Lab Assignment 09: Random Forest Classifier

Supervised Machine Learning Lab

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AIML A3

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import accuracy_score, mean_squared_error, mean_absolute_error
import warnings
warnings.filterwarnings('ignore')
```

1. Use the attached stroke prediction data

```
df = pd.read_csv('/content/Random Forest assignment dataset.csv')
df
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_st
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly sm
1	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never sm
2	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	sm
3	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never sm
4	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	formerly sm
...	...	...	...	...	...	...	...	...	...	
4976	Male	41.0	0	0	No	Private	Rural	70.15	29.8	formerly sm
4977	Male	40.0	0	0	Yes	Private	Urban	191.15	31.1	sm
4978	Female	45.0	1	0	Yes	Govt_job	Rural	95.02	31.8	sm
4979	Male	40.0	0	0	Yes	Private	Rural	83.94	30.0	sm
4980	Female	80.0	1	0	Yes	Private	Urban	83.75	29.1	never sm

4981 rows × 11 columns

```
df.dtypes
```

```
gender                object
age                  float64
hypertension           int64
heart_disease          int64
ever_married          object
work_type             object
Residence_type        object
avg_glucose_level    float64
bmi                  float64
smoking_status        object
stroke                 int64
dtype: object
```

```
df.describe
```

```
<bound method NDFrame.describe of        gender   age  hypertension  heart_disease ever_married      work_type  \
0        Male  67.0             0              1          Yes        Private
1        Male  80.0             0              1          Yes        Private
2      Female  49.0             0              0          Yes        Private
3      Female  79.0             1              0          Yes  Self-employed
4        Male  81.0             0              0          Yes        Private
...       ...   ...           ...            ...          ...            ...
4976     Male  41.0             0              0           No        Private
4977     Male  40.0             0              0          Yes        Private
4978   Female  45.0             1              0          Yes       Govt_job
4979     Male  40.0             0              0          Yes        Private
4980   Female  80.0             1              0          Yes        Private
```

```
      Residence_type  avg_glucose_level   bmi   smoking_status  stroke
0              Urban             228.69  36.6  formerly smoked       1
1              Rural             105.92  32.5     never smoked       1
2              Urban             171.23  34.4           smokes       1
3              Rural             174.12  24.0     never smoked       1
4              Urban             186.21  29.0  formerly smoked       1
...              ...                ...   ...              ...     ...
4976           Rural              70.15  29.8  formerly smoked       0
4977           Urban             191.15  31.1           smokes       0
4978           Rural              95.02  31.8           smokes       0
4979           Rural              83.94  30.0           smokes       0
4980           Urban              83.75  29.1     never smoked       0

[4981 rows x 11 columns]>
```

```
df.shape
```

```
(4981, 11)
```

```
df.dtypes
```

```
gender                object
age                  float64
hypertension           int64
heart_disease          int64
ever_married          object
work_type             object
Residence_type        object
avg_glucose_level    float64
bmi                  float64
smoking_status        object
stroke                 int64
dtype: object
```

```
df.isnull().sum()
```

```
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

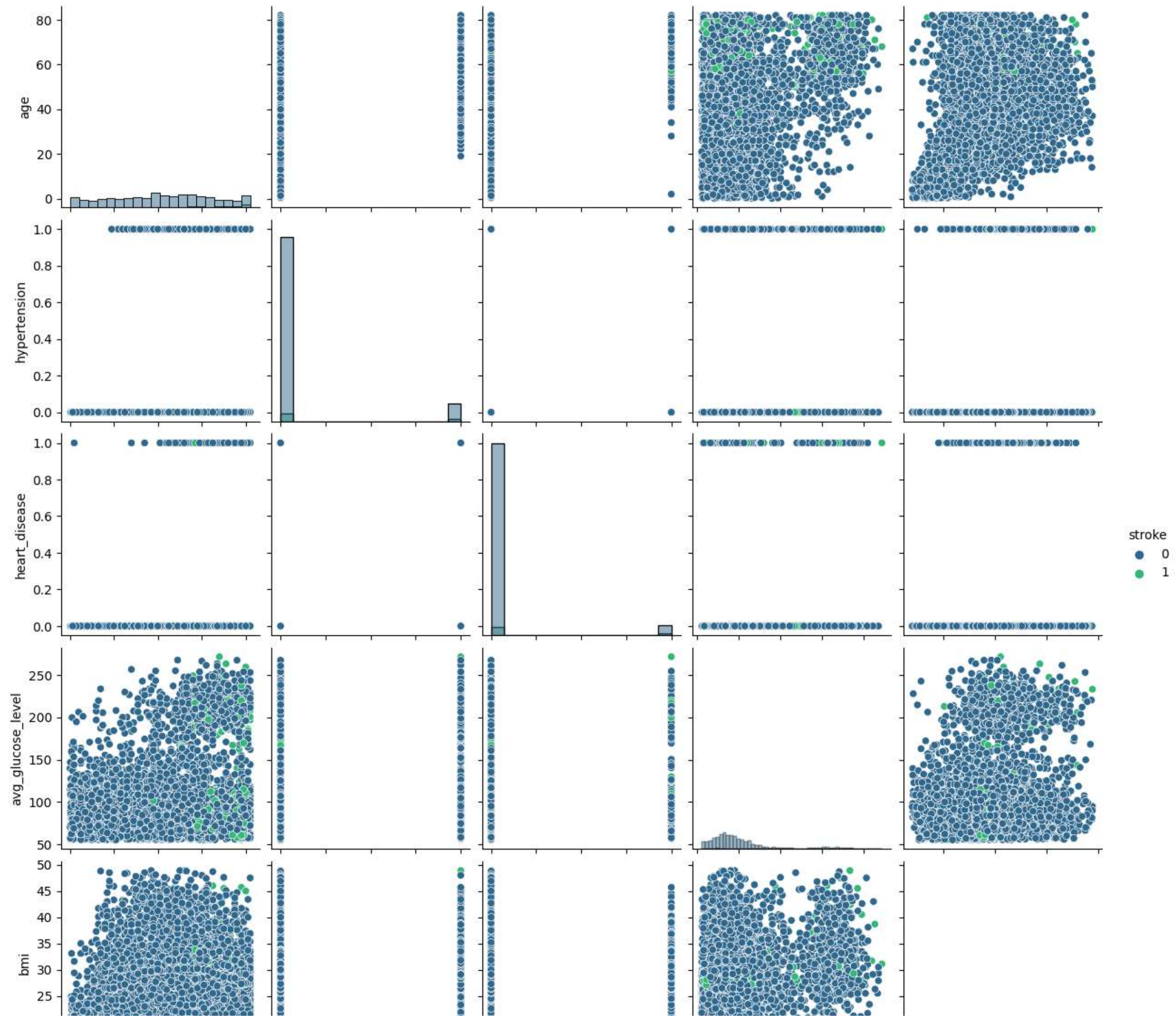
```
print(df.columns)
```

```
Index(['gender', 'age', 'hypertension', 'heart_disease', 'ever_married',
       'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
       'smoking_status', 'stroke'],
      dtype='object')
```

2. Apply EDA for the dataset

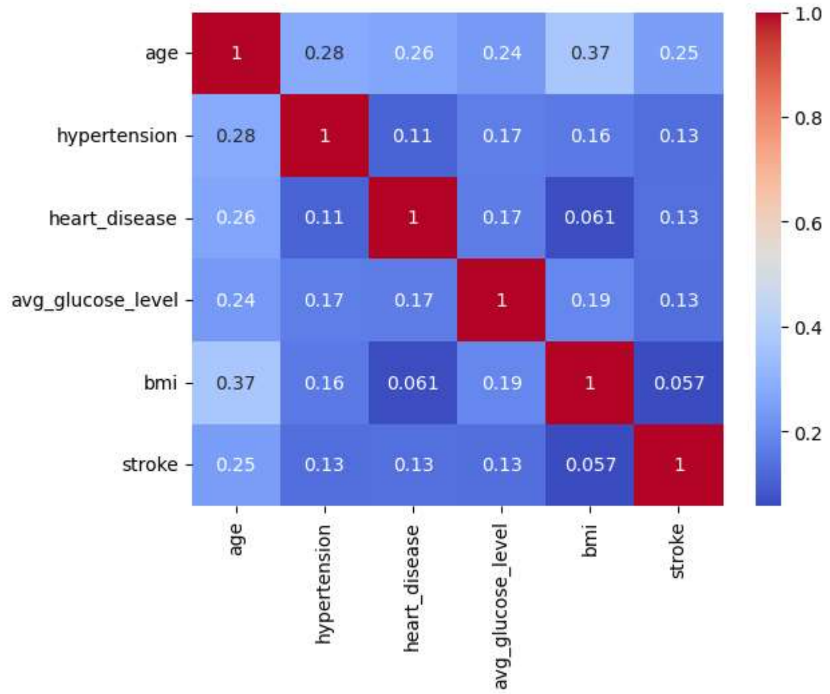
```
import seaborn as sns

cols = ['gender', 'age', 'hypertension', 'heart_disease', 'ever_married',
        'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
        'smoking_status', 'stroke']
sns.pairplot(df[cols], hue='stroke', diag_kind='hist', palette='viridis')
```

```
<seaborn.axisgrid.PairGrid at 0x7f4f52fbb3a0>
```

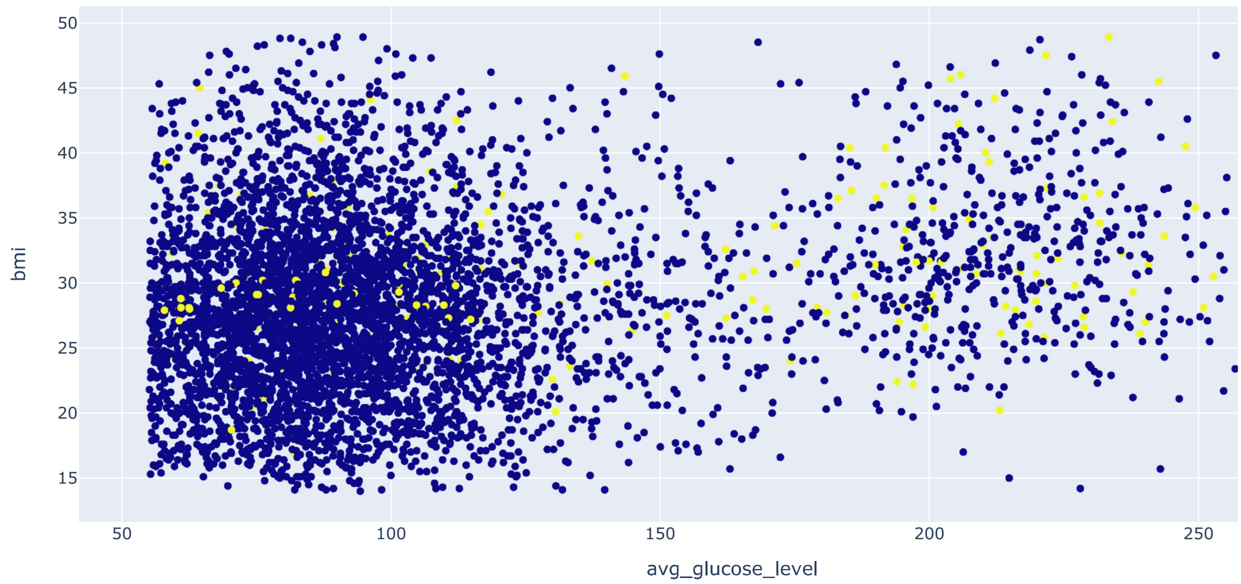



```
sns.heatmap(df.corr(), cmap='coolwarm', annot=True)
```

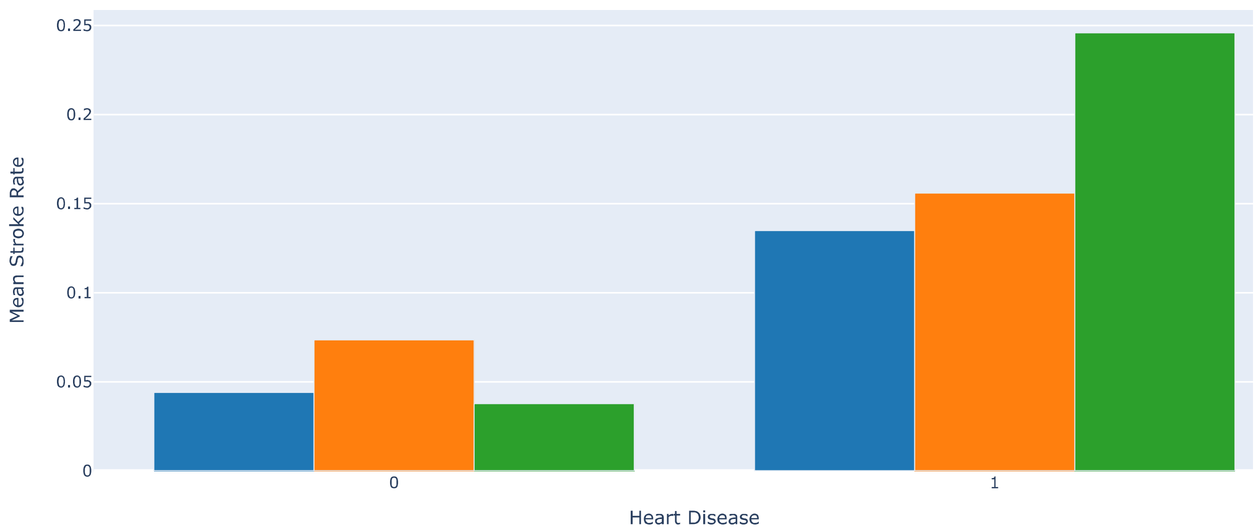
```
<Axes: >
```



```
import plotly.express as px

fig = px.scatter(df, x="avg_glucose_level", y="bmi", color="stroke")
fig.show()
```




```
import plotly.graph_objs as go

df_grouped = df.groupby(['heart_disease', 'smoking_status'], as_index=False)['stroke'].mean()

fig = go.Figure(data=[
    go.Bar(name='Never smoked', x=df_grouped[df_grouped['smoking_status'] == 'never smoked']['heart_disease'],
           y=df_grouped[df_grouped['smoking_status'] == 'never smoked']['stroke'], marker_color='#1f77b4'),
    go.Bar(name='Formerly smoked', x=df_grouped[df_grouped['smoking_status'] == 'formerly smoked']['heart_disease'],
           y=df_grouped[df_grouped['smoking_status'] == 'formerly smoked']['stroke'], marker_color='#ff7f0e'),
    go.Bar(name='Smokes', x=df_grouped[df_grouped['smoking_status'] == 'smokes']['heart_disease'],
           y=df_grouped[df_grouped['smoking_status'] == 'smokes']['stroke'], marker_color='#2ca02c')
])
# Update layout
fig.update_layout(barmode='group', xaxis_title='Heart Disease', yaxis_title='Mean Stroke Rate')
fig.show()
```




```
from sklearn.preprocessing import LabelEncoder
```

```
# Create a LabelEncoder object
le = LabelEncoder()

# Encode 'gender' column
df['gender'] = le.fit_transform(df['gender'])

# Encode 'ever_married' column
df['ever_married'] = le.fit_transform(df['ever_married'])

# Encode 'work_type' column
df['work_type'] = le.fit_transform(df['work_type'])

# Encode 'Residence_type' column
df['Residence_type'] = le.fit_transform(df['Residence_type'])

# Encode 'smoking_status' column
df['smoking_status'] = le.fit_transform(df['smoking_status'])


# Define feature and target variables
X = df.drop(['stroke'], axis=1)
y = df['stroke']
```

3. Use a combination of datasets for training and testing as 60-40 and 70-30.

```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=1)


# Print the size of the train and test sets
print('Size of X_train:', X_train.shape)
print('Size of X_test:', X_test.shape)
print('Size of y_train:', y_train.shape)
print('Size of y_test:', y_test.shape)
```

```
Size of X_train: (2988, 10)
Size of X_test: (1993, 10)
Size of y_train: (2988,)
Size of y_test: (1993,)
```

4. Try three combinations of the number of estimators and the number of jobs.

```
# Fit and evaluate random forest classifier with different combinations of n_estimators and n_jobs
n_estimators_list = [50, 100, 150]
n_jobs_list = [-1, 2, 4]
```

5. Evaluate the performance of the model in terms of accuracy, mean square error, root mean square error and mean absolute error

```
for n_estimators in n_estimators_list:
    for n_jobs in n_jobs_list:
        print(f"Training model with n_estimators={n_estimators} and n_jobs={n_jobs}")
        model = RandomForestClassifier(n_estimators=n_estimators, n_jobs=n_jobs, random_state=1)
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        acc = accuracy_score(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)
        rmse = mean_squared_error(y_test, y_pred, squared=False)
        mae = mean_absolute_error(y_test, y_pred)
        print(f"Accuracy: {acc:.3f}\nMSE: {mse:.3f}\nRMSE: {rmse:.3f}\nMAE: {mae:.3f}\n")
```

```
Training model with n_estimators=50 and n_jobs=-1
Accuracy: 0.949
MSE: 0.051
RMSE: 0.226
MAE: 0.051

Training model with n_estimators=50 and n_jobs=2
Accuracy: 0.949
MSE: 0.051
RMSE: 0.226
MAE: 0.051

Training model with n_estimators=50 and n_jobs=4
Accuracy: 0.949
```

```
MSE: 0.051
RMSE: 0.226
MAE: 0.051

Training model with n_estimators=100 and n_jobs=-1
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=100 and n_jobs=2
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=100 and n_jobs=4
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=150 and n_jobs=-1
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=150 and n_jobs=2
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=150 and n_jobs=4
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052
```

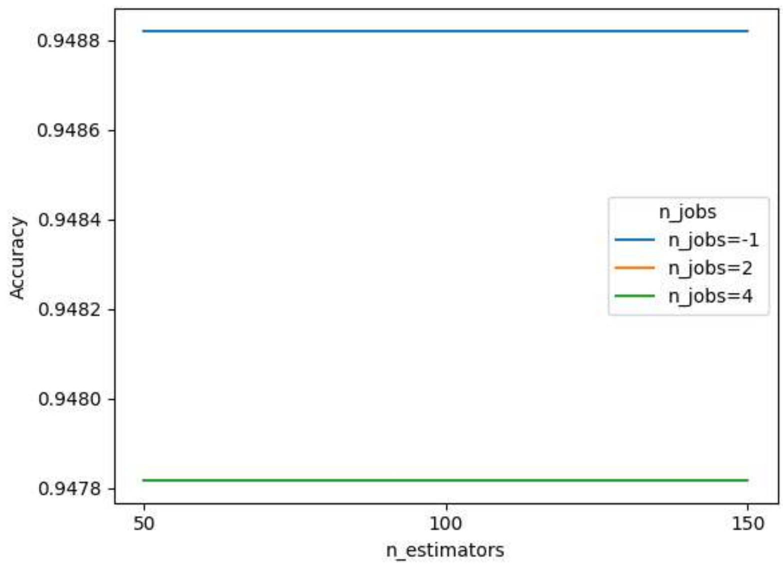
6. Show the plots for
a. Variation in performance accuracy with different combinations of training and testing datasets

```
# Define the list of n_estimators and n_jobs to try
n_estimators_list = [50, 100, 150]
n_jobs_list = [-1, 2, 4]

# Initialize empty lists to store results
acc_list = []
mse_list = []
rmse_list = []
mae_list = []

# Loop over all combinations of n_estimators and n_jobs
for n_estimators in n_estimators_list:
    for n_jobs in n_jobs_list:
        print(f"Training model with n_estimators={n_estimators} and n_jobs={n_jobs}")

        # Fit the model
        model = RandomForestClassifier(n_estimators=n_estimators, n_jobs=n_jobs, random_state=1)
        model.fit(X_train, y_train)

        # Make predictions on the test set
        y_pred = model.predict(X_test)

        # Calculate performance metrics
        acc = accuracy_score(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)
        rmse = mean_squared_error(y_test, y_pred, squared=False)
        mae = mean_absolute_error(y_test, y_pred)

        # Append results to the lists
        acc_list.append(acc)
        mse_list.append(mse)
        rmse_list.append(rmse)
        mae_list.append(mae)

        print(f"Accuracy: {acc:.3f}\nMSE: {mse:.3f}\nRMSE: {rmse:.3f}\nMAE: {mae:.3f}\n")
```

```
Training model with n_estimators=50 and n_jobs=-1
Accuracy: 0.949
MSE: 0.051
```

```
RMSE: 0.226
MAE: 0.051

Training model with n_estimators=50 and n_jobs=2
Accuracy: 0.949
MSE: 0.051
RMSE: 0.226
MAE: 0.051

Training model with n_estimators=50 and n_jobs=4
Accuracy: 0.949
MSE: 0.051
RMSE: 0.226
MAE: 0.051

Training model with n_estimators=100 and n_jobs=-1
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=100 and n_jobs=2
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=100 and n_jobs=4
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=150 and n_jobs=-1
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=150 and n_jobs=2
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052

Training model with n_estimators=150 and n_jobs=4
Accuracy: 0.948
MSE: 0.052
RMSE: 0.228
MAE: 0.052
```

```
# Create a plot of accuracy vs. n_estimators and n_jobs
fig, ax = plt.subplots()
for i, n_jobs in enumerate(n_jobs_list):
    ax.plot(n_estimators_list, acc_list[i*len(n_estimators_list):(i+1)*len(n_estimators_list)], label=f"n_jobs={n_jobs}")
ax.set_xlabel("n_estimators")
ax.set_ylabel("Accuracy")
ax.set_xticks(n_estimators_list)
ax.legend(title="n_jobs")
plt.show()
```



b. Variation in performance of mean square error, root mean square error, and mean absolute error with different combinations of training and testing datasets:

6. Show the plots for

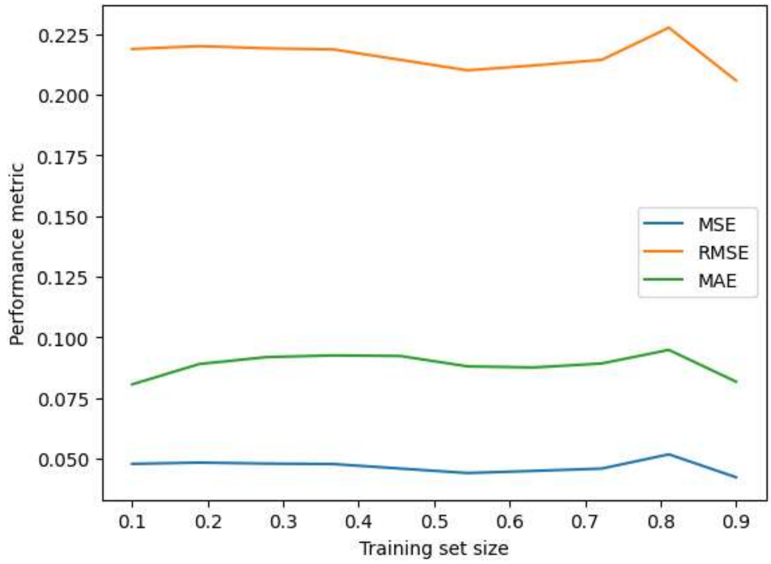
b. Variation in performance of mean square error, root mean square error, and mean absolute error with different combinations of training and testing datasets

```
# Define different sizes of training and testing datasets
train_sizes = np.linspace(0.1, 0.9, 10)

# Initialize empty lists to store results
mse_list = []
rmse_list = []
mae_list = []

# Loop over different sizes of training and testing datasets
for train_size in train_sizes:
    print(f"Training model with train_size={train_size:.1f} and test_size={1-train_size:.1f}")

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=train_size, random_state=1)

    # Fit the model
    model = RandomForestRegressor(random_state=1)
    model.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = model.predict(X_test)

    # Calculate performance metrics
    mse = mean_squared_error(y_test, y_pred)
    rmse = mean_squared_error(y_test, y_pred, squared=False)
    mae = mean_absolute_error(y_test, y_pred)

    # Append results to the lists
    mse_list.append(mse)
    rmse_list.append(rmse)
    mae_list.append(mae)

    print(f"MSE: {mse:.3f}\nRMSE: {rmse:.3f}\nMAE: {mae:.3f}\n")
```

```
Training model with train_size=0.1 and test_size=0.9
MSE: 0.048
RMSE: 0.219
MAE: 0.081

Training model with train_size=0.2 and test_size=0.8
MSE: 0.048
RMSE: 0.220
MAE: 0.089

Training model with train_size=0.3 and test_size=0.7
MSE: 0.048
RMSE: 0.219
MAE: 0.092

Training model with train_size=0.4 and test_size=0.6
MSE: 0.048
RMSE: 0.219
MAE: 0.093

Training model with train_size=0.5 and test_size=0.5
MSE: 0.046
RMSE: 0.214
MAE: 0.092

Training model with train_size=0.5 and test_size=0.5
MSE: 0.044
RMSE: 0.210
MAE: 0.088

Training model with train_size=0.6 and test_size=0.4
MSE: 0.045
RMSE: 0.212
MAE: 0.088

Training model with train_size=0.7 and test_size=0.3
MSE: 0.046
RMSE: 0.214
MAE: 0.089
```

```
Training model with train_size=0.8 and test_size=0.2
MSE: 0.052
RMSE: 0.228
MAE: 0.095

Training model with train_size=0.9 and test_size=0.1
MSE: 0.042
RMSE: 0.206
MAE: 0.082
```

```
# Create a plot of performance metrics vs. training set size
fig, ax = plt.subplots()
ax.plot(train_sizes, mse_list, label="MSE")
ax.plot(train_sizes, rmse_list, label="RMSE")
ax.plot(train_sizes, mae_list, label="MAE")
ax.set_xlabel("Training set size")
ax.set_ylabel("Performance metric")
ax.legend()
plt.show()
```



6. Show the plots for

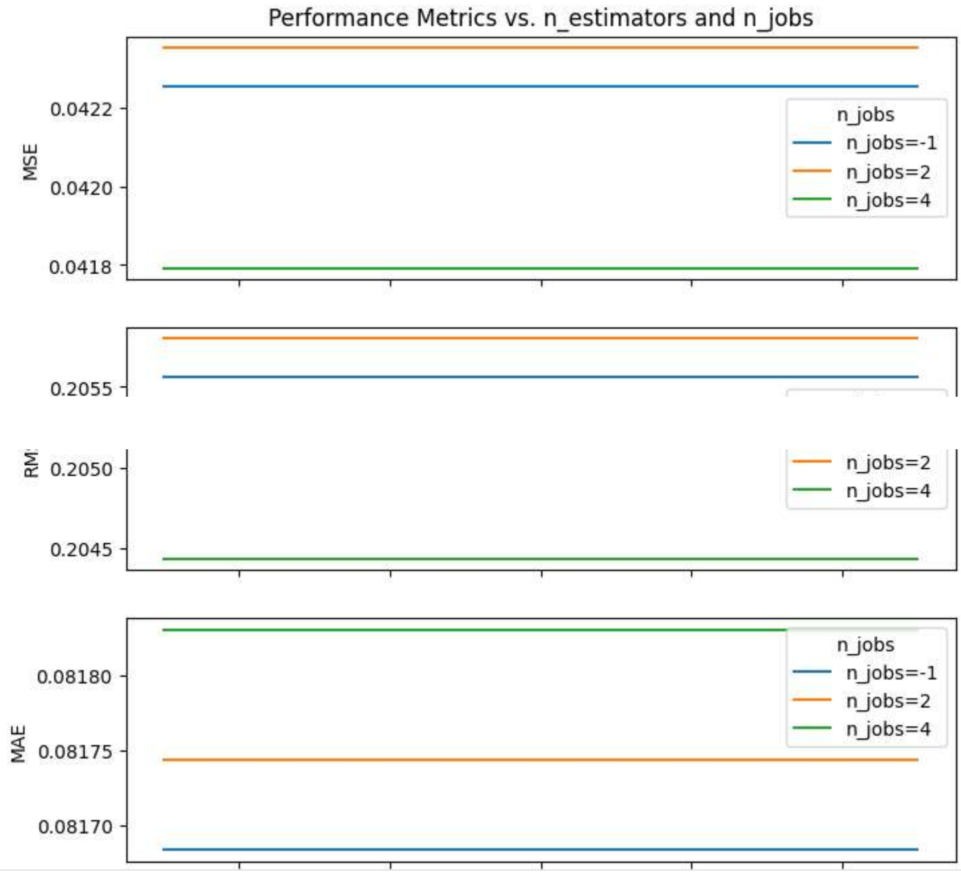
c. Variation in performance of mean square error, root mean square error, and mean absolute error with different combinations of a number of estimators and the number of jobs

```
# Define the list of n_estimators and n_jobs to try
n_estimators_list = [50, 100, 150]
n_jobs_list = [-1, 2, 4]

# Initialize empty lists to store results
mse_list = []
rmse_list = []
mae_list = []

# Loop over all combinations of n_estimators and n_jobs
for n_estimators in n_estimators_list:
    for n_jobs in n_jobs_list:
        print(f"Training model with n_estimators={n_estimators} and n_jobs={n_jobs}")

        # Fit the model
        model = RandomForestRegressor(n_estimators=n_estimators, n_jobs=n_jobs, random_state=1)
        model.fit(X_train, y_train)

        # Make predictions on the test set
        y_pred = model.predict(X_test)

        # Calculate performance metrics
        mse = mean_squared_error(y_test, y_pred)
        rmse = mean_squared_error(y_test, y_pred, squared=False)
        mae = mean_absolute_error(y_test, y_pred)

        # Append results to the lists
        mse_list.append(mse)
        rmse_list.append(rmse)
        mae_list.append(mae)
```

```
        print(f"MSE: {mse:.3f}\nRMSE: {rmse:.3f}\nMAE: {mae:.3f}\n")
```

```
    Training model with n_estimators=50 and n_jobs=-1
    MSE: 0.042
    RMSE: 0.206
    MAE: 0.082

    Training model with n_estimators=50 and n_jobs=2
    MSE: 0.042
    RMSE: 0.206
    MAE: 0.082

    Training model with n_estimators=50 and n_jobs=4
    MSE: 0.042
    RMSE: 0.206
    MAE: 0.082

    Training model with n_estimators=100 and n_jobs=-1
    MSE: 0.042
    RMSE: 0.206
    MAE: 0.082

    Training model with n_estimators=100 and n_jobs=2
    MSE: 0.042
    RMSE: 0.206
    MAE: 0.082

    Training model with n_estimators=100 and n_jobs=4
    MSE: 0.042
    RMSE: 0.206
    MAE: 0.082

    Training model with n_estimators=150 and n_jobs=-1
    MSE: 0.042
    RMSE: 0.204
    MAE: 0.082

    Training model with n_estimators=150 and n_jobs=2
    MSE: 0.042
    RMSE: 0.204
    MAE: 0.082

    Training model with n_estimators=150 and n_jobs=4
    MSE: 0.042
    RMSE: 0.204
    MAE: 0.082
```

```
# Create a plot of performance metrics vs. n_estimators and n_jobs
fig, axs = plt.subplots(nrows=3, ncols=1, sharex=True, figsize=(8,8))
axs[0].set_title('Performance Metrics vs. n_estimators and n_jobs')

for i, metric in enumerate(['MSE', 'RMSE', 'MAE']):
    for j, n_jobs in enumerate(n_jobs_list):
        axs[i].plot(n_estimators_list, eval(f'{metric.lower()}_list')[j*len(n_estimators_list):(j+1)*len(n_estimators_list)], label=f"n_j
    axs[i].set_ylabel(metric)
    axs[i].legend(title="n_jobs")

axs[-1].set_xlabel("n_estimators")
plt.show()
```



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