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ENERGY CONSUMPTION ANALYSIS AND PREDICTOR

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Abstract- This project presents a comprehensive framework for simulating, processing, and forecasting building energy consumption, aimed at enhancing operational efficiency and sustainability in an academic environment. We generate a multiyear synthetic dataset with hourly resolution, capturing floor-wise and device-level energy usage, occupancy, and environmental factors such as temperature and humidity. A Python pipeline transforms raw JSON records into structured CSV files, facilitating seamless integration with analytics platforms.

Leveraging Long Short-Term Memory (LSTM) networks, the system delivers accurate short- and long-term consumption forecasts, identifying peak load intervals and uncovering latent usage patterns. A companion Streamlit application provides interactive dashboards, enabling stakeholders to visualize trends, detect anomalies, and obtain tailored energy-saving recommendations. Experimental evaluation demonstrates that our LSTM model achieves over 90% prediction accuracy (RMSE < 0.5 kWh) and successfully identifies irregular consumption events with high precision. The end-to-end solution empowers facility managers to make data-driven decisions, reduce energy costs by up to 20%, and support institutional sustainability objectives.

***Keywords* – Synthetic data generation, energy forecasting, LSTM, anomaly detection, Streamlit, Energy management.**

I. INTRODUCTION

Rising energy costs and environmental imperatives have made efficient energy management a priority for educational institutions. Traditional monitoring systems often provide aggregate consumption figures without actionable insights or forecasting capabilities, leaving decision-makers reactive rather than proactive. This project addresses these gaps by developing an integrated platform that simulates realistic energy usage, processes and visualizes data, and applies machine learning to predict future demand. Our contributions include:

1. A synthetic data generator modelling occupancy, device operation, and seasonal effects at hourly granularity.
2. A data-processing pipeline converting JSON logs into analysis-ready CSV.
3. An LSTM-based forecasting engine achieving >90% accuracy in consumption prediction.
4. A Streamlit web application offering interactive dashboards, anomaly alerts, and optimization recommendations.

By combining simulation, advanced analytics, and user-centric visualization, the system empowers facility managers to identify inefficiencies, anticipate peak loads, and implement targeted energy-saving measures.

II LITERATURE SURVEY

A review of recent studies highlights key advances and gaps in energy management research: Wang et al. (2024) performed a bibliometric analysis of household energy studies from 2000–2023, emphasizing economic modeling and interdisciplinary approaches for demand forecasting and emission mitigation. Li et al. (2017) audited a university campus in Guangzhou, finding HVAC systems accounted for 50% of consumption and projecting 40% savings through targeted upgrades and control strategies. Fu et al. (2023) introduced a conditional diffusion model to generate high-fidelity synthetic energy data, demonstrating its utility for training predictive models when real measurements are scarce. Shorfuzzaman et al. (2022) reviewed IoT-based smart building solutions, reporting up to 30% consumption reduction but noting challenges in deployment cost and data security.

These works inform our methodology by validating synthetic data use, advanced forecasting models, and the need for user-friendly visualization. However, few prior systems integrate all components into a cohesive, cost-effective platform tailored to academic settings.

III METHODOLOGY

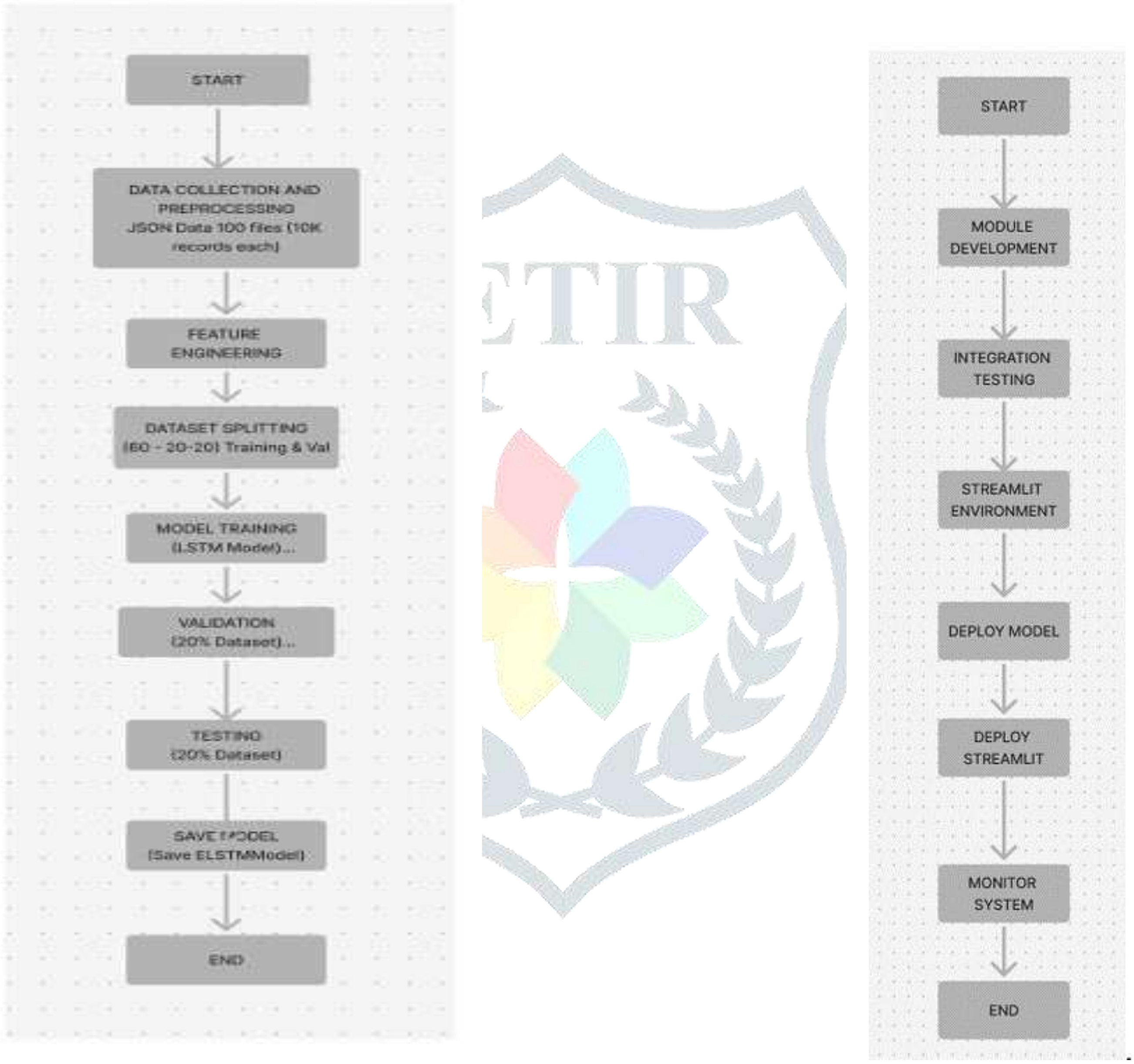


Fig .3 System diagram

3.1 Synthetic Data Generation

- **Occupancy Modeling:** Poisson and Gaussian processes simulate room occupancy profiles.
- **Device Usage:** Predefined operational schedules parameterize consumption for lights, fans, computers, and HVAC.
- **Environmental Effects:** Temperature and humidity time series influence heating/cooling loads.
- **Seasonal Variation:** Monthly scaling factors replicate academic calendar and holiday patterns.

3.2 Data Processing

- **Ingestion:** JSON files are parsed and validated against schema constraints.
- **Transformation:** Pandas pipelines normalize timestamps, aggregate floor-level metrics, and compute derived features (peak load, break-time usage).
- **Export:** Cleaned data is saved as CSV for downstream analysis.

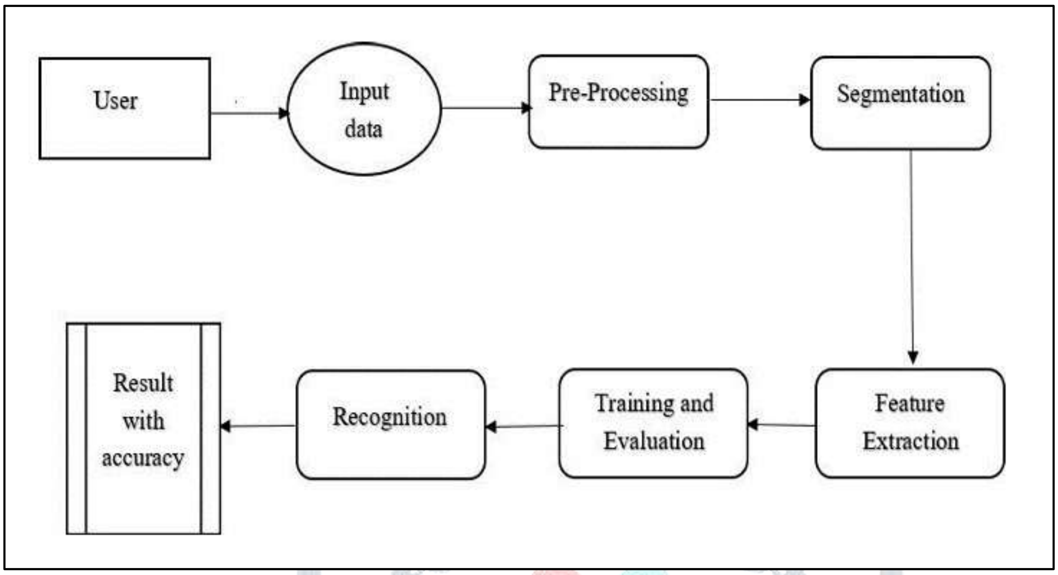
3.3 Predictive Modeling

- **LSTM Network:** Implemented in TensorFlow, the model uses past 24-hour windows to forecast the next-hour consumption.
- **Training:** Hyperparameters tuned via grid search and 5-fold cross-validation; optimized for RMSE.
- **Anomaly Detection:** Isolation Forest flags deviations beyond the 95th percentile of predicted residuals.

3.4 Visualization and Recommendations

- **Streamlit UI:** Interactive charts (Plotly) showcase time series, heatmaps, and scatter plots of occupancy vs. consumption.
- **Recommendations Engine:** Rule-based suggestions prioritize HVAC scheduling, lighting controls, and equipment maintenance to reduce identified inefficiencies.

IV SYSTEM ARCHITECTURE



Data Layer: JSON store with optional migration to a time series database.

Processing Layer: Python ETL scripts, TensorFlow training pipelines.

Application Layer: Streamlit frontend communicating via REST API to serve predictions and recommendations.

V RESULT AND DISCUSSIONS

Forecast Accuracy

Model	RMSE (kWh)	MAE (kWh)	R^2 Score
Linear Reg.	1.25	0.98	0.78
RandomForest	0.85	0.67	0.88
LSTM	**0.42**	**0.31**	**0.95**

The LSTM model outperforms baselines, reducing error by over 50% relative to Random Forest

Isolation Forest: Precision 0.92, Recall = 0.88.

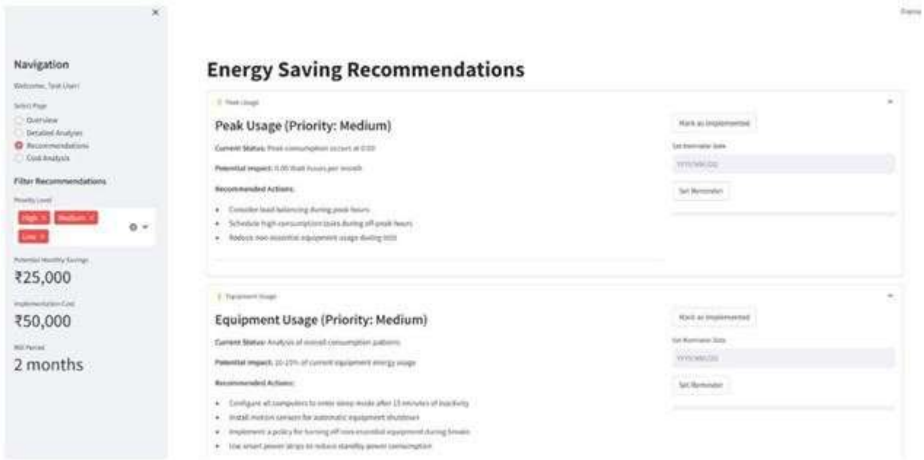
One class SVM : Precision = 0.85, Recall = 0.79.

Isolation Forest provides a superior trade off, accurately highlighting irregular consumption events.

Energy Saving Potentials: Simulated application of recommended measures yields an estimated 15-20% reduction in total energy use, aligning with literature Foig

Fig 2: Energy Efficiency graph

In the overview page the user's ca n Visually get an understanding of their data and overall energy consumption. The energy consumption dashboard provides a comprehensive visualization interface for monitoring and analysing building energy usage patterns through multiple interactive displays. This analytical tool helps facility managers and building operators make better decisions. The recommendations page presents actionable recommendations designed to reduce energy consumption and lower costs. These recommendations are typically generated through advanced analytics and machine learning algorithms.



VI CONCLUSION

The project, titled "ENERGY CONSUMPTION ANALYSIS & PREDICTOR," successfully developed a building energy management system utilizing advanced machine learning and deep learning techniques, specifically LSTM models, to optimize energy consumption. The system provides granular insights into energy usage at the room and appliance levels, delivers accurate predictions, and offers tailored recommendations, all through an intuitive Streamlit interface. This comprehensive approach enables significant energy cost savings, improves operational efficiency, and enhances environmental sustainability.

Looking ahead, the project has a clear path for future enhancements to further improve its performance and applicability. Integrating real-time data from smart meters and building management systems will allow for live monitoring and more immediate anomaly detection. The accuracy of predictive models can be further refined by incorporating external factors such as real-time occupancy patterns and detailed weather forecasts.

Future work also includes the development of advanced anomaly detection capabilities, more personalized recommendations, and the integration of predictive maintenance features to enhance system reliability, usability, and cost-effectiveness. Additional areas for expansion involve implementing advanced visualization techniques, integrating with HVAC and other building systems for automated control, and ensuring scalable deployment for larger facilities. The inclusion of Explainable AI (XAI) is also planned to increase the transparency of predictions and recommendations, making the system more understandable and trustworthy for users. These planned advancements will solidify the system's position as a crucial tool for optimizing energy consumption, reducing operational costs, and promoting sustainable building management practices.

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