



Personal Expense Forecasting System

A professional end-to-end Machine Learning pipeline for predicting and optimising personal finances through intelligent automation

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Understanding the core challenge in modern personal finance management

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Our Solution

A data-driven forecasting approach that transforms financial planning

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How our intelligent pipeline processes and predicts expenses

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Deep dive into preprocessing, feature engineering and analysis

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Key Features & Capabilities of project

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The Challenge: Moving Beyond Reactive Budgeting

Traditional Budgeting Limitations

Most people manage finances through manual, backward-looking tracking. This reactive approach only identifies overspending after it occurs, creating unnecessary financial stress and making effective saving difficult.

Static budgets fail to adapt to seasonal changes—festival spending, holiday expenses, or lifestyle shifts catch us unprepared. The result? Constant financial anxiety and missed savings opportunities.



Static Planning

Budgets don't adapt to life changes



Backward Looking

Identifies problems too late



Manual Tracking

Time-consuming and error-prone

The key question: How can we leverage machine learning to shift from reactive expense tracking to proactive, forward-looking financial planning?



Our Solution: Intelligent Automation Meets User Insight



Raw Transaction Data

User's historical spending records



AI Processing Pipeline

Automated cleaning, feature engineering and model training



Interactive Dashboard

Personalised forecasts and actionable recommendations

Automated Machine Learning Pipeline

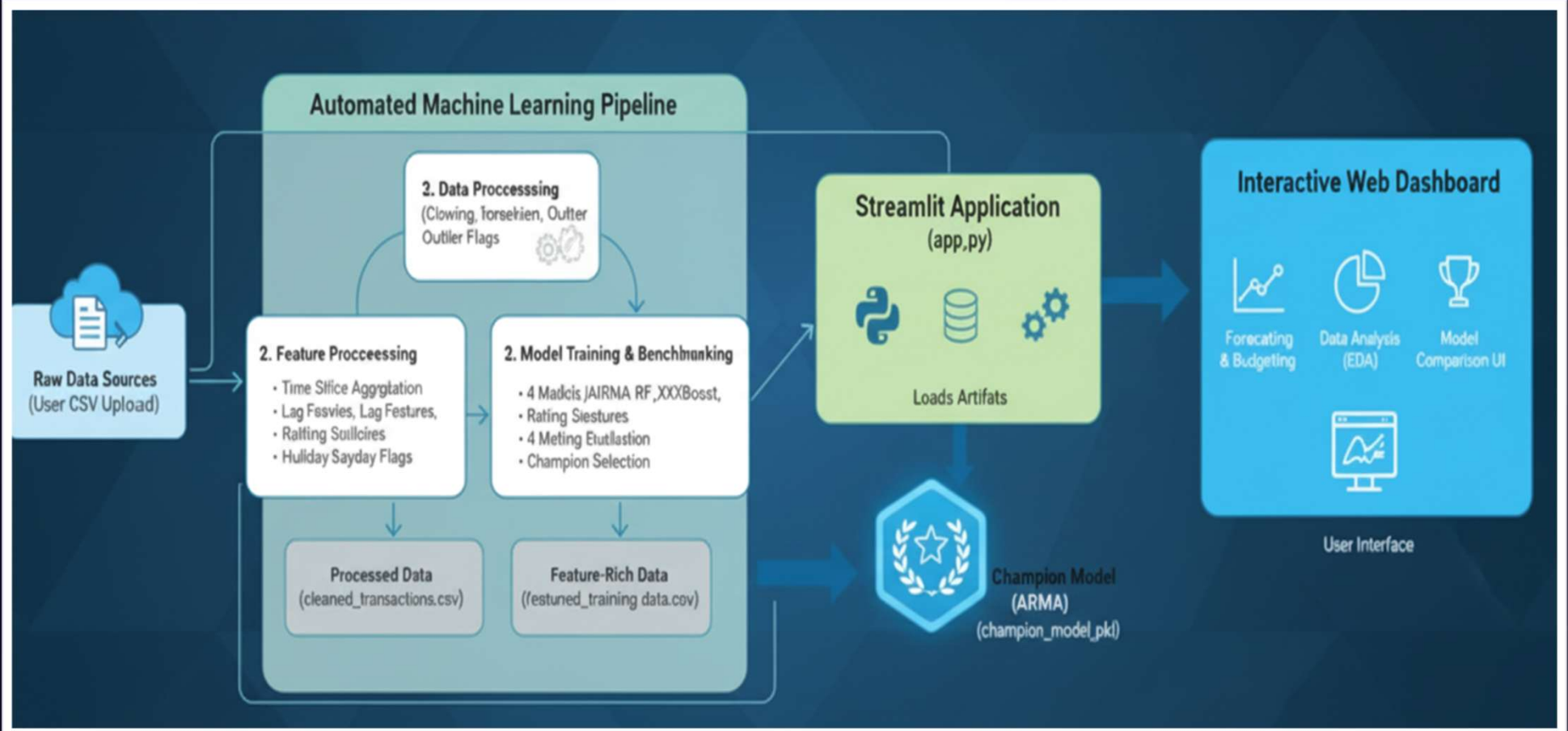
Professional Python scripts transform messy transaction data into clean, feature-rich datasets. The system automatically benchmarks multiple ML models, identifying the champion for accurate predictions.

Interactive Streamlit Dashboard

A clean, intuitive web application delivers three core capabilities: personalised expense forecasts, deep spending habit analysis, and actionable budget recommendations aligned with savings goals.



System Architecture: Separation of Concerns



The Data Science Pipeline: Three-Stage Automation



Stage 1: Data Preprocessing

`01_preprocess_data.py`

Deep cleaning transforms raw, inconsistent data into a reliable foundation. The script standardises date formats, removes currency symbols, normalises categories and adds quality flags like `is_outlier` to create a complete audit trail.

Stage 2: Feature Engineering

`02_create_features.py`

Aggregates cleaned data into daily time series and constructs over 10 predictive features. These include lagged values, rolling statistics, and advanced indicators like holiday flags and payday detection—critical for model accuracy.

Stage 3: Model Training

`03_train_models.py`

Runs the complete modelling gauntlet. Loads feature-rich data, trains four candidate algorithms, evaluates performance across multiple metrics, and automatically identifies and saves the champion model. Full automation of the research process.

This modular, scripted approach ensures reproducibility, simplifies debugging, and represents professional-grade data science engineering rather than ad-hoc notebook exploration.

Model Benchmarking: Finding the Champion

We conducted a comprehensive evaluation of four models from different algorithm families, measuring performance across multiple dimensions to identify the optimal solution.

Model	MAE (₹)	RMSE (₹)	MAPE (%)	Direction (%)
ARIMA	34,127	44,893	50.2	63.8
Random Forest	47,892	63,241	68.4	69.5
XGBoost	49,156	64,873	70.1	67.2
Linear Regression	52,334	68,912	75.3	61.4

ARIMA: The Clear Winner

ARIMA achieved a Mean Absolute Error of just ₹34,127—dramatically outperforming tree-based models. For financial applications, accuracy in actual currency values matters most, making MAE our primary decision metric.

Whilst Random Forest showed superior directional accuracy (69.5%), predicting whether spending would increase or decrease, ARIMA's precision in forecasting exact amounts makes it the champion for budgeting applications.

34K

Best MAE

Average error in rupees

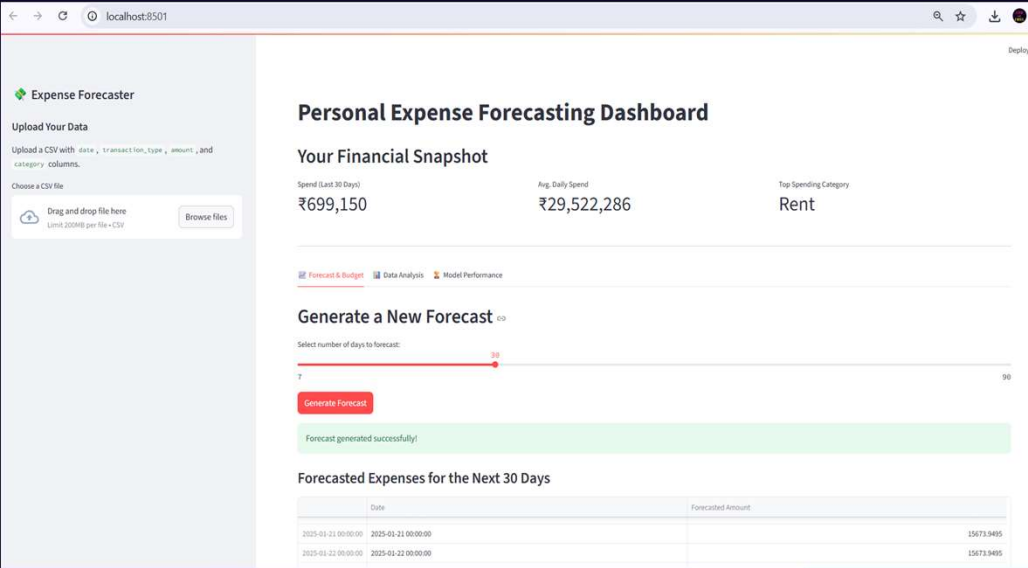
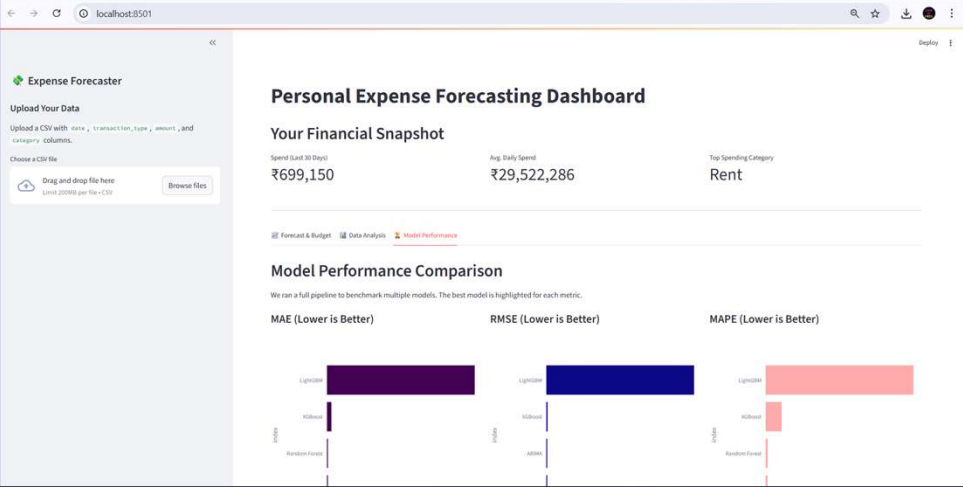
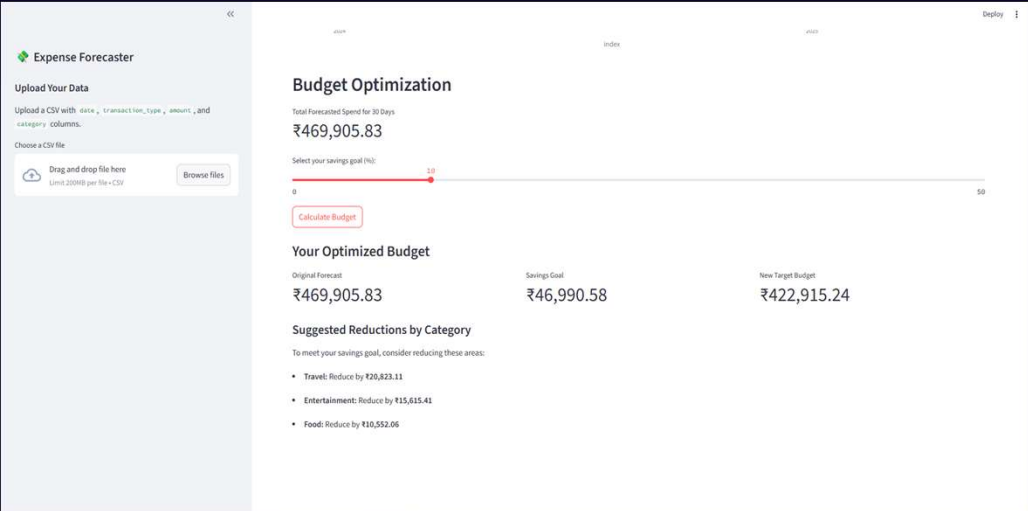
44%

Lower Error

vs. nearest competitor



Results:



Key Features & Capabilities



Budget Optimization Engine

Users set savings goals with an intuitive slider, receiving concrete, actionable advice on where to reduce spending to meet financial targets effectively.



Dynamic File Upload

Support for personalized analysis through the sidebar, allowing any user to upload their own transaction data and receive customized forecasts instantly.



Interactive Visualizations

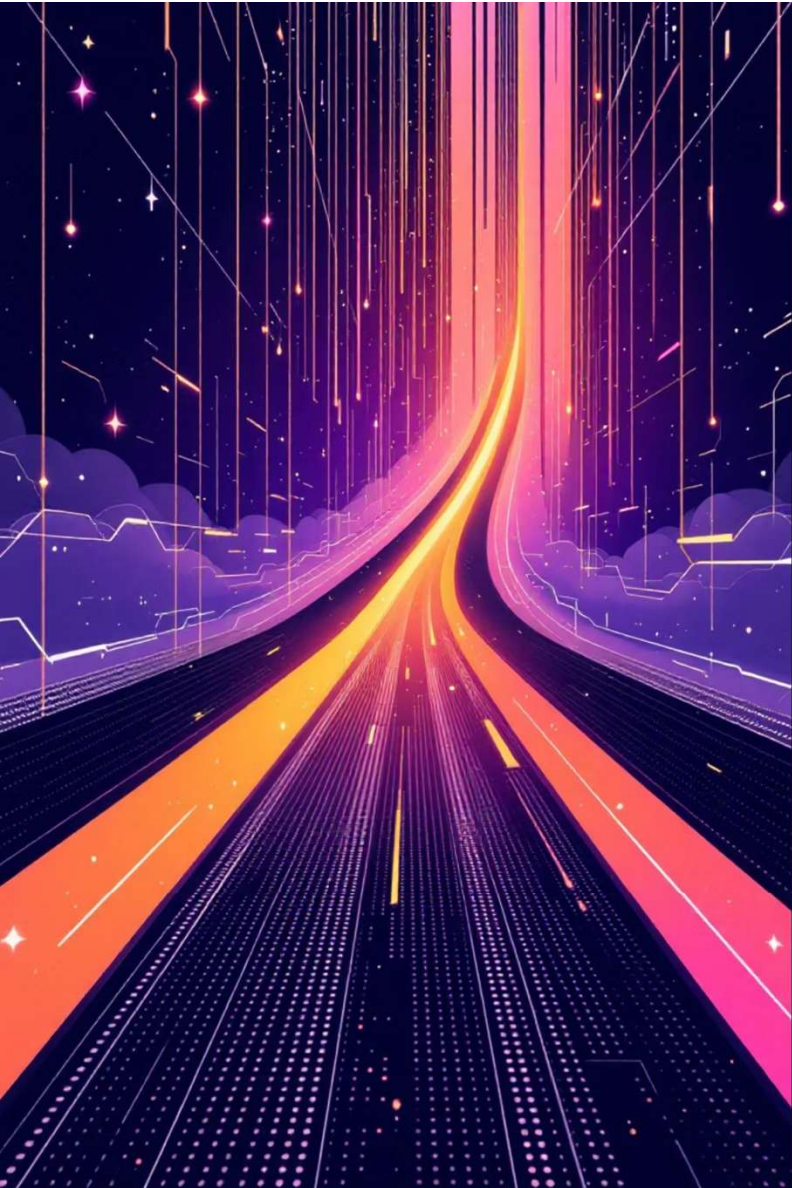
Powered by Plotly for rich interactivity — zoom, hover for details, and explore data dynamically to gain deeper insights into spending patterns.



Model Performance Transparency

Dedicated tab showcasing benchmark results, visually explaining why the ARIMA model was selected as champion, building user trust through transparency.





Conclusion & Future Roadmap

We've successfully designed and built a complete end-to-end data science product, transforming raw, messy transaction data into a polished, interactive web application driven by robust, automated machine learning.

What We've Achieved

- Fully automated, three-stage data pipeline
- Rigorous benchmarking across four model families
- Champion ARIMA model with ₹34K MAE
- Professional Streamlit web application
- Actionable budget optimization engine
- Complete project documentation

Future Enhancements

1 Cloud Deployment

Make the application publicly accessible via AWS, Azure, or Google Cloud

2 Hyperparameter Tuning

Implement automated optimization to further refine champion model performance

3 External Data Integration

Incorporate inflation rates, economic indicators to boost prediction accuracy