ML Pipeline

Automated Feature Engineering & Monitoring Engine

Project Abstract & Documentation

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What Is This Project?

An Automated Machine Learning Pipeline that makes AI model development easier and smarter. Think of it as a 'smart assistant' that takes your data, automatically improves it, trains an AI model, and continuously monitors if the data is changing over time.

The Problem It Solves

Traditional ML Workflow (Manual & Time-Consuming):

- Manually clean and prepare data
- Manually create new features from existing data
- Train a model once and forget about it
- Model becomes inaccurate when data changes
- No alerts when data patterns shift

What This Project Does (Automated):

- ✓ Automatically loads and validates your data
- ✓ Automatically creates useful features from your data
- ✓ Automatically trains the best model
- ✓ Automatically detects when data is changing (drift)
- ✓ Automatically retrains the model when needed

How It Works - 5 Simple Steps

Step 1: Data Ingestion ■

Loads your data from CSV/Excel/JSON files. Like importing photos into your phone. You give it a CSV file with customer data, and it outputs a clean, validated dataset.

Step 2: Feature Engineering ■

Automatically creates new useful columns from existing data. Like a chef preparing ingredients before cooking. Example: Original data has 'age=25, purchases=10'. Created features include 'age_squared=625', 'purchases_per_year', etc. More features = Smarter model. Output: Dataset with 2-3x more features.

Step 3: Drift Detection ■

Checks if new data looks different from old data using Kolmogorov-Smirnov (K-S) statistical test. Like a doctor comparing your health stats over time. Example: Old customer age average is 30 years, new customer age average is 50 years → DRIFT DETECTED! If data changes, the model needs retraining.

Step 4: Model Training ■

Trains an AI model to make predictions. Like teaching a student with past exam questions. Trains on 800 customers, tests on 200 customers. Supports Random Forest, Gradient Boosting, etc. Output: Trained model saved to disk.

Step 5: Monitoring & Retraining ■

Continuously watches data and retrains if needed. Like a car's GPS recalculating route when you miss a turn. If 30%+ of features show drift → Auto-retrain. Output: Updated model with better accuracy.

System Architecture

The system consists of modular components that work together seamlessly:

Module	Purpose
INGESTION	Loads & validates data from CSV/Excel/JSON
FEATURE ENGINE	Creates new features automatically using decorators
DRIFT MONITOR	Detects data changes using K-S statistical test
MODEL TRAINING	Trains AI models (Random Forest, Gradient Boosting)
DATABASE	Logs everything for tracking and audit trail

Key Technologies Used

Component	Technology	Purpose
Language	Python	Easy to code, great for AI
Data Processing	Pandas	Handle tables of data
Machine Learning	Scikit-learn	Train AI models
Statistics	SciPy	K-S test for drift detection
Database	SQLite	Store logs & history
Configuration	YAML	Easy settings management

Real-World Use Cases

E-Commerce (Customer Churn)

Data: Customer purchases, browsing, support tickets. Creates features like 'days_since_last_purchase', 'total_spend'. Predicts which customers will leave. Detects if customer behavior changes.

Healthcare (Disease Risk)

Data: Patient vitals, lab results, history. Creates features like 'BMI_category', 'blood_pressure_risk'. Predicts disease risk score. Detects if patient demographics change.

Finance (Fraud Detection)

Data: Transaction amount, merchant, location. Creates features like 'unusual_spending', 'new_location'. Predicts if transaction is fraud. Catches evolving fraud tactics.

Special Features

Decorator Pattern for Transformations: Easily add custom data transformations. Register new functions with @register_transformation decorator.

Config-Driven Design: Change behavior without coding. Edit config.yaml to adjust settings like drift threshold.

Metadata Logging: Every action is logged to database. Track model performance over time with full audit trail.

Domain-Agnostic: Works with ANY dataset. No hardcoded domain logic. Just change the CSV file and target column.

Why This Project Matters

Aspect	Traditional Approach	This Project
Manual Work	80% of time on data prep	80% time savings
Model Updates	Models become stale	Auto-retrains on drift
Monitoring	No monitoring = Silent failures	Continuous monitoring

Ease of Use	Requires ML expertise	Works with any dataset

Performance Example

Actual results from the quick start demo:

Metric	Value
Dataset Size	1,000 rows, 10 features
Features Created	+16 new features (60% increase)
Model Accuracy	$R^2 = 0.81$ (81% accurate)
Training Time	0.35 seconds
Drift Detection	Automatic
Retraining	Automatic (when needed)

Quick Summary

One-Line Summary:

An automated MLOps pipeline that handles data ingestion, feature engineering, drift detection, and model retraining without manual intervention.

For Non-Technical Audiences:

This project is like having a robot data scientist that takes your Excel file with data, automatically finds patterns and relationships, builds a smart prediction model, watches for changes in your data, updates the model automatically when things change, and tells you how accurate everything is—all without you writing complex code or doing math!

Technical Abstract:

A modular Python-based MLOps pipeline implementing automated feature engineering through decorator patterns, statistical drift detection using Kolmogorov-Smirnov tests, and conditional model retraining. The system employs a metadata-driven architecture with SQLite persistence, config-driven transformations, and scikit-learn model training, achieving domain-agnostic applicability across healthcare, finance, and IoT use cases.