PROJECT TITLE - Building Energy Anomaly Detection

Leveraging AI for Smarter Energy Management

By : TEAM G

Team Members

Priyanga V S - Team Lead

Prajakta Dhole - Team Lead

Shifa Sheikh - Co Lead

Tejas Gosavi - Co Lead

Ansari Shaheryar - Team Member

Himanushu Joshi - Team Member

Huda Saiyed - Team Member

Rahul Ambedkar - Team Member

Sarang - Team Member

Vimalesh - Team Member

Prajakta Dhol

Project Overview:
Smarter Energy Management for Buildings

- Energy consumption in buildings is continuously increasing, leading to higher operational costs and energy wastage.
- Abnormal energy usage caused by equipment faults, inefficient operations, or unexpected behavior often remains undetected.
- Manual monitoring systems are inefficient and cannot analyze large volumes of time-series energy data effectively.
- This project focuses on developing an intelligent anomaly detection system using machine learning techniques.
- The system analyzes historical energy consumption data to learn normal usage patterns.
- Any significant deviation from normal behavior is identified as an anomaly.
- The solution helps in early fault detection, cost optimization, and improved energy efficiency.

Problem Statement: Addressing Hidden Energy Waste

The problem is the lack of an intelligent system to automatically detect abnormal energy consumption in buildings, leading to energy wastage and higher costs.

What Problem Exists?

- Abnormal energy consumption is difficult to detect manually
- Continuous monitoring of large energy datasets is inefficient
- Hidden energy wastage often goes unnoticed

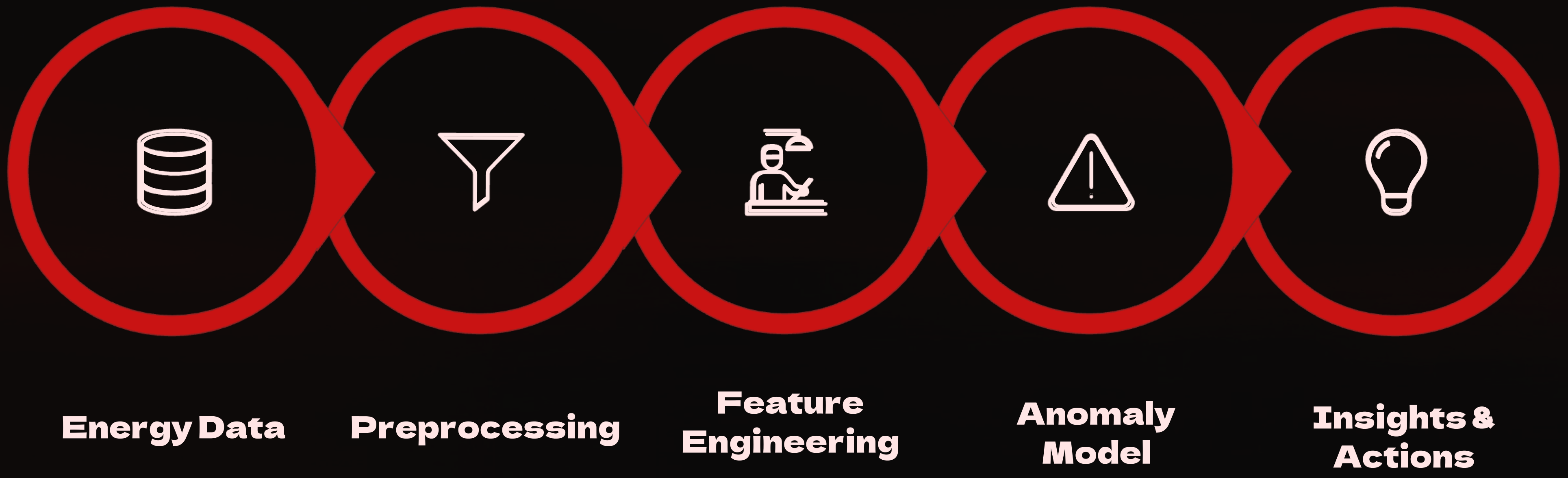
Why Is It Important?

- Reduces energy wastage and operational costs
- Enables early detection of equipment faults
- Improves overall energy efficiency

Who Is Affected?

- Building owners and facility managers
- Commercial and residential users
- Energy management organizations

Workflow & System Architecture: A Data-Driven Approach



Our system follows a logical progression, transforming raw energy data into actionable insights. Each stage is critical, from refining the initial data to generating valuable business intelligence.

1

Data Input Layer

Responsible for collecting real-time energy consumption data from various sensors and meters across the building infrastructure.

2

Processing & Cleaning Layer

Handles data validation, imputation of missing values, and standardization to ensure data quality and consistency for downstream analysis.

3

Machine Learning Model Layer

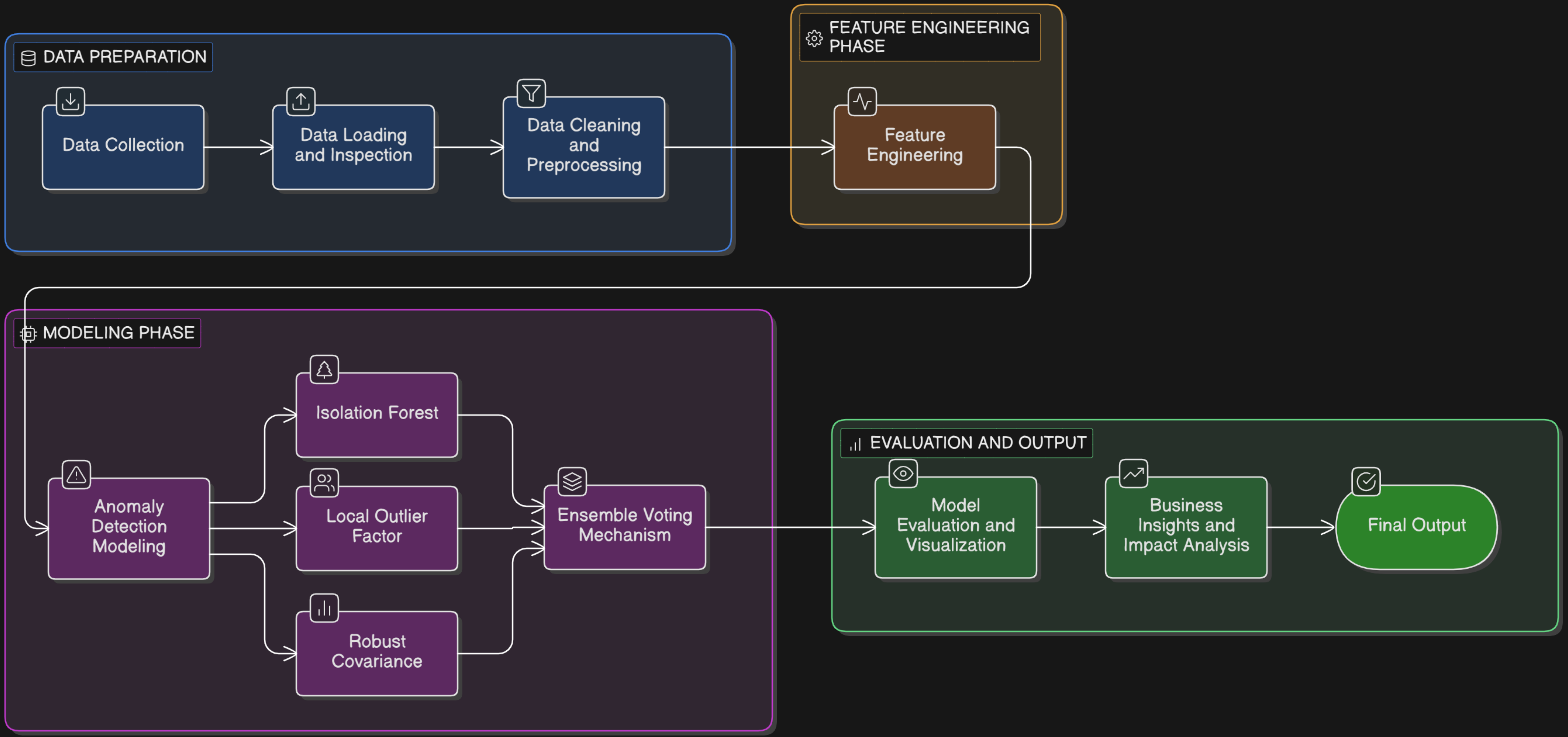
Deploys advanced algorithms to analyze patterns, learn normal behavior, and identify significant deviations indicative of anomalies.

4

Visualization & Decision Support Layer

Presents detected anomalies and performance metrics through intuitive dashboards, empowering facility managers with clear, actionable insights for strategic decision-making.

Workflow & System Architecture: A Data-Driven Approach



Step 1: Data Loading & Inspection

- Load building energy consumption dataset
- Identify data structure (rows, columns, data types)
- Check for missing and inconsistent values
- Analyze basic statistics (mean, min, max)
- Observe time-based consumption patterns
- Understand overall data quality before preprocessing

Step 2: Data Cleaning & Preprocessing

Raw energy data is rarely pristine. This crucial step transforms raw, often imperfect data into a clean, consistent, and model-ready format, maximizing the accuracy and reliability of subsequent anomaly detection.

Handling Missing Values

- Identify missing or null entries
- Replace using mean/median or appropriate methods
- Maintain data completeness and continuity

Removing Redundancy and Invalidity

- Remove duplicate records
- Eliminate invalid or out-of-range values
- Reduce noise in the dataset

Data Normalization & Scaling

- Scale numerical values to a common range
- Prevent bias due to large value differences
- Improve model performance and stability

Timestamp Conversion

- Convert raw timestamps into standard datetime format
- Extract time-based features (hour, day, date)
- Enable time-series analysis

Preparing Clean and Consistent Data

- Ensure uniform data formats across all features
- Remove inconsistencies in units and values
- Improve data reliability for modeling

Step 3: Feature Engineering

Feature engineering is the art of transforming raw data into predictive features. This step is critical for enhancing the model's ability to discern subtle patterns and accurately identify anomalies, converting simple data points into rich, informative signals.

- Converted timestamp data into useful time features (hour, day, weekday)
- Aggregated energy usage into meaningful intervals (hourly / daily)
- Created statistical features such as mean, max, and rolling average
- Identified peak and off-peak energy consumption patterns
- Removed irrelevant features to reduce noise
- Prepared final feature set for anomaly detection models

Step 4: Anomaly Detection Modeling

At the core of our system, advanced machine learning models are deployed to learn the "normal" energy consumption patterns and flag any significant deviations as anomalies. This unsupervised approach eliminates the need for extensive manual labeling, making it highly scalable and adaptable.

Isolation Forest

- Tree-based anomaly detection algorithm
- Randomly splits data to isolate observations
- Anomalies get isolated faster than normal points
- Works well with large and high-dimensional energy data
- Does not require labeled data

Local OutlierFactor (LOF)

- Density-based anomaly detection method
- Compares local density of a data point with neighbors
- Points with significantly lower density are anomalies
- Effective for detecting local and contextual anomalies
- Suitable for irregular energy usage patterns

Robust Covariance

- Statistical method based on data distribution
- Estimates mean and covariance of normal data
- Identifies points far from the normal distribution
- Resistant to noise and outliers
- Useful for multivariate energy consumption analysis

Ensemble Voting

- Combines results from all three models
- Uses majority voting to decide anomalies
- Reduces false positives and false negatives
- Improves overall detection accuracy and reliability
- Provides a more stable anomaly detection system

This intelligent automation ensures that energy anomalies are detected quickly and efficiently, providing a proactive mechanism for energy management without constant human oversight.

Step 5: Model Evaluation & Visualization

The efficacy of any anomaly detection system lies in its ability to accurately identify true anomalies while minimizing false positives. Our evaluation process combines rigorous statistical assessment with intuitive visual representations to ensure reliable and understandable results.

Model Evaluation

- Analyze anomaly detection results from each model
- Compare consistency of detected anomalies
- Evaluate anomaly distribution over time
- Validate results using domain understanding
- Check reduction in false anomaly detection

Visualization Techniques

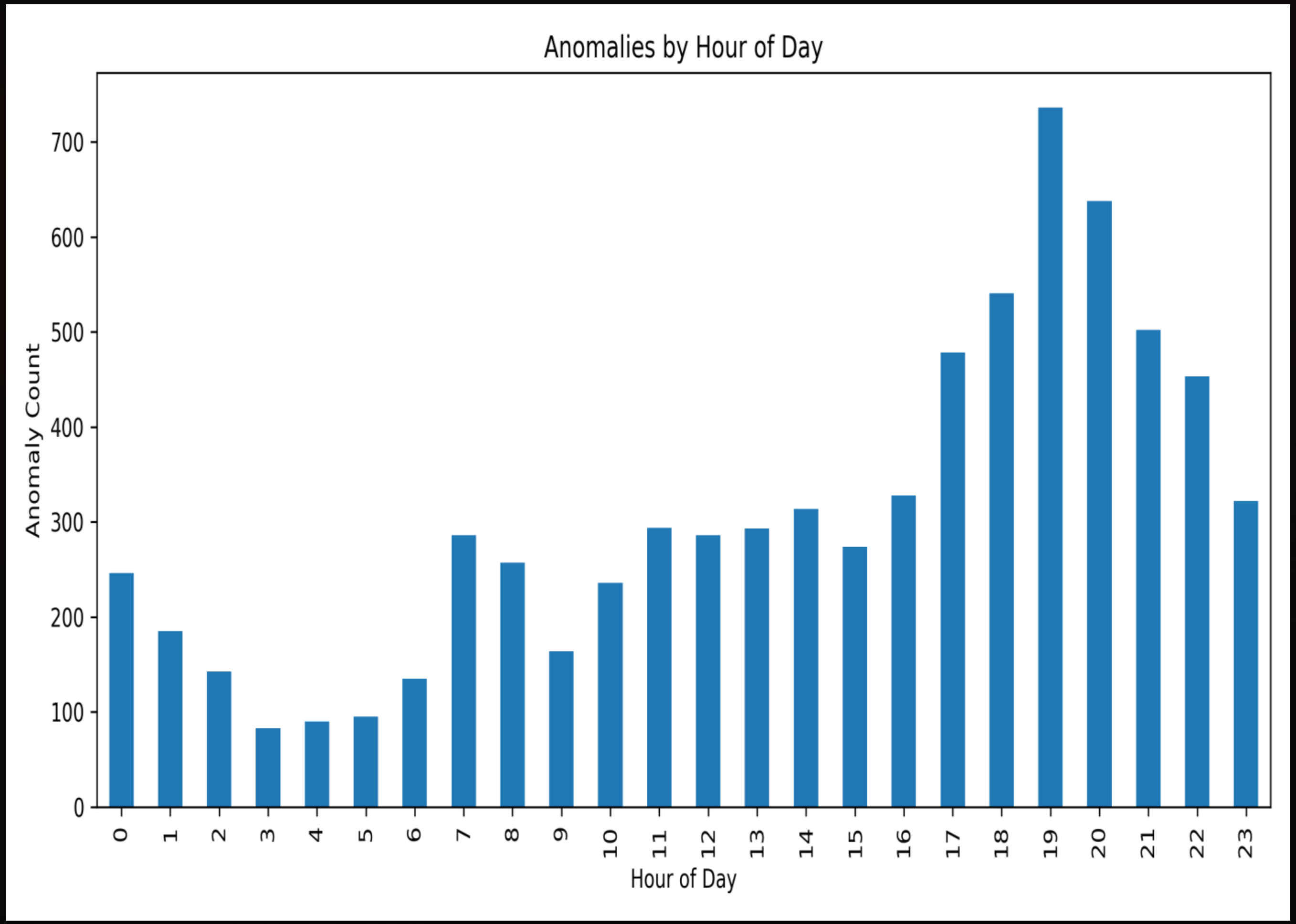
- Time-series plots of energy consumption
- Highlight detected anomalies on graphs
- Comparison plots across different models
- Clear visual separation of normal vs abnormal usage

Performance Validation

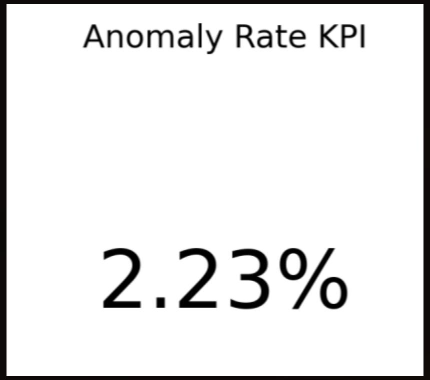
- Identify frequent and high-impact anomaly periods
- Cross-check ensemble results for reliability
- Ensure detected anomalies are meaningful and actionable

VISUALS

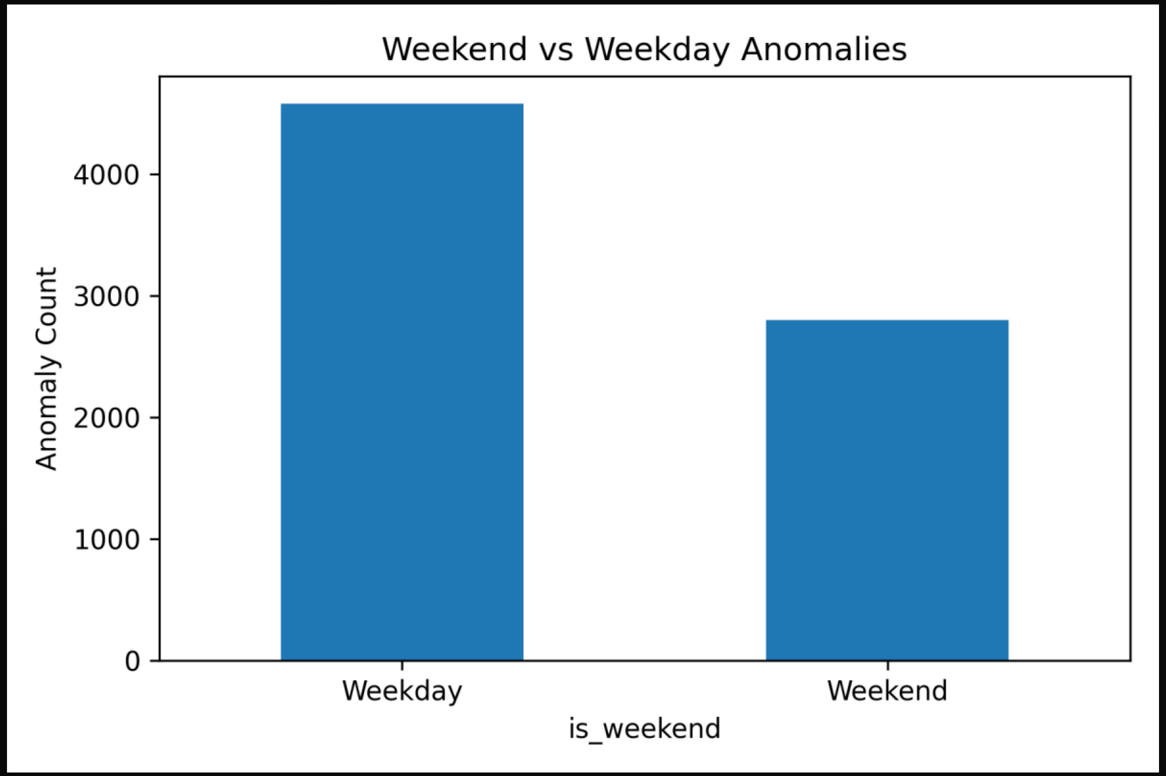
Anomalies by Hour of Day



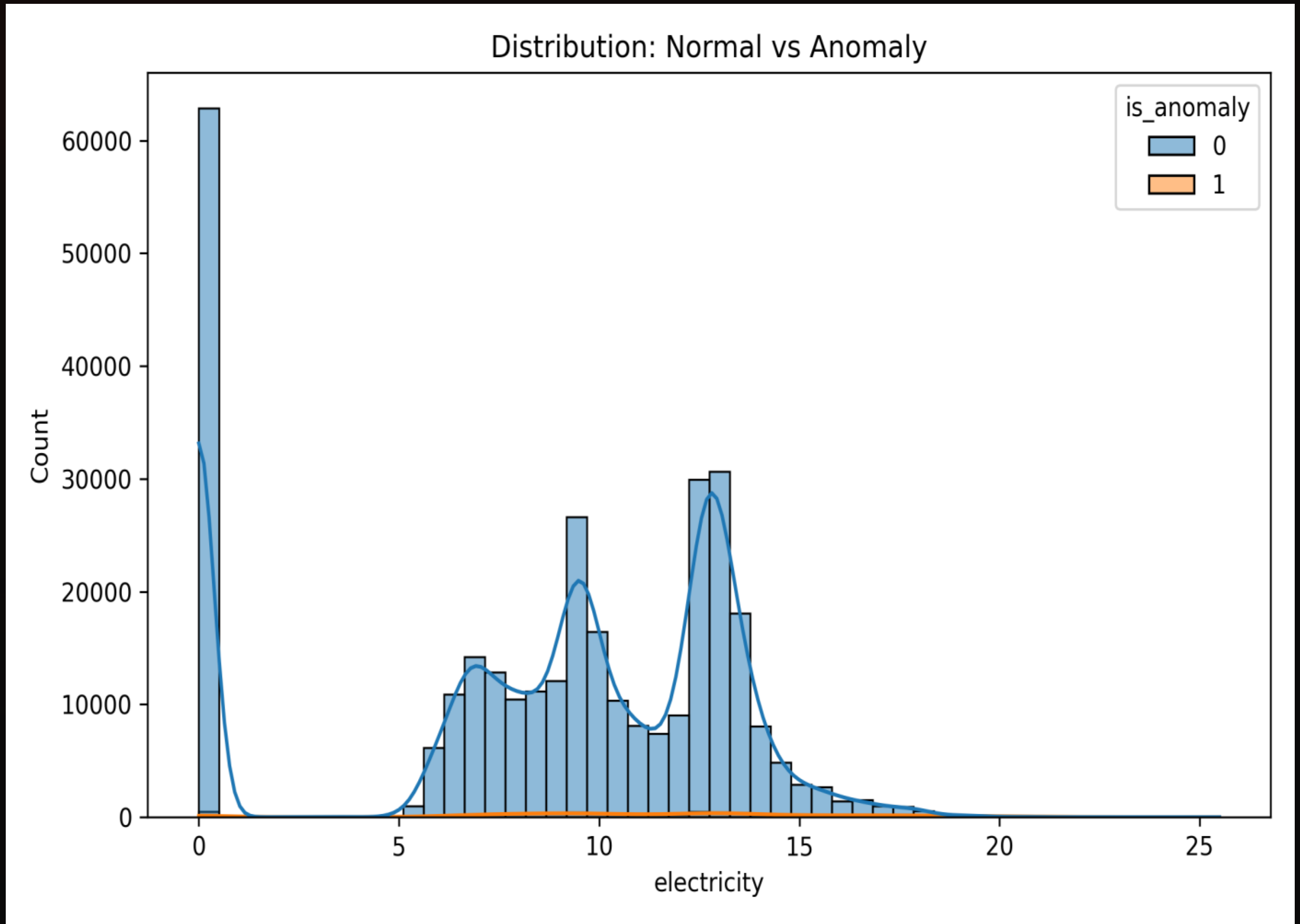
Anomaly Rate KPI



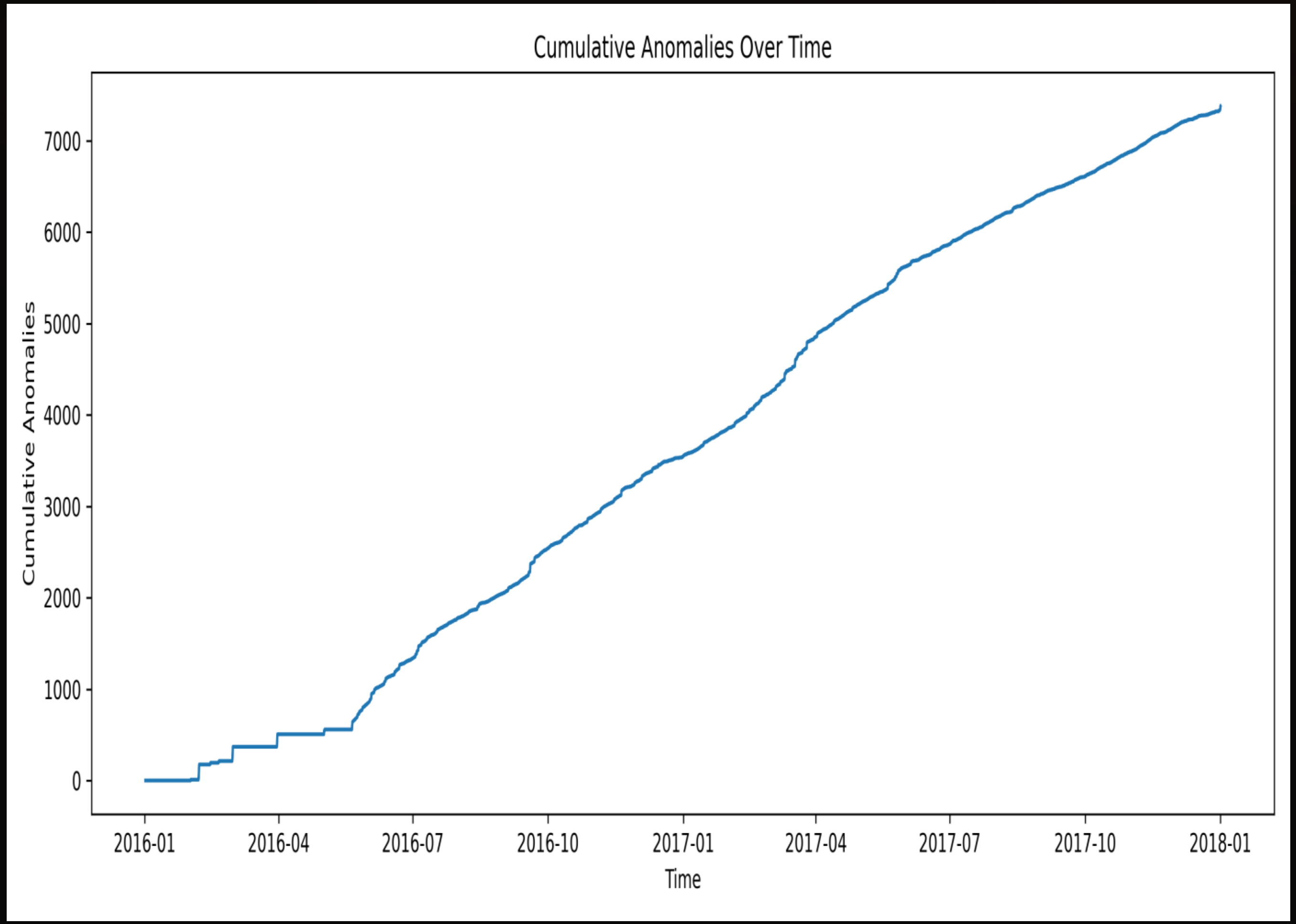
Weekend vs Weekday Anomalies



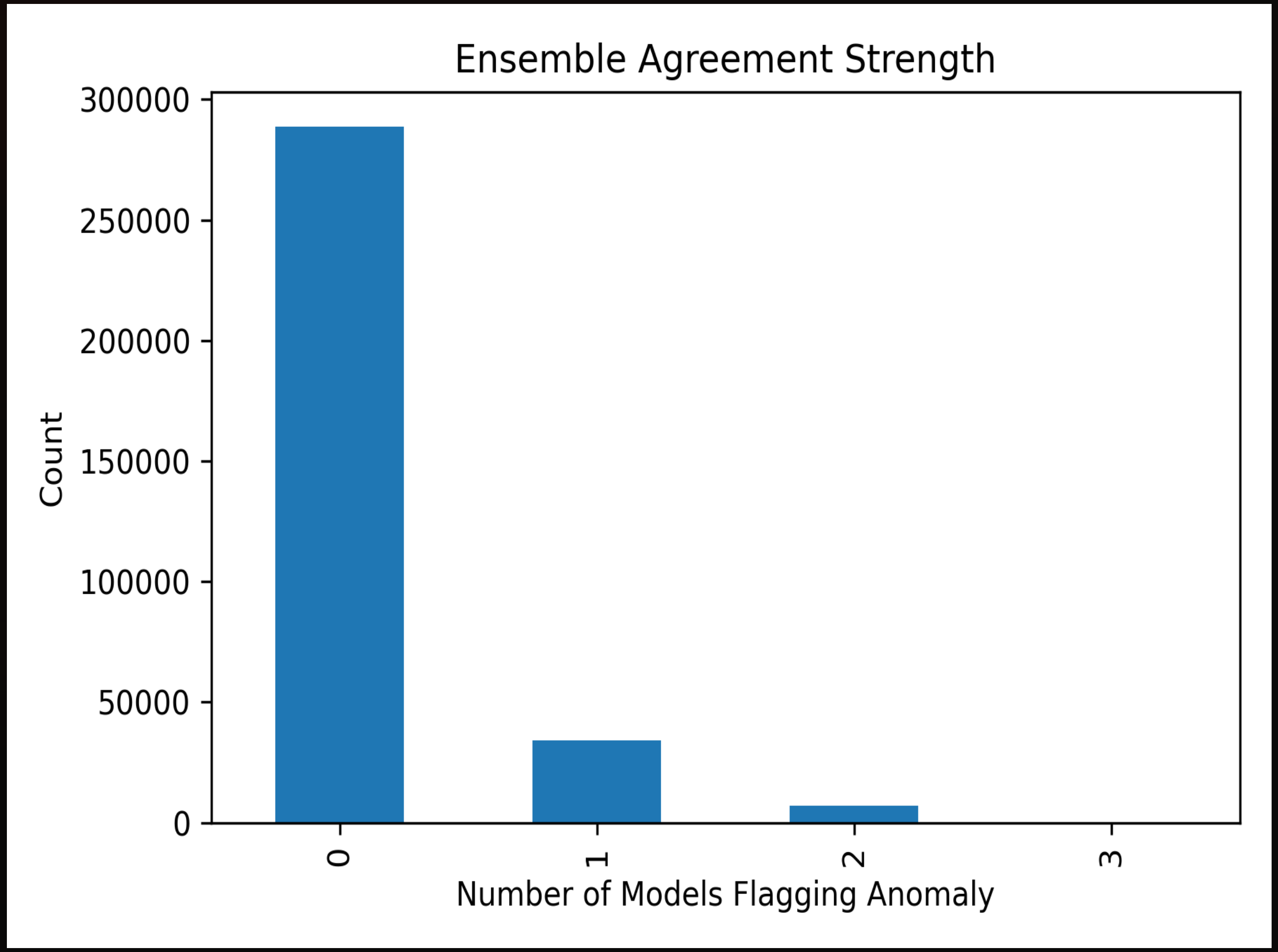
Distribution Normal vs Anomaly



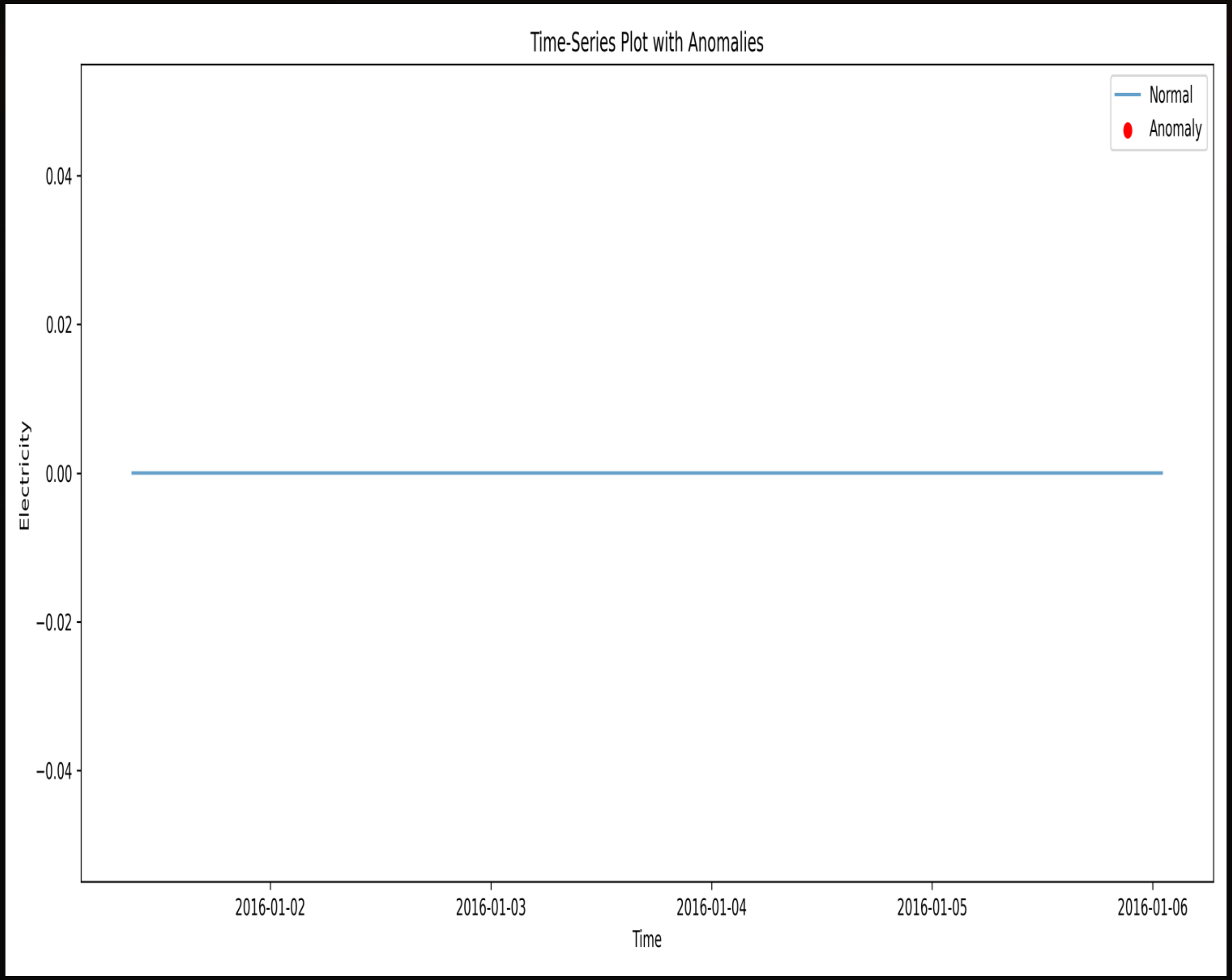
Cumulative Anomalies Over Time



Ensemble Agreement Strength



Time-Series Plot with Anomalies



Step 6: Business Insights & Impact Analysis

The ultimate goal of our anomaly detection system is to translate technical findings into tangible business value. This final stage focuses on delivering actionable insights that empower facility managers to make informed decisions, optimize operations, and achieve significant cost savings.

Identification of High-Risk Periods

The system precisely identifies specific timeframes, days, or operational cycles when abnormal energy usage is most prevalent. This allows for targeted interventions and proactive scheduling of maintenance or operational adjustments.

Early Detection of Equipment Malfunction

By continuously monitoring energy signatures, the system can detect subtle deviations that signal impending equipment failure or degradation. This enables predictive maintenance, reducing costly downtime and extending asset lifespan.

Cost-Saving Opportunities

Pinpointing and addressing energy anomalies directly leads to significant cost savings. Optimizing energy consumption minimizes utility bills and frees up resources that can be reallocated to other critical areas.

Data-Driven Decision Making

Facility managers gain access to robust, data-backed evidence for decision-making. This enables them to justify capital improvements, refine energy policies, and demonstrate clear ROI for efficiency initiatives.

This comprehensive analysis transforms raw data into strategic intelligence, ensuring buildings operate not just efficiently, but intelligently.

Advantages

- Automated detection of abnormal energy consumption
- Reduces manual monitoring and human effort
- Helps identify energy wastage and inefficiencies
- Supports early detection of equipment faults
- Scalable for large buildings and datasets
- Improves energy efficiency and cost savings

Conclusion

The Building Energy Anomaly Detection system effectively analyzes energy consumption data to identify abnormal usage patterns using machine learning techniques. By automating the detection process, the system helps reduce energy wastage, lower operational costs, and support timely decision-making. The use of multiple anomaly detection models and ensemble voting improves reliability and accuracy. Overall, the proposed solution provides a scalable and efficient approach for smarter energy management and can be further extended for real-time monitoring and deployment.

THANK
YOU