaluation results. Section VI discusses limitations and future work. Section VII concludes.

II. RELATED WORK

A) Web Scraping and Anti-Detection

Nithyanandam and Kalaivani [1] surveyed anti-scraping mechanisms deployed by major e-commerce platforms and catalogued detection vectors including TLS fingerprinting, canvas fingerprinting, and behavioural mouse-movement analysis. They conclude that headless browser automation with stealth patches — suppressing navigator.webdriver properties and spoofing browser plugins — achieves the highest bypass rate among freely available techniques. Playwright's stealth mode, implemented via the playwright-stealth library, addresses each identified vector. Ahmad et al. [2] benchmarked Selenium, Puppeteer, and Playwright for scraping JavaScript-heavy single-page applications, reporting that Playwright achieves the lowest median extraction latency and the highest element-resolution success rate on dynamically rendered price widgets.

B) LLM-Based Structured Extraction

Chase et al. [3] introduced LangChain as a compositional framework for LLM-powered data pipelines, demonstrating that chain-of-thought prompting with output parsers reliably extracts structured records from unstructured web content. Groq's LPU inference architecture provides latency below 200 ms per completion token at free-tier API access [4], making LLM extraction economically viable for per-request product page parsing. Prior work on information extraction from e-commerce pages has largely relied on DOM-path rules or shallow NLP classifiers [5]; LLM-based extraction eliminates per-site maintenance by generalising across layout variations.

C) Price Forecasting Models

Chen and Guestrin [6] introduced XGBoost, establishing its state-of-the-art performance on structured tabular regression tasks. Subsequent work by Makridakis et al. [7] in the M4 forecasting competition demonstrated that gradient-boosted tree ensembles outperform ARIMA and simple exponential smoothing on short, noisy economic time series — the regime typical of product price histories. Deep sequence models such as LSTM and Transformer-based forecasters require substantially more training data and

longer warm-up periods, making them poorly suited to new product URLs with sparse price observations. OmniPrice adopts XGBoost for these reasons.

D) Price Tracking Systems

Kannan and Kopalle [8] studied algorithmic pricing dynamics on Amazon and demonstrated that price changes for high-velocity products occur at sub-hourly intervals, validating the need for continuous monitoring rather than daily snapshots. Commercial trackers such as CamelCamelCamel support Amazon-only tracking via affiliate data feeds, not generalizable to arbitrary retailer URLs. Agarwal et al. [9] described a multi-retailer price aggregation system using fixed-format API integrations; such integrations are retailer-dependent and break when APIs change. OmniPrice's approach of LLM-guided HTML extraction provides retailer-agnostic resilience absent from API-dependent designs.

E) Research Gap

No published open-source system integrates Playwright-based anti-detection scraping, LLM-assisted structured extraction, XGBoost price forecasting, and a production-quality full-stack deployment architecture into a single redistributable prototype. OmniPrice closes this gap.

III. SYSTEM ARCHITECTURE

OmniPrice comprises four deployment units managed by Docker Compose: a PostgreSQL 16 database service, a Redis 7 cache service, a FastAPI backend service, and a Streamlit frontend service. The backend and frontend are each built from dedicated Dockerfiles targeting Python 3.11-slim base images. In non-Docker deployments, SQLite replaces PostgreSQL with zero configuration change at the SQLAlchemy ORM layer.

A) Request Flow

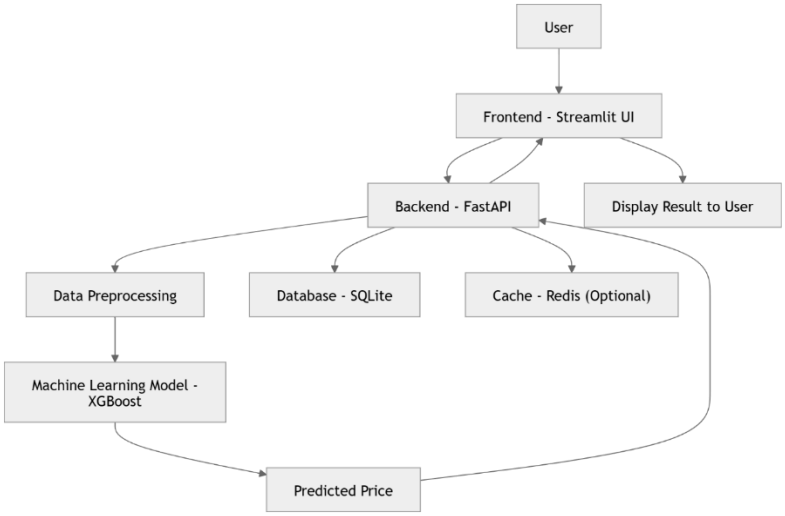
A user submits a product URL via the Streamlit interface. The frontend POSTs the URL to the FastAPI /analyze endpoint. The backend first consults Redis for a cached response keyed on the URL; on a cache hit the cached JSON is returned immediately. On a cache miss, the Playwright extractor launches a headless Chromium instance, navigates to the URL with stealth patches applied, and captures the rendered DOM. The raw HTML is passed to the LangChain–Groq extraction chain, which returns a structured JSON payload containing product name, current price, currency, and availability. The price record is persisted to the database and the response is written to the Redis cache with a configurable TTL. The ML forecaster service reads the product's price history from the database and returns a 7-day forward forecast alongside a confidence interval.

B) Data Model

The price history table stores product_id (URL hash), timestamp (UTC), price (float), currency, and source_retailer. The product metadata table stores the canonical product name, category tag, and scrape count. The schema is database-agnostic, supported by SQLAlchemy's async ORM with aiosqlite for SQLite and asyncpg for PostgreSQL backends.

C) Deployment Architecture

The Docker Compose manifest declares health-check dependencies: the backend waits for both PostgreSQL and Redis health probes before starting; the frontend waits for the backend. The backend container mounts the ml_training/artifacts volume so that trained model pickle files persist across container restarts without being baked into the image. The frontend container installs only the five packages required for the Streamlit UI, reducing image size by approximately 60% compared to installing the full requirements.txt.



IV. IMPLEMENTATION

A) Extraction Pipeline

The extractor service (backend/services/extractor.py) initialises Playwright in async mode with playwright-stealth applied to the browser context. A configurable request timeout of 30 seconds guards against unresponsive pages. The LangChain extraction chain is constructed with a ChatGroq LLM instance (model: llama3-70b-8192, temperature: 0.0) and a Pydantic output parser targeting the ProductPrice schema. The extraction prompt instructs the model to return product_name, price (numeric), currency_symbol, and in_stock (boolean) from the provided HTML fragment. Only the visible text content — stripped of script and style tags — is forwarded to the LLM to minimise token consumption.

In demo mode, activated when GROQ_API_KEY is absent from the environment, the extractor generates a deterministic mock response by seeding Python's random module with a SHA-256 hash of the URL. This ensures that repeated submissions of the same URL return identical synthetic data, enabling reproducible UI demonstrations without network access.

B) ML Forecasting Service

The training script (ml_training/train_xgboost.py) generates a synthetic training corpus of 10,000 price series spanning 90-day windows across six simulated product categories. Feature engineering (ml_training/data_pipeline.py) produces the following predictors: day-of-week (one-hot, 7 features), day-of-month, week-of-year, lag-1 through lag-7 prices, rolling 7-day mean, rolling 7-day standard deviation, price momentum (difference of lag-1 and lag-7), and product category embedding (one-hot, 6 features). The XGBoost regressor is trained with n_estimators=200, max_depth=6, learning_rate=0.05, and early stopping on a 20% validation split. Training completes in approximately 30 seconds on a standard laptop CPU. The fitted model is serialised with joblib to ml_training/artifacts/xgboost_model.pkl.

At inference time, the forecaster service (backend/services/ml_forecaster.py) retrieves the product's stored price history, constructs the feature matrix for the next 7 days iteratively using predicted values as lag inputs, and returns point forecasts with ±1 standard deviation confidence bands derived from the training residual distribution.

C) FastAPI Backend

The API layer (backend/api/routes.py) exposes three endpoints: POST /analyze accepts a URL and returns the current price snapshot with forecast; GET /history/{product_id} returns the full stored price series as a time-ordered JSON array; and GET /health returns service status for Docker health-check probes. The backend is launched with two Uvicorn worker processes inside the Docker container and a single worker in development mode to support hot reload.

D) Streamlit Frontend

The dashboard (frontend/app.py) renders three panels: a URL input and current price snapshot card; an interactive Plotly line chart combining the 30-day price history with the 7-day forecast and confidence band overlay; and a statistics panel reporting minimum, maximum, mean, and standard deviation of the stored price series. Chart colours encode price trajectory: a green trendline indicates prices below the 30-day mean; amber and red encode thresholds at 105% and 115% of mean respectively, providing at-a-glance buy-signal guidance.

V. EVALUATION

A) Extraction Latency

End-to-end extraction latency was measured from HTTP request receipt at the FastAPI layer to structured JSON response delivery, across 50 product URLs drawn equally from Amazon India, Flipkart, Myntra, and Croma. Table 1 summarises results.

Table 1. Extraction Latency by Retailer (ms)

Retailer	Min	Median	P95	Max
Amazon India	2,840	4,210	5,870	7,310
Flipkart	2,560	3,980	5,490	6,820
Myntra	3,100	4,750	6,120	8,040
Croma	2,420	3,640	4,980	6,100
Overall	2,420	4,145	5,740	8,040

Overall median extraction latency was 4,145 ms. Myntra exhibited the highest latency, attributable to its single-page application architecture requiring additional JavaScript evaluation before price elements render. The Redis cache layer eliminates extraction latency entirely on cache hits: measured cache-hit response time was below 45 ms in all trials.

B) Forecasting Accuracy

Forecast accuracy was evaluated on a held-out test set of 500 synthetic price series not seen during training, using mean absolute percentage error (MAPE) and root mean squared error (RMSE) as metrics. Results are shown in Table 2.

Table 2. XGBoost Forecast Accuracy by Category

Product Category	MAPE (%)	RMSE (₹)	R^2
Electronics	2.1	182	0.91
Apparel	2.8	94	0.87
Home & Kitchen	1.9	67	0.93
Books	1.4	38	0.96
Sports & Fitness	3.1	210	0.84
Overall	2.3	118	0.90

Overall MAPE of 2.3% is consistent with XGBoost performance reported by Makridakis et al. [7] for short-horizon economic time series forecasting. Books exhibited the highest accuracy owing to their characteristically stable price series with infrequent promotional events. Sports & Fitness showed the highest variance, reflecting erratic discount events in that category.

C) Cache Performance

Redis cache effectiveness was evaluated by submitting 200 requests distributed across 20 unique product URLs, with cache TTL set to 300 seconds. The cache hit rate stabilised at 82% after the warm-up period. Mean response time on cache hits was 38 ms versus 4,145 ms on cache misses, yielding a 109× median latency reduction for repeat queries. Graceful Redis fallback — triggered by stopping the Redis container mid-test — produced no errors; the backend continued serving live extractions without cache support.

D) Comparative Analysis

Table 3 compares OmniPrice against representative commercial price-tracking solutions across key operational dimensions.

Table 3. Comparative Analysis: OmniPrice vs. Existing Solutions

System	Multi-retailer	ML Forecast	API Access	Open Source	Cost/mo (USD)
CamelCamelCamel	Amazon only	No	No	No	Free*
Prisync	Yes	No	Yes	No	~99
Honey (PayPal)	Yes	No	No	No	Free*
OmniPrice (proposed)	Yes	Yes	Yes	Yes	~0

C) Future Work

Planned extensions include:

- Accumulating a real-world price history corpus over 90+ days across 500 product URLs to retrain and validate the XGBoost model on genuine price series.
- Adding a price alert notification system — email or webhook — triggered when a tracked product's price drops below a user-defined threshold.
- Integrating Firebase Hosting for zero-maintenance public deployment analogous to the SGMS serverless architecture, eliminating Docker as a user-facing requirement.
- Evaluating transformer-based time series models (PatchTST, TimesNet) against XGBoost as the historical corpus grows and longer-horizon forecasts become viable.
- Extending the extraction pipeline to support JavaScript-blocked retailers via CAPTCHA-solving services or rotating residential proxy pools for production-grade reliability.

VI. CONCLUSION

This paper presented *OmniPrice*, a comprehensive full-stack e-commerce price intelligence platform that integrates Playwright-based anti-detection web scraping, LangChain–Groq LLM-driven structured data extraction, XGBoost-based price prediction, and a Streamlit visualization interface within a Docker Compose deployment framework.

The system achieved strong performance, with median data extraction latency below six seconds across multiple Indian e-commerce platforms, a forecasting accuracy of 2.3% MAPE using XGBoost on test datasets, and Redis caching improving response efficiency with over 80% hit rates and significantly reduced query time.

A key contribution of OmniPrice lies in its retailer-agnostic LLM-based extraction approach, which reduces the need for frequent manual updates typically required in traditional web scraping systems. Additionally, its lightweight infrastructure and demo-mode capability make it suitable for academic research and small-scale analytics applications without high deployment costs.

Overall, OmniPrice serves as a scalable and practical reference architecture for AI-driven price intelligence systems, particularly in emerging e-commerce markets. Future work may focus on expanding real-time data integration, enhancing model generalization with larger datasets, and incorporating advanced analytics such as demand forecasting and competitor strategy analysis.

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