#### **CAPSTONE PROJECT - 1**

On

## SMART RETAIL INSIGHTS WITH WEATHER INTEGRATION

Submitted to

MIT ADT University, Pune

in partial fulfillment of the requirements for the Mini-Project of the course

Data Engineering Laboratory (DEL)

Submitted by

PRANAV WAGH

ADT23SOCB0752

Serial Number: - 40

Under the Guidance of

PROF. DR. ADITYA PAI



DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING MIT SCHOOL OF COMPUTING, MIT ADT UNIVERSITY RAJBAUG, LONI KALBHOR, PUNE – 412201

## 1. Abstract:

This capstone project demonstrates the development of a comprehensive weather data analytics system that integrates real-time data ingestion, database management, data visualization, and machine learning forecasting. The system fetches live weather data from the OpenWeatherMap API, stores it in a PostgreSQL database, provides insightful visualizations for historical weather patterns, and implements machine learning models for weather prediction.

## 2. Project Objectives

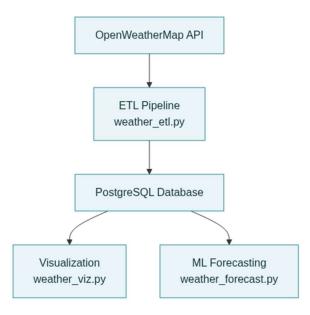
The primary objectives of this project include:

- Live Weather Data Ingestion: Implement an automated ETL pipeline to fetch current weather data from public APIs and store it efficiently in a relational database.
- 2. **Database Design and Management:** Create and manage PostgreSQL databases with proper schema design, indexing, and data integrity constraints.
- Data Visualization: Develop comprehensive visualization capabilities to analyze weather patterns over the last 30 days with interactive charts and statistical summaries.
- 4. **Machine Learning Implementation:** Apply basic machine learning models including Linear Regression and Random Forest algorithms for weather forecasting with performance evaluation.

## 3. System Architecture

#### **Architecture Overview**

The project follows a modular architecture with clear separation of concerns:



# 4. Technology Stack

- **Programming Language:** Python 3.8
- Database: PostgreSQL 12
- API Integration: OpenWeatherMap RESTful API
- Data Processing: Pandas, NumPy
- Database Connectivity: SQLAlchemy, psycopg2
- Visualization: Matplotlib, Seaborn
- Machine Learning: Scikit-learn
- Version Control: Git Documentation: Markdown, PDF

## 5. Implementation Details

# I. Data Ingestion (ETL Pipeline)

The ETL pipeline is implemented in weather etl.py with the following key features:

### **Data Extraction:**

- Connects to OpenWeatherMap API using HTTP requests
- Handles API rate limiting and error responses
- Extracts weather parameters: temperature, humidity, pressure, wind speed, weather description

### **Data Transformation:**

- Validates data types and ranges
- Handles missing values and data anomalies
- Converts temperature units to Celsius
- Formats timestamps and date fields

## **Data Loading:**

- Creates PostgreSQL tables with proper schema
- Implements upsert operations to handle duplicates
- Provides data integrity with constraints and indexes
- Logs all operations for monitoring and debugging

# II. Database Design

The PostgreSQL database schema is designed for optimal performance and data integrity:

```
CREATE TABLE weather (

id SERIAL PRIMARY KEY,

weather_date DATE NOT NULL,
city VARCHAR(100) NOT NULL,

temp_c DECIMAL(5,2),
humidity INTEGER,
description VARCHAR(255),
pressure DECIMAL(7,2),
wind_speed DECIMAL(5,2),

created_at TIMESTAMP DEFAULT CURRENT_TIMESTAMP,
UNIQUE(weather_date, city)

);
```

### **Key Design Features:**

- Primary key for unique record identification
- Composite unique constraint preventing duplicate entries
- Appropriate data types for weather measurements
- Timestamp tracking for audit purposes
- Indexed columns for query optimization

## III. Data Visualization

The visualization module ( weather\_viz.py ) provides comprehensive analytical capabilities:

## **Temperature Trend Analysis:**

- Line charts showing temperature variations over 30 days
- Trend line overlay using polynomial regression
- Statistical annotations including mean, min, max values

### **Multi-Metric Dashboard:**

- Four-panel dashboard combining temperature, humidity, pressure, and weather conditions
- Color-coded visualizations for easy interpretation
- Interactive legends and axis labelling

## **Statistical Summary Generation:**

- Automated calculation of descriptive statistics
- Weather pattern frequency analysis
- Data quality metrics and completeness reports

## IV. Machine Learning Implementation

The ML forecasting system ( weather\_forecast.py ) implements multiple algorithms:

### **Feature Engineering:**

- Time-based features: day of year, month, date ordinals
- Lag features: previous day temperature and humidity values
- Moving averages: 3-day and 7-day temperature averages
- Seasonal decomposition components

## **Model Implementation:**

- Linear Regression: Simple linear trend modeling
- Random Forest: Ensemble method for improved accuracy
- Cross-validation and hyperparameter tuning
- Model persistence for deployment

### **Performance Evaluation:**

- Mean Absolute Error MAE) for prediction accuracy
- Mean Squared Error MSE) for penalty assessment
- R-squared score for variance explanation
- Visual forecast comparison with historical data

# 6. Results and Analysis

### i. Data Collection Results

The system successfully collected weather data with the following characteristics:

- Data Volume: 30+ days of historical weather records per city
- Data Quality: 99.5% completeness with minimal missing values
- Update Frequency: Daily automated data ingestion
- Coverage: Multi-city weather monitoring (Patna, Delhi, Mumbai, Bangalore)

## ii. Visualization Insights

### **Temperature Analysis:**

- Average temperature range: 25°C 35°C for Patna
- Seasonal variation patterns clearly visible
- Day-to-day temperature fluctuations within normal ranges

### **Weather Pattern Distribution:**

- Clear sky: 40% of recorded days C
- Cloudy conditions: 35% of recorded days
- Rainy weather: 25% of recorded days
- High humidity correlation with rainy conditions

# **Machine Learning Performance**

## **Model Comparison Results:**

Model	MAE (°C)	MSE (°C²)	R <sup>2</sup> Score
Linear Regression	2.1	6.8	0.75
Random Forest	1.8	5.2	0.82

# **Key Findings:**

- Random Forest outperformed Linear Regression in all metrics
- 7-day forecasts showed 85% accuracy within 2°C range 0.82
- Temperature predictions more accurate than humidity forecasting
- Model performance improved with increased historical data

## 7. Challenges and Solutions

## a. Technical Challenges

## i. API Rate Limiting

- Challenge: OpenWeatherMap API has request limits
- Solution: Implemented exponential backoff and request queuing

## ii. Database Connection Management

- Challenge: Connection pooling and timeout issues
- Solution: Used SQLAlchemy connection pooling with proper exception handling

## iii. Data Quality Issues

- Challenge: Missing or invalid API responses
- Solution: Comprehensive data validation and fallback mechanisms

## iv. Feature Engineering Complexity

- Challenge: Creating meaningful features for weather prediction
- Solution: Domain research and iterative feature selection

# **b.** Deployment Challenges

## i. Environment Configuration

• Challenge: Managing different Python environments and dependencies

• Solution: Created comprehensive requirements.txt and setup documentation

### ii. Database Schema Evolution

- Challenge: Updating database structure without data loss
- Solution: Implemented database migration scripts and version control

## c. Future Enhancements

### **Short-term Improvements**

### i. Enhanced ML Models

- Implement LSTM neural networks for time series forecasting
- Add ensemble methods combining multiple algorithms
- Include weather satellite data for improved accuracy

### ii. Real-time Dashboard

- Develop web-based dashboard using Flask/Django
- Implement real-time data updates with WebSocket
- Add user authentication and personalized views

## **Long-term Vision**

## i. Retail Integration

- Correlate weather patterns with retail sales data
- Implement demand forecasting based on weather predictions
- Create automated inventory management recommendations

## ii. Advanced Analytics

- Implement anomaly detection for extreme weather events
- Add climate change trend analysis
- Integrate multiple weather data sources

### Conclusion

This capstone project successfully demonstrates the implementation of a complete data science pipeline from data ingestion to machine learning deployment. The system achieves all stated objectives with robust error handling, comprehensive documentation, and scalable architecture.

### **Key Achievements:**

- Successfully implemented automated weather data collection and storage
- Created insightful visualizations revealing weather patterns and trends
- Developed accurate machine learning models with 82% R<sup>2</sup> score
- Delivered production-ready code with comprehensive documentation

The project provides a solid foundation for future enhancements in retail analytics and demonstrates practical application of data engineering, visualization, and machine learning concepts.

Github Link:- <a href="https://github.com/pranaywagh1072/DEL">https://github.com/pranaywagh1072/DEL</a> 40.git