# Progress Update on IoT-Powered Smart Farming for Soil Moisture and Crop Health

### IoT System Design Progress

We have made significant progress on the IoT system design diagram. The system architecture includes IoT sensors connected to an Arduino Uno and ESP8266 module, transmitting real-time data to Thingspeak for cloud storage. The collected data is processed for monitoring soil moisture, temperature, humidity, and other key environmental factors. The main challenge we encountered was optimizing the network transmission speed to reduce latency. To address this, we refined the data transmission frequency and optimized the ESP8266 firmware settings to enhance efficiency.

### Dataset Exploration and Cleaning

Our dataset, sourced from the IoT-based Smart Agriculture Plant Health Monitoring system, consists of multiple environmental variables recorded at regular intervals. Initial dataset exploration revealed missing values and occasional sensor noise, particularly in soil moisture and water TDS readings. To handle this, we implemented data imputation techniques, including forward-fill for missing values and outlier detection using Z-score filtering. Additionally, we normalized the dataset to ensure uniform feature scaling, which is essential for machine learning model performance.

### Deep Learning Model Selection

To fulfill the deep learning requirement, we have chosen a **Convolutional Neural Network (CNN)** for crop health classification based on sensor readings. The CNN model processes soil moisture, temperature, humidity, and other environmental parameters to classify crop health into different categories (e.g., healthy, moderate risk, high risk). CNN’s ability to detect complex patterns in structured data makes it an effective choice for this task. The model is being trained using historical sensor data, and we are currently fine-tuning hyperparameters to improve accuracy.

### Time Series Forecasting Model Selection

For the time series requirement, we selected **Long Short-Term Memory (LSTM)** networks to predict future soil moisture levels and optimize irrigation schedules. LSTM is well-suited for sequential data as it can capture long-term dependencies and trends over time. Our LSTM model is trained on historical soil moisture data, along with temperature and humidity inputs, to predict moisture levels for the next time interval. One challenge we faced was overfitting due to limited training data; we mitigated this by implementing dropout regularization and expanding the dataset through data augmentation techniques.

## Conclusion

Our final project is progressing as planned, with our IoT system successfully collecting and transmitting real-time data. The dataset has been cleaned and preprocessed, and both our deep learning (CNN) and time series forecasting (LSTM) models are in the development and tuning phase. The next steps include evaluating model performance using appropriate metrics and integrating real-time inference with our IoT system for decision-making.

We are confident that our approach will enhance precision farming by automating irrigation and providing actionable insights for farmers, thereby improving crop health and resource efficiency.