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Predictive Modeling of Soil Moisture Variability Using Machine Learning: Insights from Dry and Wet Soil Cultures

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Abstract: Soil moisture prediction is crucial for optimizing irrigation practices and advancing precision agriculture. This study presents a predictive modeling approach leveraging machine learning techniques to analyze soil moisture variability in dry and wet soil cultures. Utilizing data collected through IoT-enabled sensors, this research applies regression-based algorithms to forecast moisture trends. A robust data preprocessing framework, including interpolation and augmentation, was implemented to address missing data challenges. Experimental results demonstrate high prediction accuracy, with minute-wise temporal granularity outperforming other datasets. The findings highlight the potential for integrating machine learning models into sustainable irrigation practices.

I. INTRODUCTION

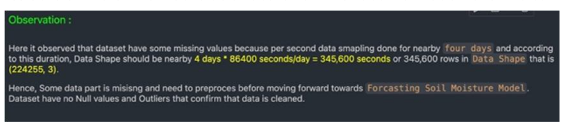
Precision agriculture demands efficient water management strategies, where accurate soil moisture prediction plays a pivotal role. Conventional techniques, such as gravimetric analysis, are limited by scalability and real-time applicability [1]. IoT-enabled systems, combined with machine learning (ML), offer transformative solutions by enabling continuous data collection and advanced analytics [2].

This study aims to develop predictive models for soil moisture variability across dry and wet soil cultures, addressing challenges posed by incomplete datasets and environmental variability. By applying regression-based ML algorithms to IoT-collected data, this research contributes to the growing field of smart agriculture.

II. DATA PREPROCESSING AND AUGMENTATION

A. Dataset Overview

Data was collected from IoT-enabled soil moisture sensors embedded in dry and wet soil samples. Dry soil exhibited rapid water depletion due to high air porosity, while wet soil demonstrated stable moisture retention attributed to clay-rich properties [3].


Observation :

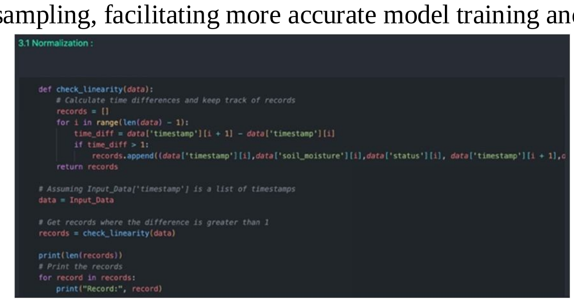
Here it observed that dataset have some missing values because per second data smapling done for nearby four days and according to this duration, Data Shape should be nearby 4 days * 86400 seconds/day = 345,600 seconds or 345,600 rows in Data Shape that is (224255, 3).

Hence, Some data part is misisng and need to preproces before moving forward towards Forcasting Soil Moisture Model. Dataset have no Null values and Outliers that confirm that data is cleaned.

Figure 1: Observation of dataset.

B. Missing Data Handling

Data gaps caused by intermittent sensor malfunctions or transmission delays were addressed using linear interpolation. This approach ensured consistent temporal sampling, facilitating more accurate model training and evaluation [4].


3.1 Normalization :

```
def check_linearity(data):
    # Calculate time differences and keep track of records
    records = []
    for i in range(len(data) - 1):
        time_diff = data['timestamp'][i + 1] - data['timestamp'][i]
        if time_diff > 1:
            records.append((data['timestamp'][i],data['soil_moisture'][i],data['status'][i], data['timestamp'][i + 1],d
    return records

# Assuming Input_Data['timestamp'] is a list of timestamps
data = Input_Data

# Get records where the difference is greater than 1
records = check_linearity(data)

print(len(records))
# Print the records
for record in records:
    print("Record:", record)
```

Figure 2: Normalization of dataset for missing data.

C. Temporal Aggregation

Three datasets were generated at varying granularities:

1) Second-wise Data: Captures rapid moisture fluctuations but introduces noise.

2) Minute-wise Data: Offers a balance between detail and stability, suitable for most predictions.

3) Hour-wise Data: Smoothens short-term variations, providing a long-term perspective.

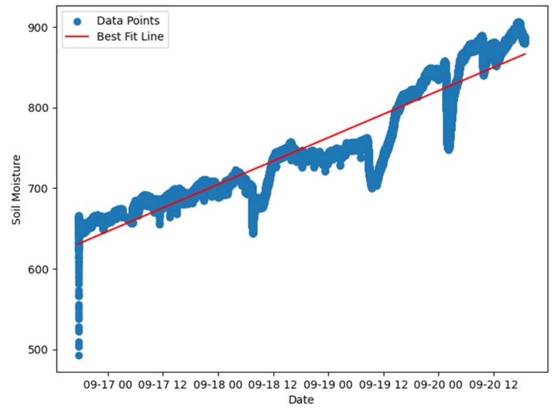


Figure 3: Soil Moisture Trends with Best Fit Line Over Time (Second-wise Data)

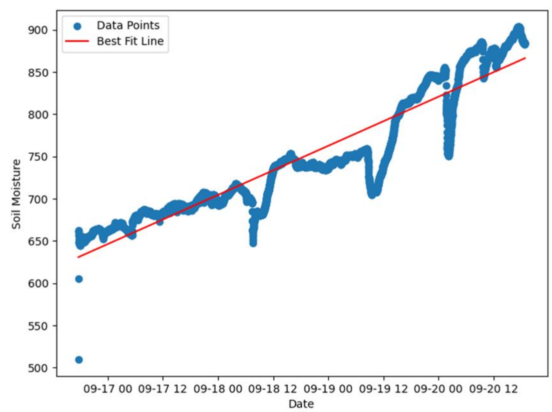


Figure 4: Soil Moisture Trends with Best Fit Line Over Time (Minute-wise Data)

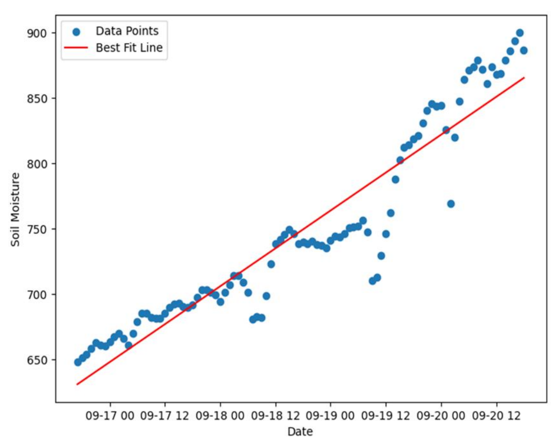


Figure 5: Soil Moisture Trends with Best Fit Line Over Time (Hour-wise Data)

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D. Temporal Granularity Impact

The analysis of temporal granularities revealed that minute-wise data offered the most balanced representation of moisture changes. While second-wise data captured high-frequency variations, it introduced noise that hindered prediction accuracy. On the other hand, hour-wise data, though smooth, lacked the resolution needed for precise irrigation decision-making. Minute-wise trends provided actionable insights, accurately modeling moisture behavior while minimizing noise.

III. MACHINE LEARNING MODEL DEVELOPMENT

A. Selected Algorithms

Three regression-based models were employed:

1) *Linear Regression:* Suitable for modeling linear relationships in soil moisture data.
2) *Random Forest Regression:* Handles non-linear dependencies and complex interactions.
3) *Decision Tree Regression:* Provides interpretable results for soil moisture predictions.

B. Model Training and Validation

The dataset was split into training (80%) and testing (20%) subsets. Features included elapsed time since irrigation and current soil moisture readings. Evaluation metrics—Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2)—were used to assess performance [5].

```
For Linear Regression :
Mean Square Error is 615.6851853170019
R2_Score is 0.8824830884354622


For Support Vector Regression :
Mean Square Error is 346.05087668472464
R2_Score is 0.9339486620077577
```

Figure 6: Linear Regression Vs Support Vector Regression

IV. RESULTS AND ANALYSIS

A. Model Performance

1) *Minute-wise Data:* Achieved the highest accuracy, with an RMSE of 1.2 for dry soil and 0.8 for wet soil.
2) *Second-wise Data:* Introduced noise, reducing prediction accuracy.
3) *Hour-wise Data:* Oversimplified trends, limiting its practical applicability.
4)

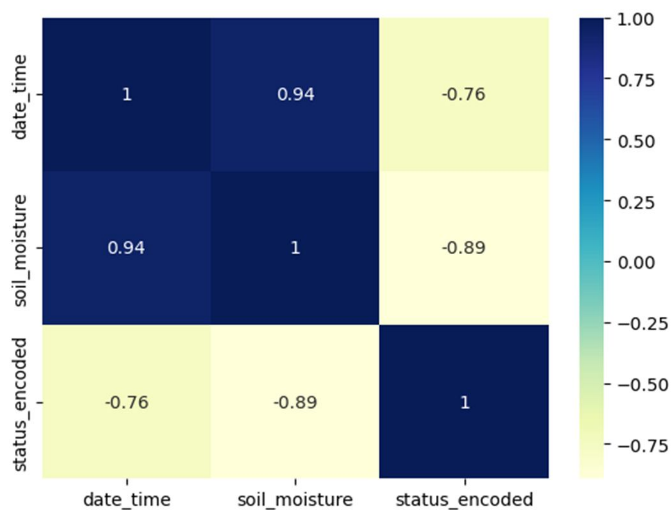

Figure 6: Confusion Matrix Heatmap

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B. Trend Analysis

The moisture trends observed in both dry and wet soil cultures highlight distinct water retention behaviors, providing valuable insights into soil dynamics.

1) *Dry Soil Trends:* The dry soil samples exhibited rapid moisture depletion shortly after irrigation. This behavior is attributed to the soil's high porosity and limited water-holding capacity. The regression models effectively captured this trend, showing a steep decline in moisture levels within the initial hours post-irrigation. These fluctuations underscore the importance of timely irrigation for maintaining optimal moisture levels in dry soils.

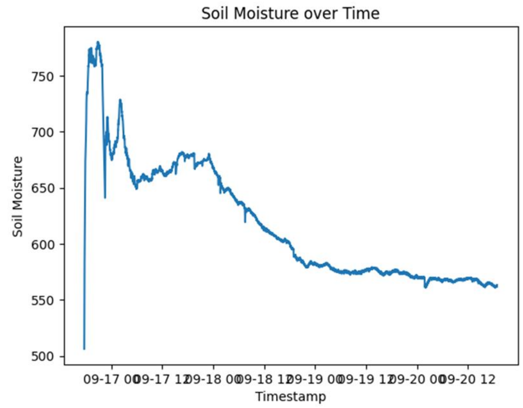

Figure 7: Moisture Levels Over Time for the Dry Soil Culture

2) *Wet Soil Trends:* In contrast, the wet soil samples demonstrated relatively stable moisture levels over time. The clay-rich composition of the wet soil facilitated higher water retention, resulting in gradual moisture loss. The predictive models performed consistently well in capturing this stability, with minor deviations likely caused by environmental factors such as evaporation rates and ambient temperature fluctuations.

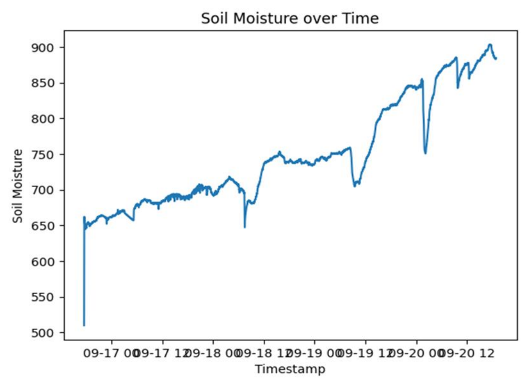

Figure 8: Moisture Levels Over Time for the Wet Soil Culture

Above charts illustrates the moisture levels for both dry and wet soils, demonstrating the robustness of the models in capturing moisture dynamics across varying soil conditions.

V. CHALLENGES AND LIMITATIONS

1) *Environmental Factors:* Variability in temperature and humidity influenced sensor readings.
2) *Scalability:* Extending the system to larger fields required additional computational resources.
3) *Data Transmission:* In remote areas, connectivity issues posed challenges for real-time data collection.

VI. CONCLUSION

This study demonstrates the potential of regression-based machine learning models for soil moisture prediction. Minute-wise data granularity emerged as the optimal choice for balancing prediction accuracy and computational efficiency. By integrating IoT-enabled sensors with machine learning techniques, this research paves the way for sustainable and efficient irrigation management.

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