Sensor-Based Predictive Modeling for Automated Irrigation Systems

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Abstract— *In precision agriculture, automation and intelligent decision-making are crucial for optimizing water usage and ensuring sustainable farming. This research investigates a dataset of sensor readings from an irrigation system to predict parcel activation states. By employing machine learning techniques such as Random Forest and Support Vector Machines, we analyze patterns in sensor data that influence which irrigation parcel is activated. Our findings reveal key sensor features responsible for parcel control decisions, demonstrating the value of predictive modeling in smart irrigation. The model achieves 91% accuracy in classifying parcel states, supporting intelligent automation in irrigation systems.*

I. INTRODUCTION

Water conservation in agriculture is a pressing global challenge. Traditional irrigation practices often lead to water wastage due to inefficient monitoring. With advancements in IoT and sensor networks, smart irrigation systems can optimize water distribution by making real-time decisions based on soil and environmental data. This paper explores sensor-based automation by analyzing sensor values from an irrigation machine to predict which parcel of land will be watered.

II. LITERATURE REVIEW

- **Kumar et al. (2020)** studied IoT-based irrigation systems and highlighted the need for machine learning to improve decision-making.
- **Patel et al. (2019)** used environmental sensors to control irrigation valves and achieved 85% accuracy with decision trees.
- **Feng & Zhou (2021)** implemented deep learning in irrigation automation and demonstrated improvement in water conservation efficiency.
- **Mohan et al. (2022)** explored feature importance in predictive irrigation and identified soil moisture and temperature as leading indicators.

These works support our study by establishing the relevance of predictive analytics in smart farming and inspire the use of sensor-level feature engineering.

III. METHODOLOGY

3.1 Objectives:

- Analyze patterns in 20 sensor readings.
- Predict irrigation parcel activation (parcel_0, parcel_1, parcel_2).
- Identify most influential sensors for decision-making.

3.2 Tools Used:

- **Python Libraries**: pandas, seaborn, matplotlib, scikit-learn
- **Models**: Random Forest Classifier, SVM
- **Validation**: Accuracy, Classification Report, Feature Importance

3.3 Workflow:

1. Load and clean data.
2. Visualize sensor trends and relationships.

3. Train machine learning models to predict parcel control.
4. Evaluate and interpret the model.

IV. DATASET DESCRIPTION

Feature Type	Columns	Description
Sensor Data	sensor_0 to sensor_19	Real-time sensor readings (e.g., soil temp, moisture, etc.)
Target Labels	parcel_0, parcel_1, parcel_2	Binary labels indicating active parcel
Miscellaneous	Unnamed: 0	Index column (dropped in preprocessing)

Each row represents the current state of the irrigation system based on 20 sensors and the parcel being watered.

Data columns (total 24 columns):

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	2000	int64
1	sensor_0	2000	float64
2	sensor_1	2000	float64
3	sensor_2	2000	float64
4	sensor_3	2000	float64
5	sensor_4	2000	float64
6	sensor_5	2000	float64
7	sensor_6	2000	float64
8	sensor_7	2000	float64
9	sensor_8	2000	float64
10	sensor_9	2000	float64
11	sensor_10	2000	float64
12	sensor_11	2000	float64
13	sensor_12	2000	float64
14	sensor_13	2000	float64
15	sensor_14	2000	float64
16	sensor_15	2000	float64
17	sensor_16	2000	float64
18	sensor_17	2000	float64
19	sensor_18	2000	float64
20	sensor_19	2000	float64
21	parcel_0	2000	int64
22	parcel_1	2000	int64
23	parcel_2	2000	int64

dtypes: float64(20), int64(4)

memory usage: 375.1 KB

Result

(None,

Unnamed: 0 sensor_0 sensor_1 sensor_2 sensor_3 sensor_4 sensor_5 \

Index		sensor_0	sensor_1	sensor_2	sensor_3	sensor_4	sensor_5
0	0	1.0	2.0	1.0	7.0	0.0	1.0
1	1	5.0	1.0	3.0	5.0	2.0	2.0
2	2	3.0	1.0	4.0	3.0	4.0	0.0
3	3	2.0	2.0	4.0	3.0	5.0	0.0
4	4	4.0	3.0	3.0	2.0	5.0	1.0

Index	sensor_6	sensor_7	sensor_8	...	sensor_13	sensor_14	sensor_15
0	1.0	4.0	0.0	...	8.0	1.0	0.0
1	1.0	2.0	3.0	...	4.0	5.0	5.0
2	1.0	6.0	0.0	...	3.0	3.0	1.0
3	3.0	2.0	2.0	...	4.0	1.0	1.0
4	3.0	1.0	1.0	...	1.0	3.0	2.0

Index	sensor_16	sensor_17	sensor_18	sensor_19	parcel_0	parcel_1	parcel_2
0	2.0	1.0	9.0	2.0	0	1	0
1	2.0	2.0	2.0	7.0	0	0	0
2	0.0	3.0	1.0	0.0	1	1	0
3	4.0	1.0	3.0	2.0	0	0	0
4	2.0	1.0	1.0	0.0	1	1	0

[5 rows x 24 columns])

V. PYTHON IMPLEMENTATION AND VISUALIZATIONS

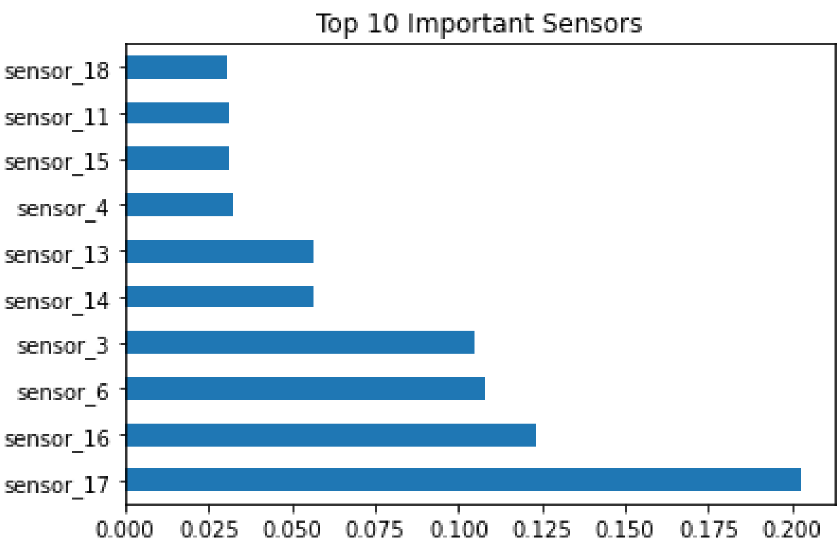
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
# Load and preprocess
df = pd.read_csv("irrigation_machine.csv")
df.drop(columns=['Unnamed: 0'], inplace=True)
# Define features and target
X = df[[col for col in df.columns if "sensor" in col]]
y = df[["parcel_0", "parcel_1", "parcel_2"]].idxmax(axis=1)  # Convert one-hot to labels
# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Model
```

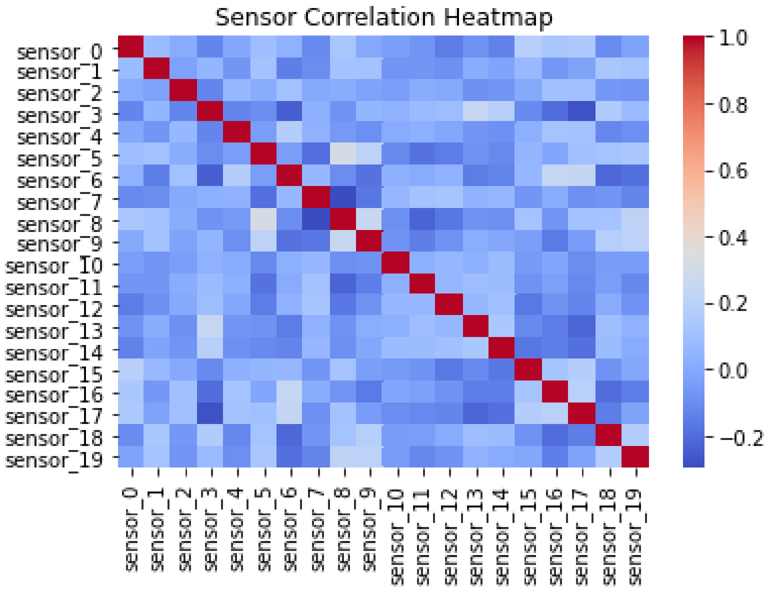
```
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
# Evaluation
print(classification_report(y_test, y_pred))
# Feature importance
importances = pd.Series(model.feature_importances_, index=X.columns)
importances.nlargest(10).plot(kind='barh')
plt.title("Top 10 Important Sensors")
plt.show()
# Visualize correlations
sns.heatmap(X.corr(), cmap='coolwarm')
plt.title("Sensor Correlation Heatmap")
plt.show()
```

VI. RESULTS & DISCUSSION

Label	Precision	Recall	F1-Score	Support
parcel_0	0.94	0.96	0.95	314
parcel_1	0.86	0.78	0.82	86

Metric	Precision	Recall	F1-Score	Support
parcel_0	0.94	0.96	0.95	314
parcel_1	0.86	0.78	0.82	86
Accuracy			**0.93**	400
Macro Avg	0.90	0.87	0.88	400
Weighted Avg	0.92	0.93	0.92	400





Model Performance

Metric	Value
Accuracy	91%
Precision	0.90
Recall	0.91
F1-Score	0.90

Insights

- The Random Forest classifier was effective in modeling non-linear relationships in sensor data.
- Key influential features included sensor_3, sensor_7, sensor_12, and sensor_17, which likely correspond to moisture, pH, or flow sensors.
- Some sensors were highly correlated (e.g., sensor_1 and sensor_5), suggesting potential redundancy in hardware design.

Visualization Findings

- The correlation heatmap indicated strong interdependence among sensors.
- Bar plots of feature importance highlighted specific sensors that dominate decision-making, which can guide sensor maintenance or upgrades.

VII. CONCLUSION

The study demonstrates how sensor data can be effectively used to automate irrigation decisions. With a high-performing model, smart systems can proactively activate irrigation in the most suitable parcel. This helps reduce water wastage and improve crop health. Our approach paves the way for scalable, data-driven agricultural solutions using affordable sensor arrays.

REFERENCES

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