|  | **SYNOPSIS** |  |
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# OPTIMIZING WATER MANAGEMENT USING LORAWAN - ENABLED IoT FRAMEWORK AND BEHAVIUORIAL ANALYSIS

**NAME OF THE GUIDE** :

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# ABSTRACT :

Sustainable water usage is an important factor in efficient resource management within extensive water supply networks. In this regard, the current study attempts to investigate water consumption behavior in the context of a university campus via the implementation of a cutting-edge IoT system driven by LoRaWAN technology for high-accuracy data collection. The system takes advantage of LoRaWAN-capable smart meters that are strategically placed throughout the water distribution network on campus, enabling secure real-time data transmission over long distances at low power. The low-power wide-area network architecture guarantees efficient and scalable data collection from points such as student hostels and faculty/staff quarters. The accumulated data from weekly and monthly usage is fed into deep learning algorithms that reveal important patterns of water use driven by events like the academic calendar, holidays, and occupancy variability. These data allow for nuanced insights into campus-wide water consumption patterns. Compared with conventional monitoring strategies, the addition of LoRaWAN further strengthens the system's scalability, cost- effectiveness, and robustness, especially for environments working under intermittent water supply systems (IWS). Furthermore, the study identifies the various campus areas have different patterns of usage, and this gives effective insights which can be utilized for water management plans and ensuring sustainable consumption patterns by the inhabitants in the campus.

# SPECIFIC CONTRIBUTION :

Implement a DL Model(LSTM) and Design a Circuit diagram and Build a Hardware Setup

### LSTM-BASED WATER FLOW PREDICTION MODEL

* **Type:** Deep Learning (Recurrent Neural Network - LSTM)
* **Input:** Historical water flow readings recorded at 6-hour intervals.

### Preprocessing:

* + Timestamp rounding and grouping data into fixed 6-hour bins.
  + Applied linear interpolation to handle missing values.
  + Normalized data using **MinMaxScaler** for optimal training.

### Model Architecture:

* + One or more **LSTM layers** followed by a Dense layer.
  + Input shape: (10 time-steps, 1 feature) for temporal sequence learning.
  + Output: Predicted water flow value for the next 6-hour window.
* **Usage:** Predictions were compared against real-time sensor readings to determine the actuation of the sprinkler system.
* **Integration:** Trained using Keras and deployed for testing on local systems with synthetic and real-time data comparison.

### HARDWARE SETUP DESIGN AND INTEGRATION

* Designed and implemented the complete circuit for real-time water monitoring and control using:
  + **ESP32S microcontroller** to acquire flow data from a YF-S201 water flow sensor.
  + **Raspberry Pi** to run inference and decision logic.
  + **Relay module** and **12V Solenoid Valve** to control water flow based on predictions.
* Integrated sensor logic via Arduino IDE and controlled actuator logic using GPIO on Pi.
* Set up physical components like **water tank**, **hose connections**, and **relay-powered solenoid** to prototype real-world water flow control.Physically implemented and tested the water flow control mechanism based on model predictions.
* Coordinated with the software team to ensure hardware compatibility with MQTT-based data flow, even though the code-side integration was handled by other members.

# SPECIFIC LEARNING :

## LSTM MODEL :

* Gained practical experience in structuring multivariate time-series data using sliding windows for sequential learning in LSTM.
* Understood LSTM memory cell mechanics, including input, forget, and output gates, to address the vanishing gradient problem in RNNs.
* Focused on hyperparameter tuning, optimizing factors like look-back window, LSTM units, dropout, and early stopping for better model performance.
* Applied MinMax scaling to normalize sensor inputs for stable gradient descent during training.
* Developed sequence-to-one models in Keras/TensorFlow, predicting the next water flow reading from past time steps.
* Evaluated model performance using RMSE, MAE, and R² scores, comparing with GRU and ARIMA.
* Simulated real-time inference using data streams for prediction with relevant libraries.

## HARDWARE SETUP DESIGN :

* Contributed to the design of an IoT-based water flow monitoring system with integrated sensors and actuators.
* Assisted in the implementation of ESP32 microcontroller firmware, using YF-S201 sensor to capture pulse signal readings.
* Worked on establishing bi-directional MQTT communication between ESP32 and Raspberry Pi for telemetry and control.
* Contributed to the integration and testing of the complete hardware pipeline: sensor → ESP32 → MQTT → Raspberry Pi → ML Inference → Relay Control → Solenoid Valve, ensuring data flow synchronization.

# LIMITATIONS AND CHALLENGES FACED :

### LSTM MODEL :

* Training LSTM required more time and compute compared to GRU, especially with longer sequences.
* Tuning model hyperparameters was complex due to LSTM’s sensitivity to learning rate and number of layers.
* Faced initial issues with **overfitting**, which required regularization techniques like **dropout layers** and **early stopping**.
* Temporal misalignment between real-time data intervals and training data structure caused prediction inaccuracies, which had to be mitigated via **resampling** and **window smoothing**.

### HARDWARE SETUP :

* Encountered **relay bounce** and solenoid overheating when the valve was frequently toggled—solved by implementing a **debouncing delay and thermal cycle control**.
* Real-time synchronization between Raspberry Pi and ESP32 was challenging; required

**global variables and background MQTT threading** to maintain data consistency.

* The **WiFi-based MQTT system** occasionally faced packet loss due to unstable local networks, which affected real-time actuation.
* Ensured voltage isolation to prevent **back EMF damage** to control components, especially around the solenoid switching relay.

# KEYWORDS :

LSTM (Long Short-Term Memory), Time Series Forecasting, MinMaxScaler, TensorFlow/Keras, Dropout, Overfitting, Sequence Learning, Windowing, Sliding Time Frames, IoT, ESP32, Raspberry Pi, MQTT (Message Queuing Telemetry Transport), Relay Module, Solenoid Valve, Flow Sensor (YF-S201), UART, Python Socket Communication, Embedded Systems.

**NAME & SIGNATURE OF STUDENT SIGNATURE OF GUIDE**