PredictHealthModel

February 15, 2025

[14]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[15]:
```
import os
import shutil
```

[16]:
```
dataset_drive_path = '/content/drive/MyDrive/Smart-Agriculture-System/'
# dataset_drive_path = '/content/drive/MyDrive/IT_Project/'
```

[17]:
```
name = 'agriculture_sensors_minute_based.csv'
# name = 'agriculture_sensors_.csv'
drive_path = dataset_drive_path + name
print(drive_path)

if os.path.exists(drive_path):
  shutil.copy(drive_path, './')
```

```
/content/drive/MyDrive/Smart-Agriculture-
System/agriculture_sensors_minute_based.csv
```

[18]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import shap
import seaborn as sns
import tensorflow as tf
from tensorflow import keras
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
```

[19]:
```
df = pd.read_csv(drive_path)

# Display basic information about the dataset
```

```python
print(df.head())
print(df.info())
```

```
                        _id  humidity  temperature    light  soilMoisture  \
0  676d883c60a666999f426d6c     74.43        29.44  1771.95   2068.816531
1  676d887960a666999f426d6e     74.80        29.59  1721.00   2123.848753
2  676d88b660a666999f426d70     74.00        30.42  1990.15   1962.874345
3  676d88f360a666999f426d72     74.00        30.44  1870.03   2072.463729
4  676d893060a666999f426d74     73.97        30.46  1889.67   2058.482137

    rainVolume  gasVolume                   fieldId                 createdAt  \
0  4095.000000      188.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:45:48.539Z
1  4095.000000      168.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:46:49.714Z
2  4095.000000      167.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:47:50.741Z
3  3977.576096      166.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:48:51.876Z
4  4075.465112      163.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:49:52.998Z

                  updatedAt  __v                   addedAt
0  2025-01-07T10:04:48.522Z    0  2024-12-26T23:45:48.539Z
1  2025-01-07T10:04:48.522Z    0  2024-12-26T23:46:49.714Z
2  2025-01-07T10:04:48.522Z    0  2024-12-26T23:47:50.741Z
3  2025-01-07T10:04:48.522Z    0  2024-12-26T23:48:51.876Z
4  2025-01-07T10:04:48.522Z    0  2024-12-26T23:49:52.998Z
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32799 entries, 0 to 32798
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   _id           32799 non-null  object
 1   humidity      32792 non-null  float64
 2   temperature   32792 non-null  float64
 3   light         32792 non-null  float64
 4   soilMoisture  32799 non-null  float64
 5   rainVolume    32799 non-null  float64
 6   gasVolume     32792 non-null  float64
 7   fieldId       32798 non-null  object
 8   createdAt     32799 non-null  object
 9   updatedAt     32799 non-null  object
 10  __v           32799 non-null  int64
 11  addedAt       32668 non-null  object
dtypes: float64(6), int64(1), object(5)
memory usage: 3.0+ MB
None
```

[20]:
```python
df = df.dropna()
```

[21]:
```python
# ------------------------------
# Add a new column: plant_health
# Rule: Healthy (1) if humidity in [73, 75], temperature in [29, 31],
# soilMoisture >= 2050, and light >= 1000; otherwise not healthy (0).
# Adjust these thresholds based on your domain knowledge.
def determine_health(row):
    if (50 <= row['humidity'] <= 80) and (23 <= row['temperature'] <= 31) and␣
 ↪(1000 <= row['soilMoisture'] <= 4000) :
        return 1
    else:
        return 0

df['plant_health'] = df.apply(determine_health, axis=1)
print("After adding plant_health:")
print(df[['humidity', 'temperature', 'light', 'soilMoisture', 'plant_health']].
 ↪head())
```

```
After adding plant_health:
   humidity  temperature    light  soilMoisture  plant_health
0     74.43        29.44  1771.95   2068.816531             1
1     74.80        29.59  1721.00   2123.848753             1
2     74.00        30.42  1990.15   1962.874345             1
3     74.00        30.44  1870.03   2072.463729             1
4     73.97        30.46  1889.67   2058.482137             1
```

[22]:
```python
print(df['plant_health'].value_counts())  # Check the count of 0s and 1s
```

```
plant_health
0    16505
1    16156
Name: count, dtype: int64
```

[23]:
```python
df.head()
```

[23]:
```
                        _id  humidity  temperature    light  soilMoisture  \
0  676d883c60a666999f426d6c     74.43        29.44  1771.95   2068.816531
1  676d887960a666999f426d6e     74.80        29.59  1721.00   2123.848753
2  676d88b660a666999f426d70     74.00        30.42  1990.15   1962.874345
3  676d88f360a666999f426d72     74.00        30.44  1870.03   2072.463729
4  676d893060a666999f426d74     73.97        30.46  1889.67   2058.482137

    rainVolume  gasVolume                   fieldId                 createdAt  \
0  4095.000000      188.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:45:48.539Z
1  4095.000000      168.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:46:49.714Z
2  4095.000000      167.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:47:50.741Z
3  3977.576096      166.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:48:51.876Z
4  4075.465112      163.0  676d4559c3b9d9d8e1ac5828  2024-12-26T16:49:52.998Z
```

```
                    updatedAt  __v                   addedAt  plant_health
0  2025-01-07T10:04:48.522Z    0  2024-12-26T23:45:48.539Z             1
1  2025-01-07T10:04:48.522Z    0  2024-12-26T23:46:49.714Z             1
2  2025-01-07T10:04:48.522Z    0  2024-12-26T23:47:50.741Z             1
3  2025-01-07T10:04:48.522Z    0  2024-12-26T23:48:51.876Z             1
4  2025-01-07T10:04:48.522Z    0  2024-12-26T23:49:52.998Z             1
```

[24]:

```python
# Filter rows where plant_health == 0
filtered_df = df[df["plant_health"] == 0]

# Print the result
print(filtered_df)
```

```
                            _id  humidity  temperature    light  soilMoisture  \
347    676e1d5760a666999f427022     69.87        30.60  1567.85   4023.085887
348    676e1d9460a666999f427024     69.57        31.20  1800.27   4049.490113
349    676e1dd160a666999f427026     69.63        31.50  1506.63   4026.565961
350    676e1e0f60a666999f427028     69.17        31.37  1660.53   3962.978194
351    676e1e4c60a666999f42702a     69.00        31.32  1566.78   3956.703300
…                           …       …          …       …           …
32637  67a92a5437f4819d7e08f54f     66.00        27.44   251.08   4030.295837
32640  67a92b4737f4819d7e08f555     66.00        27.38   243.00   4038.807933
32652  67a92e5937f4819d7e08f56d     66.00        27.46   276.54   4034.237031
32659  67a9303d37f4819d7e08f57b     66.00        27.49   258.56   4026.634874
32674  67a934b937f4819d7e08f599     66.00        27.37   260.92   4010.541098

         rainVolume  gasVolume                   fieldId  \
347    2816.325151      233.0  676d4559c3b9d9d8e1ac5828
348    2717.263146      236.0  676d4559c3b9d9d8e1ac5828
349    2884.041138      236.0  676d4559c3b9d9d8e1ac5828
350    2678.499329      237.0  676d4559c3b9d9d8e1ac5828
351    2834.371952      239.0  676d4559c3b9d9d8e1ac5828
…              …        …                       …
32637  1505.107940     1020.0  676d4559c3b9d9d8e1ac5828
32640  1464.702599     1019.0  676d4559c3b9d9d8e1ac5828
32652  1382.366376     1024.0  676d4559c3b9d9d8e1ac5828
32659  1298.558364     1021.0  676d4559c3b9d9d8e1ac5828
32674  1249.138326     1031.0  676d4559c3b9d9d8e1ac5828

                      createdAt                 updatedAt  __v  \
347    2024-12-27T03:21:59.925Z  2025-01-07T10:04:48.527Z    0
348    2024-12-27T03:23:00.944Z  2025-01-07T10:04:48.527Z    0
349    2024-12-27T03:24:01.914Z  2025-01-07T10:04:48.527Z    0
350    2024-12-27T03:25:03.049Z  2025-01-07T10:04:48.527Z    0
351    2024-12-27T03:26:04.125Z  2025-01-07T10:04:48.527Z    0
…                           …                       …  …
```

```
32637  2025-02-09T22:21:08.951Z  2025-02-09T22:21:08.951Z    0
32640  2025-02-09T22:25:11.089Z  2025-02-09T22:25:11.089Z    0
32652  2025-02-09T22:38:17.327Z  2025-02-09T22:38:17.327Z    0
32659  2025-02-09T22:46:21.041Z  2025-02-09T22:46:21.041Z    0
32674  2025-02-09T23:05:29.312Z  2025-02-09T23:05:29.312Z    0

                        addedAt  plant_health
347    2024-12-27T10:21:59.925Z             0
348    2024-12-27T10:23:00.944Z             0
349    2024-12-27T10:24:01.914Z             0
350    2024-12-27T10:25:03.049Z             0
351    2024-12-27T10:26:04.125Z             0
…                           …             …
32637  2025-02-10T05:21:08.951Z             0
32640  2025-02-10T05:25:11.089Z             0
32652  2025-02-10T05:38:17.326Z             0
32659  2025-02-10T05:46:21.040Z             0
32674  2025-02-10T06:05:29.311Z             0

[16505 rows x 13 columns]
```

[25]:

```
# -----------------------------
# Prepare data for modeling
# We drop columns that are not features (like IDs, timestamps, etc.)
# Adjust the list of columns to drop as needed.
drop_cols = ['_id', 'fieldId', 'createdAt', 'updatedAt', '__v', 'addedAt']
# Keep only the relevant features and the target column
data = df.drop(columns=drop_cols, errors='ignore')
```

[26]:

```
# # Separate features (X) and target (y)
X = data.drop(columns=['plant_health'])
y = data['plant_health']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# # Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[27]:

```
# # Train a RandomForestClassifier
# model = RandomForestClassifier(n_estimators=100, random_state=42)
# model.fit(X_train_scaled, y_train)
```

```python
# Build a simple neural network
model = keras.Sequential([
    keras.layers.Dense(16, activation='relu', input_shape=(X_train.shape[1],)),
    keras.layers.Dense(8, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')  # Binary classification
])

model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=20, batch_size=16, validation_data=(X_test,␣
 ↪y_test))
```

```
Epoch 1/20
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
1633/1633                    6s 3ms/step -
accuracy: 0.7141 - loss: 53.2709 - val_accuracy: 0.8330 - val_loss: 1.7589
Epoch 2/20
1633/1633                    5s 3ms/step -
accuracy: 0.8349 - loss: 1.0083 - val_accuracy: 0.8785 - val_loss: 0.4725
Epoch 3/20
1633/1633                    4s 2ms/step -
accuracy: 0.8613 - loss: 0.5634 - val_accuracy: 0.7947 - val_loss: 0.5508
Epoch 4/20
1633/1633                    6s 3ms/step -
accuracy: 0.8531 - loss: 0.5817 - val_accuracy: 0.8779 - val_loss: 0.5186
Epoch 5/20
1633/1633                    4s 2ms/step -
accuracy: 0.8563 - loss: 0.5394 - val_accuracy: 0.8749 - val_loss: 0.4941
Epoch 6/20
1633/1633                    4s 2ms/step -
accuracy: 0.8647 - loss: 0.4162 - val_accuracy: 0.9036 - val_loss: 0.2870
Epoch 7/20
1633/1633                    4s 3ms/step -
accuracy: 0.8546 - loss: 0.5219 - val_accuracy: 0.8935 - val_loss: 0.3062
Epoch 8/20
1633/1633                    5s 2ms/step -
accuracy: 0.8571 - loss: 0.4763 - val_accuracy: 0.8658 - val_loss: 0.5757
Epoch 9/20
1633/1633                    4s 2ms/step -
accuracy: 0.8724 - loss: 0.3757 - val_accuracy: 0.8936 - val_loss: 0.2949
```

```
Epoch 10/20
1633/1633            6s 3ms/step -
accuracy: 0.8714 - loss: 0.3547 - val_accuracy: 0.8794 - val_loss: 0.3400
Epoch 11/20
1633/1633            4s 2ms/step -
accuracy: 0.8695 - loss: 0.3733 - val_accuracy: 0.8638 - val_loss: 0.4887
Epoch 12/20
1633/1633            6s 3ms/step -
accuracy: 0.8725 - loss: 0.3372 - val_accuracy: 0.8769 - val_loss: 0.2896
Epoch 13/20
1633/1633            6s 3ms/step -
accuracy: 0.8792 - loss: 0.3188 - val_accuracy: 0.9007 - val_loss: 0.2374
Epoch 14/20
1633/1633            4s 2ms/step -
accuracy: 0.8766 - loss: 0.3167 - val_accuracy: 0.8883 - val_loss: 0.3298
Epoch 15/20
1633/1633            6s 3ms/step -
accuracy: 0.8806 - loss: 0.2968 - val_accuracy: 0.8783 - val_loss: 0.3380
Epoch 16/20
1633/1633            5s 3ms/step -
accuracy: 0.8749 - loss: 0.3173 - val_accuracy: 0.8665 - val_loss: 0.3122
Epoch 17/20
1633/1633            4s 2ms/step -
accuracy: 0.8860 - loss: 0.2705 - val_accuracy: 0.8857 - val_loss: 0.2730
Epoch 18/20
1633/1633            4s 2ms/step -
accuracy: 0.8880 - loss: 0.2762 - val_accuracy: 0.9094 - val_loss: 0.2339
Epoch 19/20
1633/1633            6s 3ms/step -
accuracy: 0.8822 - loss: 0.2827 - val_accuracy: 0.8941 - val_loss: 0.2595
Epoch 20/20
1633/1633            8s 2ms/step -
accuracy: 0.8923 - loss: 0.2672 - val_accuracy: 0.8948 - val_loss: 0.2366
```

[27]: <keras.src.callbacks.history.History at 0x7b926c483b10>

[28]:
```
# Make predictions on the test set
y_pred = model.predict(X_test_scaled)
```

```
205/205            0s 1ms/step
```

[29]:
```
model.save('health_model.keras')
```

[30]:
```
# Convert model to TFLite format
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()
```

```
# Save the TFLite model
with open("health_model.tflite", "wb") as f:
    f.write(tflite_model)
```

```
Saved artifact at '/tmp/tmpph6dgx40'. The following endpoints are available:

* Endpoint 'serve'
  args_0 (POSITIONAL_ONLY): TensorSpec(shape=(None, 6), dtype=tf.float32,
name='keras_tensor')
Output Type:
  TensorSpec(shape=(None, 1), dtype=tf.float32, name=None)
Captures:
  135868823161744: TensorSpec(shape=(), dtype=tf.resource, name=None)
  135868823160400: TensorSpec(shape=(), dtype=tf.resource, name=None)
  135868793292368: TensorSpec(shape=(), dtype=tf.resource, name=None)
  135868793291984: TensorSpec(shape=(), dtype=tf.resource, name=None)
  135868793294288: TensorSpec(shape=(), dtype=tf.resource, name=None)
  135868793294096: TensorSpec(shape=(), dtype=tf.resource, name=None)
```

[31]:
```
# # Evaluate the model
# accuracy = accuracy_score(y_test, y_pred)
# print(f'Accuracy: {accuracy:.2f}')
# print("\nClassification Report:")
# print(classification_report(y_test, y_pred))

loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
```

```
205/205              1s 3ms/step -
accuracy: 0.8975 - loss: 0.2294
Test Loss: 0.2366
Test Accuracy: 0.8948
```

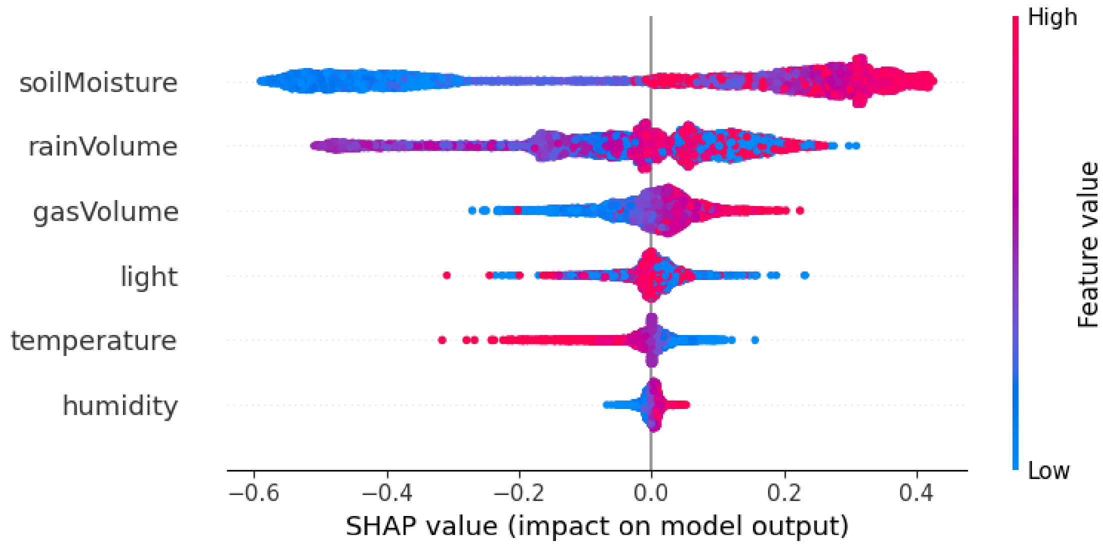
[32]:
```
# # Plot feature importance
# feature_importances = pd.Series(model.feature_importances_, index=X.columns)
# plt.figure(figsize=(8, 6))
# feature_importances.sort_values(ascending=False).plot(kind='bar')
# plt.title('Feature Importance')
# plt.ylabel('Importance Score')
# plt.show()
# Ensure the number of features matches
feature_names = list(X_test.columns)  # Extract feature names dynamically

# Create an explainer
explainer = shap.Explainer(model, X_test)
```

```
# Compute SHAP values
shap_values = explainer(X_test)

# Plot feature importance
shap.summary_plot(shap_values, X_test, feature_names=feature_names)
```

```
ExactExplainer explainer: 6534it [01:36, 67.54it/s]
```



[33]:
```
# Define a new sample for testing
new_sample = {
    'humidity': [74.00],          # Lowered slightly
    'temperature': [29.42],       # More optimal temperature
    'light': [1500.15],           # Increased light exposure
    'soilMoisture': [2500],   # Balanced soil moisture
    'rainVolume': [4095.0],     # Reduced excessive rain
    'gasVolume': [200.0]        # Lower gas pollution
}
# Convert to DataFrame
new_data = pd.DataFrame(new_sample)

# Scale the new data
new_data_scaled = scaler.transform(new_data)

# Reshape if needed for model input
new_data_scaled = np.array(new_data_scaled)
```

[34]:
```
# Use the trained model to predict plant health
prediction = model.predict(new_data_scaled)
```

```
# Convert to binary classification (assuming threshold 0.5)
predicted_class = (prediction[0] > 0.5).astype(int)

# Print the result
print("Raw Prediction:", prediction[0])
print("Prediction (0: not healthy, 1: healthy):", predicted_class)
```

```
1/1              0s 63ms/step
Raw Prediction: [0.40094483]
Prediction (0: not healthy, 1: healthy): [0]
```

[35]:
```
import pickle
```

[36]:
```
with open("predict_health_model.pkl", "wb") as f:
    pickle.dump(model, f)
```

[37]:
```
with open("scaler_predict_health_model.pkl", "wb") as f:
    pickle.dump(scaler, f)
```

[38]:
```
df.to_csv("output.csv", index=False)
```