

Washington NDVI and EPA landcove Deeplearning model and ermutation_importance

```
In [ ]: import numpy as np
import tensorflow as tf
np.random.seed(42)
tf.random.set_seed(42)
import random
random.seed(42)
```

```
In [ ]: import pandas as pd
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
from concurrent.futures import ThreadPoolExecutor, as_completed
```

```
In [ ]: # Load the data
file_path = r"C:\Users\nahid\Desktop\USFS\Project_USFS\Data\WASHINGTON_DC_2013_ndvi.csv"
df = pd.read_csv(file_path)

# Select the dependent variable (NDVI)
y = df['NDVIMEAN']

# Select the independent variables (land cover classifications)
X = df[['WATER', 'IMPERVIOUS', 'SOIL_BARREN', 'TREES_FOREST',
         'GRASS_Herbaceous', 'AGRICULTURE', 'WOODY_WETLANDS',
         'EMERGENT_WETLANDS']]
```

```
In [ ]: # Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

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

```
In [ ]: # Build the model
model = Sequential()

# Input Layer
model.add(Dense(64, input_dim=X_train_scaled.shape[1], activation='relu'))

# Hidden Layers
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))

# Output Layer
```

```
model.add(Dense(1, activation='linear'))  
  
# Compile the model  
model.compile(optimizer='adam', loss='mse', metrics=[ 'mae' ])  
  
# Train the model  
history = model.fit(X_train_scaled, y_train, epochs=100, batch_size=32, validation_  
  
c:\Users\nahid\Desktop\USFS\Project_USFS\venv\lib\site-packages\keras\src\layers\cor  
e\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a l  
ayer. When using Sequential models, prefer using an `Input(shape)` object as the fir  
st layer in the model instead.  
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Epoch 1/100
92107/92107  **81s** 872us/step - loss: 0.0121 - mae: 0.0796 - val_l
oss: 0.0101 - val_mae: 0.0739

Epoch 2/100
92107/92107  **76s** 819us/step - loss: 0.0108 - mae: 0.0759 - val_l
oss: 0.0100 - val_mae: 0.0737

Epoch 3/100
92107/92107  **74s** 806us/step - loss: 0.0108 - mae: 0.0758 - val_l
oss: 0.0100 - val_mae: 0.0734

Epoch 4/100
92107/92107  **73s** 791us/step - loss: 0.0108 - mae: 0.0759 - val_l
oss: 0.0099 - val_mae: 0.0735

Epoch 5/100
92107/92107  **73s** 789us/step - loss: 0.0108 - mae: 0.0758 - val_l
oss: 0.0100 - val_mae: 0.0736

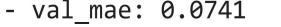
Epoch 6/100
92107/92107  **73s** 786us/step - loss: 0.0108 - mae: 0.0760 - val_l
oss: 0.0100 - val_mae: 0.0736

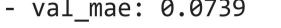
Epoch 7/100
92107/92107  **73s** 793us/step - loss: 0.0108 - mae: 0.0760 - val_l
oss: 0.0100 - val_mae: 0.0734

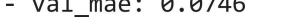
Epoch 8/100
92107/92107  **72s** 785us/step - loss: 0.0109 - mae: 0.0761 - val_l
oss: 0.0101 - val_mae: 0.0741

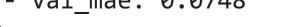
Epoch 9/100
92107/92107  **72s** 785us/step - loss: 0.0109 - mae: 0.0763 - val_l
oss: 0.0101 - val_mae: 0.0741

Epoch 10/100
92107/92107  **73s** 786us/step - loss: 0.0110 - mae: 0.0763 - val_l
oss: 0.0100 - val_mae: 0.0740

Epoch 11/100
92107/92107  **72s** 776us/step - loss: 0.0111 - mae: 0.0769 - val_l
oss: 0.0101 - val_mae: 0.0741

Epoch 12/100
92107/92107  **72s** 783us/step - loss: 0.0110 - mae: 0.0767 - val_l
oss: 0.0100 - val_mae: 0.0739

Epoch 13/100
92107/92107  **72s** 784us/step - loss: 0.0110 - mae: 0.0766 - val_l
oss: 0.0102 - val_mae: 0.0746

Epoch 14/100
92107/92107  **72s** 778us/step - loss: 0.0114 - mae: 0.0774 - val_l
oss: 0.0104 - val_mae: 0.0748

Epoch 15/100
92107/92107  **72s** 781us/step - loss: 0.0116 - mae: 0.0779 - val_l
oss: 0.0107 - val_mae: 0.0751

Epoch 16/100
92107/92107  **72s** 778us/step - loss: 0.0118 - mae: 0.0782 - val_l
oss: 0.0103 - val_mae: 0.0747

Epoch 17/100
92107/92107  **72s** 776us/step - loss: 0.0115 - mae: 0.0776 - val_l
oss: 0.0103 - val_mae: 0.0746

Epoch 18/100
92107/92107  **128s** 1ms/step - loss: 0.0115 - mae: 0.0777 - val_lo
ss: 0.0106 - val_mae: 0.0751

Epoch 19/100
92107/92107  **81s** 875us/step - loss: 0.0122 - mae: 0.0791 - val_l

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oss: 0.0106 - val_mae: 0.0750
Epoch 20/100
92107/92107 73s 789us/step - loss: 0.0122 - mae: 0.0792 - val_1
oss: 0.0109 - val_mae: 0.0759
Epoch 21/100
92107/92107 74s 806us/step - loss: 0.0120 - mae: 0.0788 - val_1
oss: 0.0113 - val_mae: 0.0758
Epoch 22/100
92107/92107 73s 790us/step - loss: 0.0119 - mae: 0.0786 - val_1
oss: 0.0109 - val_mae: 0.0757
Epoch 23/100
92107/92107 73s 786us/step - loss: 0.0116 - mae: 0.0780 - val_1
oss: 0.0114 - val_mae: 0.0771
Epoch 24/100
92107/92107 73s 792us/step - loss: 0.0114 - mae: 0.0776 - val_1
oss: 0.0113 - val_mae: 0.0762
Epoch 25/100
92107/92107 73s 794us/step - loss: 0.0118 - mae: 0.0784 - val_1
oss: 0.0115 - val_mae: 0.0768
Epoch 26/100
92107/92107 72s 782us/step - loss: 0.0116 - mae: 0.0778 - val_1
oss: 0.0112 - val_mae: 0.0761
Epoch 27/100
92107/92107 72s 775us/step - loss: 0.0114 - mae: 0.0774 - val_1
oss: 0.0106 - val_mae: 0.0751
Epoch 28/100
92107/92107 72s 783us/step - loss: 0.0113 - mae: 0.0772 - val_1
oss: 0.0110 - val_mae: 0.0754
Epoch 29/100
92107/92107 72s 781us/step - loss: 0.0112 - mae: 0.0770 - val_1
oss: 0.0122 - val_mae: 0.0770
Epoch 30/100
92107/92107 72s 775us/step - loss: 0.0127 - mae: 0.0800 - val_1
oss: 0.0116 - val_mae: 0.0765
Epoch 31/100
92107/92107 72s 780us/step - loss: 0.0118 - mae: 0.0783 - val_1
oss: 0.0102 - val_mae: 0.0742
Epoch 32/100
92107/92107 71s 774us/step - loss: 0.0113 - mae: 0.0772 - val_1
oss: 0.0104 - val_mae: 0.0746
Epoch 33/100
92107/92107 72s 779us/step - loss: 0.0112 - mae: 0.0771 - val_1
oss: 0.0102 - val_mae: 0.0743
Epoch 34/100
92107/92107 74s 797us/step - loss: 0.0112 - mae: 0.0770 - val_1
oss: 0.0102 - val_mae: 0.0740
Epoch 35/100
92107/92107 72s 783us/step - loss: 0.0112 - mae: 0.0770 - val_1
oss: 0.0103 - val_mae: 0.0744
Epoch 36/100
92107/92107 72s 775us/step - loss: 0.0112 - mae: 0.0770 - val_1
oss: 0.0102 - val_mae: 0.0740
Epoch 37/100
92107/92107 72s 780us/step - loss: 0.0112 - mae: 0.0770 - val_1
oss: 0.0103 - val_mae: 0.0742
Epoch 38/100
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92107/92107 73s 793us/step - loss: 0.0112 - mae: 0.0770 - val_1
oss: 0.0102 - val_mae: 0.0740
Epoch 39/100

92107/92107 71s 775us/step - loss: 0.0131 - mae: 0.0822 - val_1
oss: 0.0136 - val_mae: 0.0798
Epoch 40/100

92107/92107 72s 778us/step - loss: 0.0153 - mae: 0.0905 - val_1
oss: 0.0118 - val_mae: 0.0789
Epoch 41/100

92107/92107 72s 781us/step - loss: 0.0133 - mae: 0.0830 - val_1
oss: 0.0117 - val_mae: 0.0767
Epoch 42/100

92107/92107 72s 780us/step - loss: 0.0132 - mae: 0.0821 - val_1
oss: 0.0118 - val_mae: 0.0775
Epoch 43/100

92107/92107 72s 778us/step - loss: 0.0131 - mae: 0.0819 - val_1
oss: 0.0119 - val_mae: 0.0784
Epoch 44/100

92107/92107 72s 776us/step - loss: 0.0132 - mae: 0.0822 - val_1
oss: 0.0120 - val_mae: 0.0787
Epoch 45/100

92107/92107 72s 780us/step - loss: 0.0132 - mae: 0.0826 - val_1
oss: 0.0113 - val_mae: 0.0767
Epoch 46/100

92107/92107 72s 781us/step - loss: 0.0132 - mae: 0.0824 - val_1
oss: 0.0119 - val_mae: 0.0776
Epoch 47/100

92107/92107 72s 778us/step - loss: 0.0130 - mae: 0.0819 - val_1
oss: 0.0109 - val_mae: 0.0765
Epoch 48/100

92107/92107 71s 773us/step - loss: 0.0126 - mae: 0.0809 - val_1
oss: 0.0106 - val_mae: 0.0757
Epoch 49/100

92107/92107 72s 778us/step - loss: 0.0126 - mae: 0.0810 - val_1
oss: 0.0112 - val_mae: 0.0769
Epoch 50/100

92107/92107 72s 785us/step - loss: 0.0126 - mae: 0.0811 - val_1
oss: 0.0110 - val_mae: 0.0766
Epoch 51/100

92107/92107 71s 775us/step - loss: 0.0126 - mae: 0.0813 - val_1
oss: 0.0111 - val_mae: 0.0776
Epoch 52/100

92107/92107 72s 780us/step - loss: 0.0127 - mae: 0.0816 - val_1
oss: 0.0115 - val_mae: 0.0773
Epoch 53/100

92107/92107 72s 780us/step - loss: 0.0126 - mae: 0.0810 - val_1
oss: 0.0112 - val_mae: 0.0774
Epoch 54/100

92107/92107 72s 779us/step - loss: 0.0126 - mae: 0.0812 - val_1
oss: 0.0107 - val_mae: 0.0758
Epoch 55/100

92107/92107 72s 778us/step - loss: 0.0126 - mae: 0.0812 - val_1
oss: 0.0112 - val_mae: 0.0769
Epoch 56/100

92107/92107 72s 778us/step - loss: 0.0126 - mae: 0.0811 - val_1
oss: 0.0106 - val_mae: 0.0757

Epoch 57/100
92107/92107 71s 774us/step - loss: 0.0126 - mae: 0.0810 - val_l
oss: 0.0108 - val_mae: 0.0767
Epoch 58/100
92107/92107 72s 782us/step - loss: 0.0126 - mae: 0.0809 - val_l
oss: 0.0106 - val_mae: 0.0761
Epoch 59/100
92107/92107 72s 781us/step - loss: 0.0125 - mae: 0.0808 - val_l
oss: 0.0113 - val_mae: 0.0773
Epoch 60/100
92107/92107 72s 775us/step - loss: 0.0124 - mae: 0.0805 - val_l
oss: 0.0112 - val_mae: 0.0774
Epoch 61/100
92107/92107 72s 780us/step - loss: 0.0126 - mae: 0.0810 - val_l
oss: 0.0109 - val_mae: 0.0769
Epoch 62/100
92107/92107 72s 781us/step - loss: 0.0125 - mae: 0.0808 - val_l
oss: 0.0116 - val_mae: 0.0777
Epoch 63/100
92107/92107 72s 776us/step - loss: 0.0125 - mae: 0.0808 - val_l
oss: 0.0112 - val_mae: 0.0768
Epoch 64/100
92107/92107 71s 772us/step - loss: 0.0125 - mae: 0.0808 - val_l
oss: 0.0110 - val_mae: 0.0765
Epoch 65/100
92107/92107 71s 772us/step - loss: 0.0125 - mae: 0.0808 - val_l
oss: 0.0106 - val_mae: 0.0755
Epoch 66/100
92107/92107 71s 775us/step - loss: 0.0127 - mae: 0.0812 - val_l
oss: 0.0106 - val_mae: 0.0754
Epoch 67/100
92107/92107 72s 781us/step - loss: 0.0128 - mae: 0.0814 - val_l
oss: 0.0109 - val_mae: 0.0763
Epoch 68/100
92107/92107 72s 783us/step - loss: 0.0127 - mae: 0.0813 - val_l
oss: 0.0111 - val_mae: 0.0770
Epoch 69/100
92107/92107 72s 778us/step - loss: 0.0127 - mae: 0.0813 - val_l
oss: 0.0110 - val_mae: 0.0763
Epoch 70/100
92107/92107 72s 775us/step - loss: 0.0127 - mae: 0.0814 - val_l
oss: 0.0110 - val_mae: 0.0767
Epoch 71/100
92107/92107 72s 779us/step - loss: 0.0127 - mae: 0.0813 - val_l
oss: 0.0107 - val_mae: 0.0754
Epoch 72/100
92107/92107 72s 778us/step - loss: 0.0127 - mae: 0.0813 - val_l
oss: 0.0107 - val_mae: 0.0761
Epoch 73/100
92107/92107 71s 774us/step - loss: 0.0127 - mae: 0.0813 - val_l
oss: 0.0110 - val_mae: 0.0769
Epoch 74/100
92107/92107 72s 776us/step - loss: 0.0127 - mae: 0.0812 - val_l
oss: 0.0110 - val_mae: 0.0767
Epoch 75/100
92107/92107 72s 777us/step - loss: 0.0127 - mae: 0.0811 - val_l

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oss: 0.0107 - val_mae: 0.0761
Epoch 76/100
92107/92107 72s 775us/step - loss: 0.0127 - mae: 0.0813 - val_1
oss: 0.0110 - val_mae: 0.0768
Epoch 77/100
92107/92107 72s 777us/step - loss: 0.0128 - mae: 0.0818 - val_1
oss: 0.0111 - val_mae: 0.0768
Epoch 78/100
92107/92107 72s 777us/step - loss: 0.0128 - mae: 0.0818 - val_1
oss: 0.0109 - val_mae: 0.0765
Epoch 79/100
92107/92107 72s 778us/step - loss: 0.0128 - mae: 0.0819 - val_1
oss: 0.0109 - val_mae: 0.0762
Epoch 80/100
92107/92107 73s 788us/step - loss: 0.0128 - mae: 0.0818 - val_1
oss: 0.0113 - val_mae: 0.0773
Epoch 81/100
92107/92107 72s 776us/step - loss: 0.0128 - mae: 0.0818 - val_1
oss: 0.0108 - val_mae: 0.0770
Epoch 82/100
92107/92107 73s 788us/step - loss: 0.0127 - mae: 0.0817 - val_1
oss: 0.0108 - val_mae: 0.0768
Epoch 83/100
92107/92107 72s 777us/step - loss: 0.0128 - mae: 0.0817 - val_1
oss: 0.0110 - val_mae: 0.0770
Epoch 84/100
92107/92107 72s 775us/step - loss: 0.0128 - mae: 0.0816 - val_1
oss: 0.0107 - val_mae: 0.0761
Epoch 85/100
92107/92107 72s 782us/step - loss: 0.0127 - mae: 0.0816 - val_1
oss: 0.0107 - val_mae: 0.0759
Epoch 86/100
92107/92107 72s 782us/step - loss: 0.0128 - mae: 0.0817 - val_1
oss: 0.0113 - val_mae: 0.0777
Epoch 87/100
92107/92107 72s 782us/step - loss: 0.0127 - mae: 0.0816 - val_1
oss: 0.0110 - val_mae: 0.0768
Epoch 88/100
92107/92107 72s 782us/step - loss: 0.0128 - mae: 0.0817 - val_1
oss: 0.0109 - val_mae: 0.0763
Epoch 89/100
92107/92107 73s 791us/step - loss: 0.0128 - mae: 0.0817 - val_1
oss: 0.0110 - val_mae: 0.0766
Epoch 90/100
92107/92107 72s 784us/step - loss: 0.0127 - mae: 0.0815 - val_1
oss: 0.0112 - val_mae: 0.0773
Epoch 91/100
92107/92107 72s 785us/step - loss: 0.0128 - mae: 0.0816 - val_1
oss: 0.0109 - val_mae: 0.0761
Epoch 92/100
92107/92107 72s 783us/step - loss: 0.0127 - mae: 0.0815 - val_1
oss: 0.0110 - val_mae: 0.0763
Epoch 93/100
92107/92107 72s 781us/step - loss: 0.0128 - mae: 0.0816 - val_1
oss: 0.0109 - val_mae: 0.0765
Epoch 94/100
```

```
92107/92107 ━━━━━━━━ 72s 780us/step - loss: 0.0128 - mae: 0.0816 - val_l
oss: 0.0106 - val_mae: 0.0759
Epoch 95/100
92107/92107 ━━━━━━━━ 72s 778us/step - loss: 0.0128 - mae: 0.0815 - val_l
oss: 0.0113 - val_mae: 0.0778
Epoch 96/100
92107/92107 ━━━━━━━━ 71s 774us/step - loss: 0.0128 - mae: 0.0815 - val_l
oss: 0.0112 - val_mae: 0.0774
Epoch 97/100
92107/92107 ━━━━━━━━ 72s 776us/step - loss: 0.0128 - mae: 0.0815 - val_l
oss: 0.0109 - val_mae: 0.0767
Epoch 98/100
92107/92107 ━━━━━━━━ 73s 796us/step - loss: 0.0129 - mae: 0.0816 - val_l
oss: 0.0111 - val_mae: 0.0771
Epoch 99/100
92107/92107 ━━━━━━━━ 73s 790us/step - loss: 0.0129 - mae: 0.0816 - val_l
oss: 0.0112 - val_mae: 0.0782
Epoch 100/100
92107/92107 ━━━━━━━━ 73s 790us/step - loss: 0.0129 - mae: 0.0816 - val_l
oss: 0.0115 - val_mae: 0.0787
```

```
In [ ]: # Define a function to evaluate and predict using the model
def evaluate_and_predict():
    test_loss, test_mae = model.evaluate(X_test_scaled, y_test, verbose=0)
    y_pred = model.predict(X_test_scaled, verbose=0)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    return test_mae, rmse, y_pred

# Use ThreadPoolExecutor to parallelize evaluation and prediction
with ThreadPoolExecutor(max_workers=2) as executor:
    future = executor.submit(evaluate_and_predict)
    test_mae, rmse, y_pred = future.result()

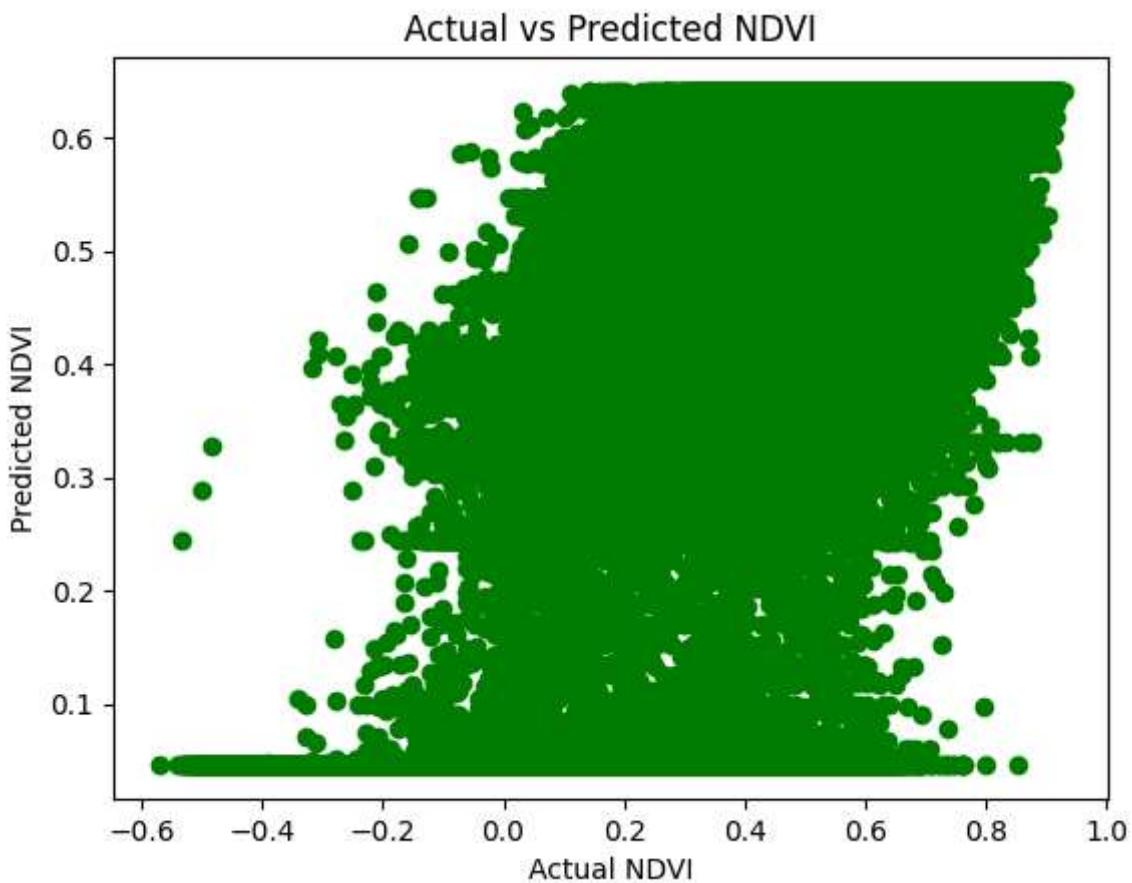
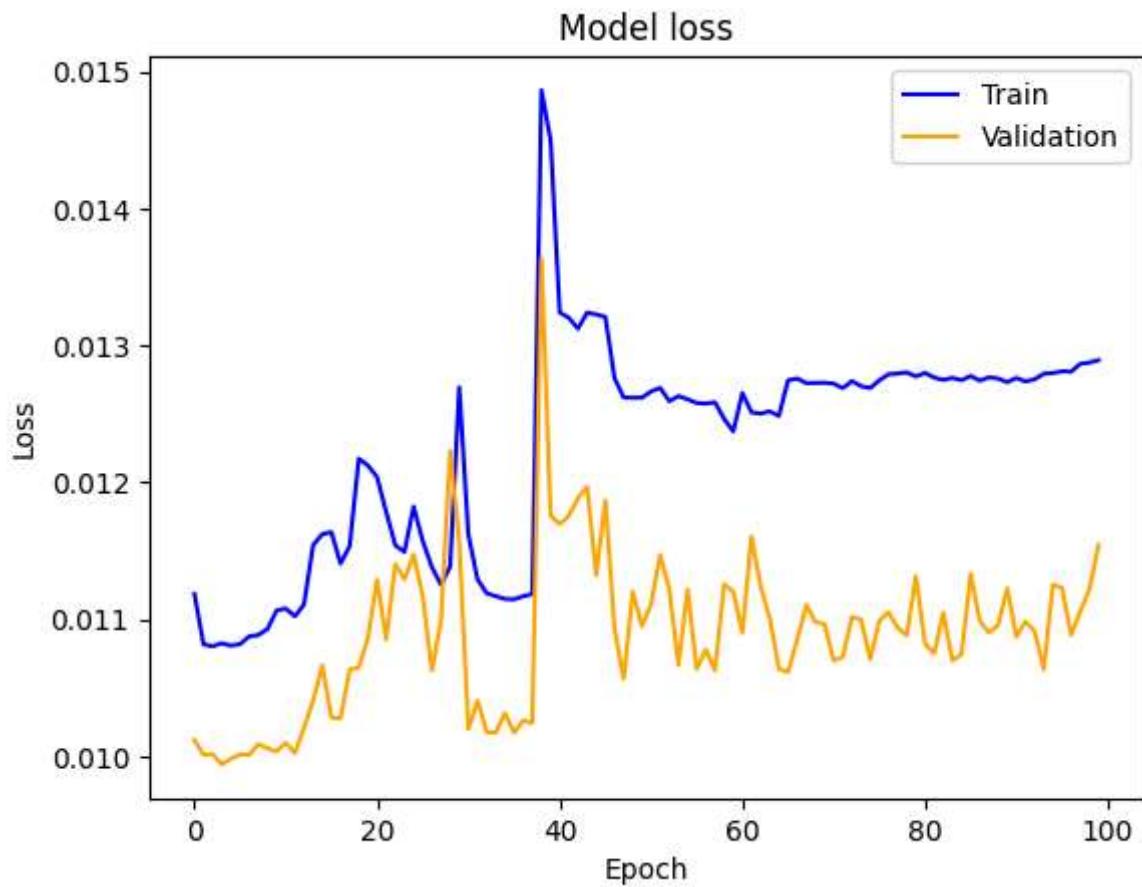
print(f"Test MAE: {test_mae}")
print(f"Test RMSE: {rmse}")
```

Test MAE: 0.07874850928783417
 Test RMSE: 0.10757747558241011

```
In [ ]: import matplotlib.pyplot as plt

# Plot training & validation loss values
plt.plot(history.history['loss'], color='blue')
plt.plot(history.history['val_loss'], color='orange')
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()

# Plot predictions vs actual with different colors
plt.scatter(y_test, y_pred, c='green') # Use green color for the scatter plot
plt.xlabel('Actual NDVI')
plt.ylabel('Predicted NDVI')
plt.title('Actual vs Predicted NDVI')
plt.show()
```



```
In [ ]: from sklearn.inspection import permutation_importance
import matplotlib.pyplot as plt
import numpy as np

# Compute permutation importance
result = permutation_importance(model, X_test_scaled, y_test, n_repeats=10, random_

# Get the importance of each feature
importance = result.importances_mean

# Normalize importance by the maximum value to show relative importance
relative_importance = importance / np.max(importance)
```

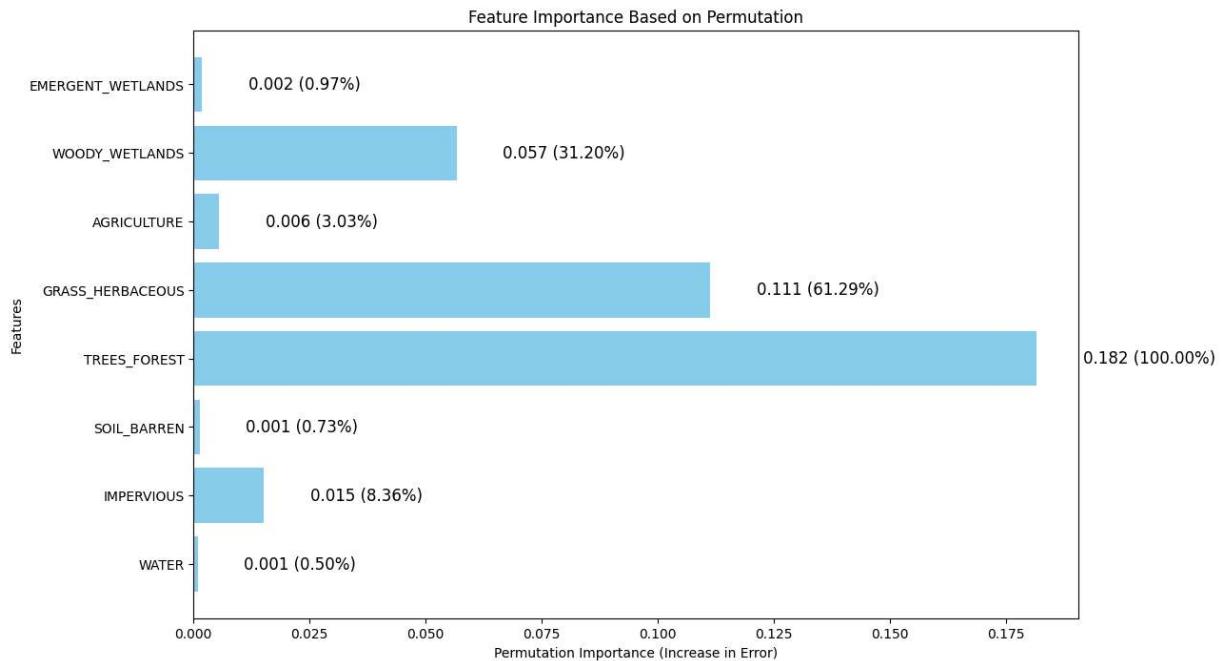
56392/56392	22s	399us/step
56392/56392	23s	412us/step
56392/56392	23s	399us/step
56392/56392	23s	401us/step
56392/56392	22s	396us/step
56392/56392	22s	397us/step
56392/56392	22s	397us/step
56392/56392	22s	397us/step
56392/56392	22s	396us/step
56392/56392	22s	399us/step
56392/56392	22s	395us/step
56392/56392	22s	395us/step
56392/56392	22s	389us/step
56392/56392	22s	394us/step
56392/56392	22s	393us/step
56392/56392	22s	395us/step
56392/56392	22s	394us/step
56392/56392	22s	396us/step
56392/56392	23s	400us/step
56392/56392	22s	393us/step
56392/56392	22s	393us/step
56392/56392	22s	397us/step
56392/56392	22s	395us/step
56392/56392	23s	401us/step
56392/56392	23s	404us/step
56392/56392	23s	410us/step
56392/56392	23s	410us/step
56392/56392	23s	403us/step
56392/56392	23s	407us/step
56392/56392	23s	407us/step
56392/56392	23s	414us/step
56392/56392	23s	410us/step
56392/56392	23s	408us/step
56392/56392	23s	409us/step
56392/56392	23s	405us/step
56392/56392	23s	409us/step
56392/56392	23s	403us/step
56392/56392	23s	412us/step
56392/56392	23s	412us/step
56392/56392	23s	405us/step
56392/56392	23s	409us/step
56392/56392	23s	407us/step
56392/56392	23s	404us/step
56392/56392	23s	409us/step
56392/56392	23s	407us/step
56392/56392	23s	399us/step
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56392/56392	22s	398us/step
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56392/56392	22s	398us/step
56392/56392	22s	395us/step
56392/56392	22s	394us/step
56392/56392	22s	396us/step
56392/56392	23s	400us/step

56392/56392	—————	23s	402us/step
56392/56392	—————	23s	399us/step
56392/56392	—————	23s	399us/step
56392/56392	—————	22s	395us/step
56392/56392	—————	22s	393us/step
56392/56392	—————	23s	405us/step
56392/56392	—————	23s	404us/step
56392/56392	—————	21s	370us/step
56392/56392	—————	21s	368us/step
56392/56392	—————	21s	379us/step
56392/56392	—————	21s	374us/step
56392/56392	—————	22s	382us/step
56392/56392	—————	21s	370us/step
56392/56392	—————	21s	371us/step
56392/56392	—————	21s	372us/step
56392/56392	—————	21s	373us/step
56392/56392	—————	21s	367us/step
56392/56392	—————	21s	370us/step
56392/56392	—————	21s	376us/step
56392/56392	—————	21s	374us/step
56392/56392	—————	21s	374us/step
56392/56392	—————	21s	372us/step
56392/56392	—————	21s	373us/step
56392/56392	—————	21s	376us/step
56392/56392	—————	21s	367us/step

```
In [ ]: # Plot the feature importance
plt.figure(figsize=(12, 8))
bars = plt.barh(X.columns, importance, color='skyblue')

# Add exact values on the bars
for bar, val, rel_val in zip(bars, importance, relative_importance):
    plt.text(bar.get_width() + 0.01, bar.get_y() + bar.get_height()/2,
             f'{val:.3f} ({rel_val:.2%})',
             va='center', ha='left', color='black', fontsize=12)

plt.xlabel('Permutation Importance (Increase in Error)')
plt.ylabel('Features')
plt.title('Feature Importance Based on Permutation')
plt.show()
```



```
In [ ]: # Define a function to compute the gradient of the output with respect to the input
def compute_saliency(model, X):
    with tf.GradientTape() as tape:
        tape.watch(X)
        predictions = model(X)
    gradient = tape.gradient(predictions, X)
    return tf.reduce_mean(tf.abs(gradient), axis=0).numpy()

# Compute saliency for the test set
X_test_tensor = tf.convert_to_tensor(X_test_scaled)
saliency = compute_saliency(model, X_test_tensor)

# Normalize the saliency scores
normalized_saliency = saliency / np.max(saliency)

# Display the saliency scores for each feature
feature_importance = pd.Series(normalized_saliency, index=X.columns)
feature_importance.sort_values(ascending=False, inplace=True)
print(feature_importance)
```

GRASS_Herbaceous	1.000000
TREES_FOREST	0.999318
IMPERVIOUS	0.681450
WATER	0.453456
WOODY_WETLANDS	0.392386
AGRICULTURE	0.288267
EMERGENT_WETLANDS	0.278362
SOIL_BARREN	0.199849

dtype: float64