```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd

# Load dataset
file_path = ('/content/drive/MyDrive/bdl/Mental_Health_Dataset.csv')
data = pd.read_csv(file_path)

data.info()
data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 292364 entries, 0 to 292363
Data columns (total 17 columns):
 #   Column                   Non-Null Count   Dtype 
---  ------                   --------------   ----- 
 0   Timestamp                292364 non-null  object
 1   Gender                   292364 non-null  object
 2   Country                  292364 non-null  object
 3   Occupation               292364 non-null  object
 4   self_employed            287162 non-null  object
 5   family_history           292364 non-null  object
 6   treatment                292364 non-null  object
 7   Days_Indoors             292364 non-null  object
 8   Growing_Stress           292364 non-null  object
 9   Changes_Habits           292364 non-null  object
 10  Mental_Health_History    292364 non-null  object
 11  Mood_Swings              292364 non-null  object
 12  Coping_Struggles         292364 non-null  object
 13  Work_Interest            292364 non-null  object
 14  Social_Weakness          292364 non-null  object
 15  mental_health_interview  292364 non-null  object
 16  care_options             292364 non-null  object
dtypes: object(17)
memory usage: 37.9+ MB
```

	Timestamp	Gender	Country	Occupation	self_employed	family_history	treatment	Days_Indoors	Growing_Stress	Changes_Habits	M
0	8/27/2014 11:29	Female	United States	Corporate	NaN	No	Yes	1-14 days	Yes	No	
1	8/27/2014 11:31	Female	United States	Corporate	NaN	Yes	Yes	1-14 days	Yes	No	
2	8/27/2014 11:32	Female	United States	Corporate	NaN	Yes	Yes	1-14 days	Yes	No	
3	8/27/2014 11:37	Female	United States	Corporate	No	Yes	Yes	1-14 days	Yes	No	
4	8/27/2014 11:43	Female	United States	Corporate	No	Yes	Yes	1-14 days	Yes	No	

Preprocessing Data

```
# Mengganti nama kolom untuk konsistensi (mengubah huruf kapital dan mengganti spasi dengan garis bawah)
data.rename(columns=lambda x: x.strip().replace(" ", "_").lower(), inplace=True)

# Menampilkan nama kolom setelah perubahan
data.columns.tolist()
```

```
['timestamp',
 'gender',
 'country',
 'occupation',
 'self_employed',
 'family_history',
 'treatment',
 'days_indoors',
 'growing_stress',
 'changes_habits',
 'mental_health_history',
 'mood_swings',
 'coping_struggles',
 'work_interest',
 'social_weakness',
 'mental_health_interview',
 'care_options']
```

```
# Menghapus baris yang memiliki nilai kosong di kolom 'self_employed'
data = data.dropna(subset=['self_employed'])


# Convert 'Timestamp' to datetime format
data['timestamp'] = pd.to_datetime(data['timestamp'], errors='coerce')

data.head()
```

	timestamp	gender	country	occupation	self_employed	family_history	treatment	days_indoors	growing_stress	changes_habits	m
3	2014-08-27 11:37:00	Female	United States	Corporate	No	Yes	Yes	1-14 days	Yes	No	
4	2014-08-27 11:43:00	Female	United States	Corporate	No	Yes	Yes	1-14 days	Yes	No	
5	2014-08-27 11:49:00	Female	Poland	Corporate	No	No	Yes	1-14 days	Yes	No	
6	2014-08-27 11:51:00	Female	Australia	Corporate	No	Yes	Yes	1-14 days	Yes	No	
7	2014-08-27 11:52:00	Female	United States	Corporate	No	No	No	1-14 days	Yes	No	

```
# Menampilkan Statistik Deskriptif
print(data.describe(include='all'))
```

```
                             timestamp  gender        country occupation  \
count                           287162  287162         287162     287162   
unique                             NaN       2             35          5   
top                                NaN    Male  United States  Housewife   
freq                               NaN  235950         168056      65173   
mean    2014-09-09 09:40:05.724155648     NaN            NaN        NaN   
min               2014-08-27 11:35:00     NaN            NaN        NaN   
25%               2014-08-27 14:27:00     NaN            NaN        NaN   
50%               2014-08-28 02:32:00     NaN            NaN        NaN   
75%               2014-08-28 22:46:00     NaN            NaN        NaN   
max               2016-02-01 23:04:00     NaN            NaN        NaN   

       self_employed family_history treatment days_indoors growing_stress  \
count         287162         287162    287162       287162         287162   
unique             2              2         2            5              3   
top               No             No       Yes    1-14 days          Maybe   
freq          257994         173668    144744        62429          98225   
mean             NaN            NaN       NaN          NaN            NaN   
min              NaN            NaN       NaN          NaN            NaN   
25%              NaN            NaN       NaN          NaN            NaN   
50%              NaN            NaN       NaN          NaN            NaN   
75%              NaN            NaN       NaN          NaN            NaN   
max              NaN            NaN       NaN          NaN            NaN   

       changes_habits mental_health_history mood_swings coping_struggles  \
count          287162                287162      287162           287162   
unique              3                     3           3                2   
top               Yes                    No      Medium               No   
freq           107579                102179       99272           151609   
mean              NaN                   NaN         NaN              NaN   
min               NaN                   NaN         NaN              NaN   
25%               NaN                   NaN         NaN              NaN   
50%               NaN                   NaN         NaN              NaN   
75%               NaN                   NaN         NaN              NaN   
max               NaN                   NaN         NaN              NaN   

       work_interest social_weakness mental_health_interview care_options
count         287162          287162                  287162       287162
unique             3               3                       3            3
top               No           Maybe                      No           No
freq          103964          101559                  229304       116502
mean             NaN             NaN                     NaN          NaN
min              NaN             NaN                     NaN          NaN
25%              NaN             NaN                     NaN          NaN
50%              NaN             NaN                     NaN          NaN
75%              NaN             NaN                     NaN          NaN
max              NaN             NaN                     NaN          NaN
```

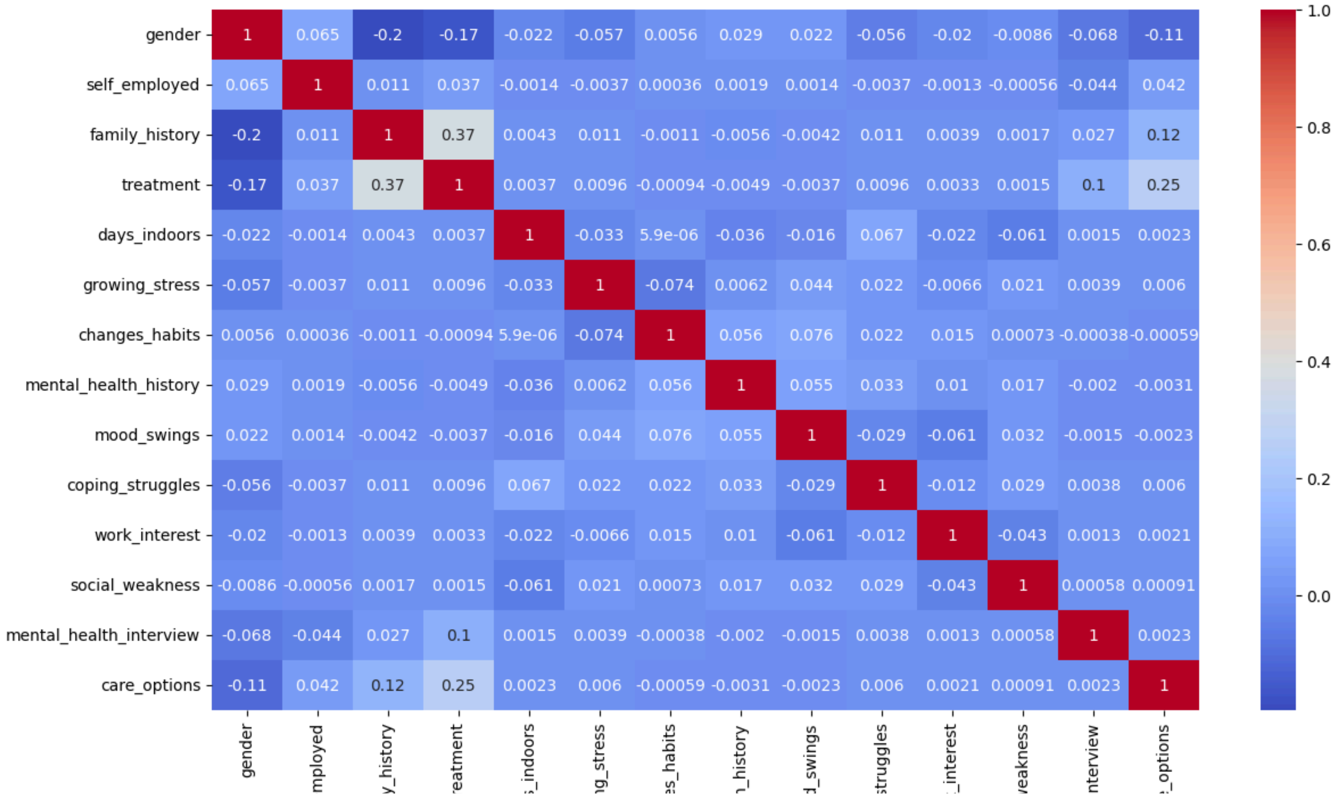
```
from sklearn.preprocessing import LabelEncoder

# Inisialisasi LabelEncoder
label_encoder = LabelEncoder()
```

```
# Menghapus kolom yang tidak relevan untuk korelasi
data_cleaned = data.drop(columns=['timestamp', 'occupation', 'country'])

# Mengonversi kolom menjadi numerik
data_cleaned['gender'] = label_encoder.fit_transform(data_cleaned['gender'])
data_cleaned['self_employed'] = label_encoder.fit_transform(data_cleaned['self_employed'])
data_cleaned['family_history'] = label_encoder.fit_transform(data_cleaned['family_history'])
data_cleaned['treatment'] = label_encoder.fit_transform(data_cleaned['treatment'])
data_cleaned['mental_health_history'] = label_encoder.fit_transform(data_cleaned['mental_health_history'])
data_cleaned['mood_swings'] = label_encoder.fit_transform(data_cleaned['mood_swings'])
data_cleaned['coping_struggles'] = label_encoder.fit_transform(data_cleaned['coping_struggles'])
data_cleaned['work_interest'] = label_encoder.fit_transform(data_cleaned['work_interest'])
data_cleaned['social_weakness'] = label_encoder.fit_transform(data_cleaned['social_weakness'])
data_cleaned['days_indoors'] = label_encoder.fit_transform(data_cleaned['days_indoors'])
data_cleaned['mental_health_interview'] = label_encoder.fit_transform(data_cleaned['mental_health_interview'])
data_cleaned['growing_stress'] = label_encoder.fit_transform(data_cleaned['growing_stress'])
data_cleaned['changes_habits'] = label_encoder.fit_transform(data_cleaned['changes_habits'])
data_cleaned['care_options'] = label_encoder.fit_transform(data_cleaned['care_options'])

# Menggunakan One-Hot Encoding untuk kolom kategorikal
data = pd.get_dummies(data_cleaned, drop_first=True)
```

```
data.corr()
```

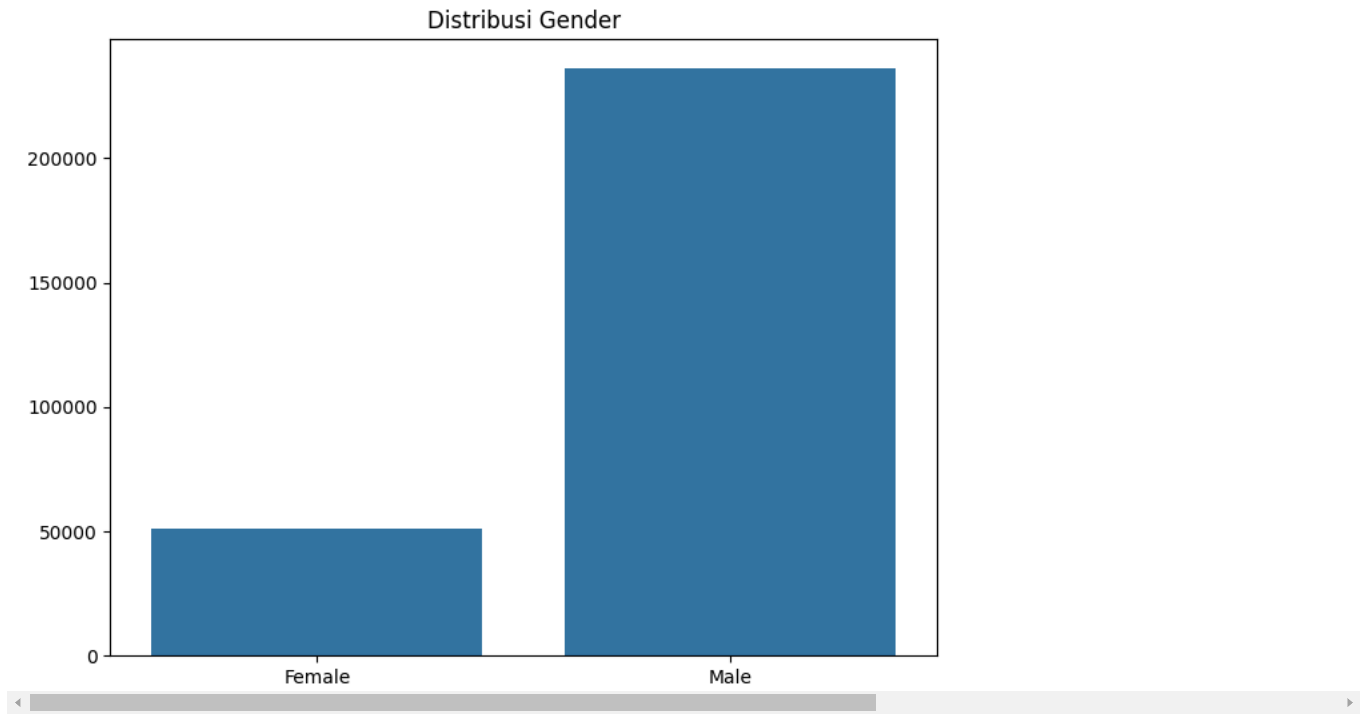
	gender	self_employed	family_history	treatment	days_indoors	growing_stress	changes_habits	mental_heal
gender	1.000000	0.065161	-0.196748	-0.169951	-0.021896	-0.056589	0.005550	
self_employed	0.065161	1.000000	0.011319	0.036795	-0.001427	-0.003687	0.000362	
family_history	-0.196748	0.011319	1.000000	0.371474	0.004308	0.011134	-0.001092	
treatment	-0.169951	0.036795	0.371474	1.000000	0.003721	0.009617	-0.000943	
days_indoors	-0.021896	-0.001427	0.004308	0.003721	1.000000	-0.033005	0.000006	
growing_stress	-0.056589	-0.003687	0.011134	0.009617	-0.033005	1.000000	-0.074421	
changes_habits	0.005550	0.000362	-0.001092	-0.000943	0.000006	-0.074421	1.000000	
mental_health_history	0.028698	0.001870	-0.005646	-0.004877	-0.036459	0.006191	0.056243	
mood_swings	0.021544	0.001404	-0.004239	-0.003661	-0.016356	0.043551	0.076288	
coping_struggles	-0.056194	-0.003662	0.011056	0.009550	0.067112	0.021527	0.021899	
work_interest	-0.019600	-0.001277	0.003856	0.003331	-0.021780	-0.006585	0.015352	
social_weakness	-0.008562	-0.000558	0.001685	0.001455	-0.060981	0.020738	0.000726	
mental_health_interview	-0.068213	-0.043773	0.026578	0.100620	0.001494	0.003860	-0.000379	
care_options	-0.106555	0.041898	0.119625	0.252841	0.002333	0.006030	-0.000591	

```
import seaborn as sns
import matplotlib.pyplot as plt

correlation_matrix = data.corr()
plt.figure(figsize=(14, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')

plt.show()
```



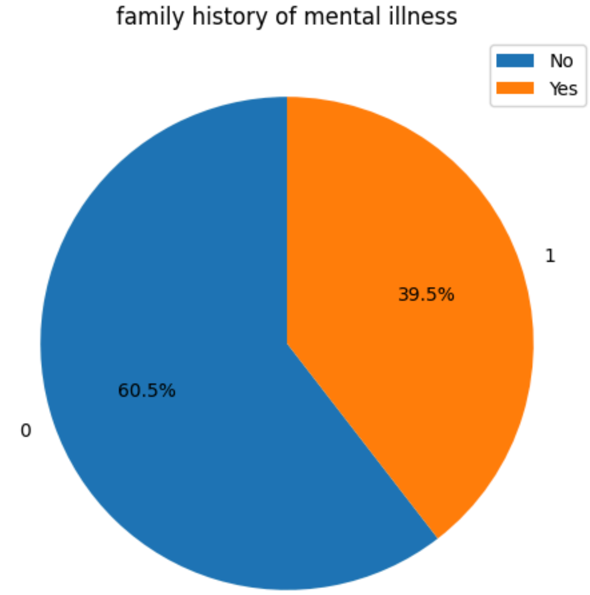
EDA

```
# 1. Bar Chart
plt.figure(figsize=(8,6))

data = data_cleaned
sns.countplot(x='gender', data=data)

plt.xticks(ticks=[0, 1], labels=['Female', 'Male'])

plt.xlabel('')
plt.ylabel('')
plt.title('Distribusi Gender')
plt.show()
```

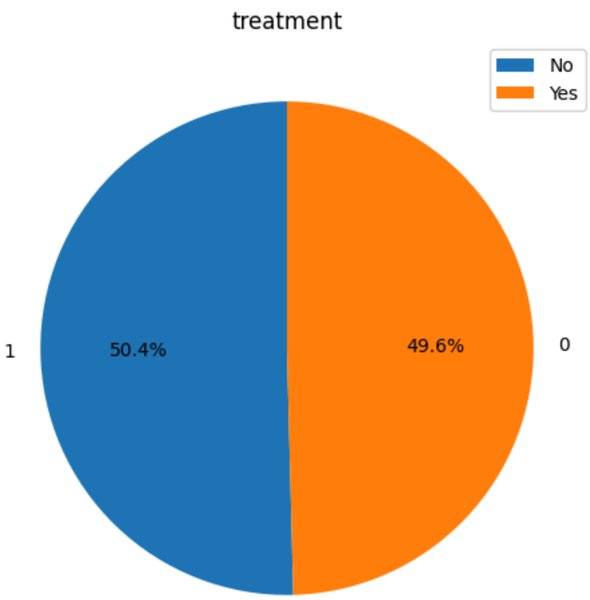



```
# 2. Pie Chart
plt.figure(figsize=(8,6))
data['family_history'].value_counts().plot.pie(autopct='%1.1f%%', startangle=90)
```

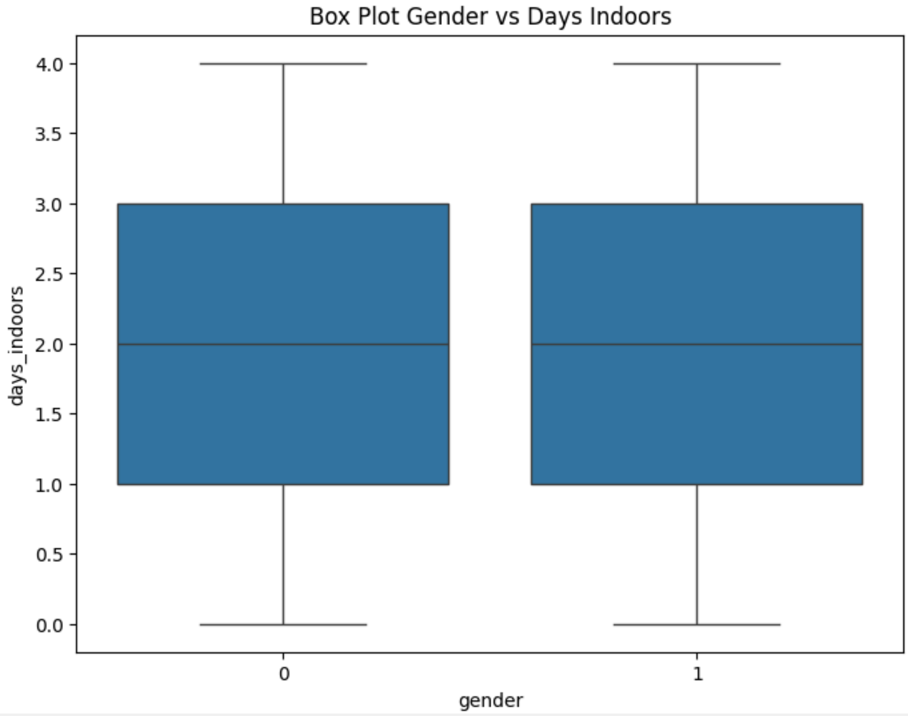
```
plt.legend(labels=['No', 'Yes'],)
plt.title('family history of mental illness')
plt.xlabel('')
plt.ylabel('')
plt.show()
```




```
plt.figure(figsize=(8,6))
data['treatment'].value_counts().plot.pie(autopct='%1.1f%%', startangle=90)
plt.legend(labels=['No', 'Yes'],)
plt.title('treatment')
plt.xlabel('')
plt.ylabel('')
plt.show()
```




```
# 4. Box Plot
plt.figure(figsize=(8,6))
sns.boxplot(x='gender', y='days_indoors', data=data)
plt.title('Box Plot Gender vs Days Indoors')
plt.show()
```



Modeling

```
from pyspark.sql import SparkSession
from pyspark.ml.classification import RandomForestClassifier, GBTClassifier, LogisticRegression, MultilayerPerceptronClassifier
from pyspark.ml.evaluation import BinaryClassificationEvaluator, MulticlassClassificationEvaluator
from pyspark.ml.feature import VectorAssembler
from pyspark.ml import Pipeline
from pyspark.sql.functions import rand

# Create a Spark session
spark = SparkSession.builder.appName("MentalHealthAnalysis").getOrCreate()

# Assuming 'data' is your Pandas DataFrame, convert it to a Spark DataFrame
spark_df = spark.createDataFrame(data)

# Define features and label
feature_cols = data.drop('treatment', axis=1).columns.tolist()
label_col = 'treatment'

# Create a VectorAssembler to combine features into a single vector column
assembler = VectorAssembler(inputCols=feature_cols, outputCol="features")

# Split the data into training and testing sets
training_data, testing_data = spark_df.randomSplit([0.7, 0.3], seed=42) # Use a seed for reproducibility

# Create a pipeline to chain the assembler and the classifier
pipeline = Pipeline(stages=[assembler, RandomForestClassifier(featuresCol="features", labelCol=label_col, numTrees=50)])

model = pipeline.fit(training_data)

# Make predictions on the testing data
predictions = model.transform(testing_data)


# Inisialisasi evaluator untuk berbagai metrik
evaluator_auc = BinaryClassificationEvaluator(labelCol=label_col, rawPredictionCol="rawPrediction", metricName="areaUnderROC")
evaluator_accuracy = MulticlassClassificationEvaluator(labelCol=label_col, predictionCol="prediction", metricName="accuracy")
evaluator_f1 = MulticlassClassificationEvaluator(labelCol=label_col, predictionCol="prediction", metricName="f1")
evaluator_precision = MulticlassClassificationEvaluator(labelCol=label_col, predictionCol="prediction", metricName="weightedPrecision")
evaluator_recall = MulticlassClassificationEvaluator(labelCol=label_col, predictionCol="prediction", metricName="weightedRecall")


# List model yang akan digunakan
models = [
    ("Random Forest", RandomForestClassifier(featuresCol="features", labelCol=label_col, numTrees=50)),
    ("Gradient Boosted Tree", GBTClassifier(featuresCol="features", labelCol=label_col, maxIter=50)),
    ("Logistic Regression", LogisticRegression(featuresCol="features", labelCol=label_col, maxIter=50)),
    ("Multilayer Perceptron", MultilayerPerceptronClassifier(featuresCol="features", labelCol=label_col, layers=[len(feature_cols), 32,
]
```

```
# Menampilkan hasil evaluasi untuk setiap model
for model_name, model in models:
    # Buat pipeline dengan model dan assembler
    pipeline = Pipeline(stages=[assembler, model])

    # Melatih model dengan data training
    trained_model = pipeline.fit(training_data)

    # Membuat prediksi pada data testing
    predictions = trained_model.transform(testing_data)

    # Evaluasi metrik
    auc = evaluator_auc.evaluate(predictions)
    accuracy = evaluator_accuracy.evaluate(predictions)
    f1_score = evaluator_f1.evaluate(predictions)
    precision = evaluator_precision.evaluate(predictions)
    recall = evaluator_recall.evaluate(predictions)

    # Menampilkan hasil metrik
    print(f"Model: {model_name}")
    print(f"  AUC: {auc:.3f}")
    print(f"  Accuracy: {accuracy:.3f}")
    print(f"  F1 Score: {f1_score:.3f}")
    print(f"  Precision: {precision:.3f}")
    print(f"  Recall: {recall:.3f}")
    print("-" * 50)
```

```
Model: Random Forest
  AUC: 0.771
  Accuracy: 0.715
  F1 Score: 0.714
  Precision: 0.717
  Recall: 0.715
--------------------------------------------------
Model: Gradient Boosted Tree
  AUC: 0.783
  Accuracy: 0.720
  F1 Score: 0.719
  Precision: 0.722
  Recall: 0.720
--------------------------------------------------
Model: Logistic Regression
  AUC: 0.756
  Accuracy: 0.701
  F1 Score: 0.701
  Precision: 0.702
  Recall: 0.701
--------------------------------------------------
Model: Multilayer Perceptron
  AUC: 0.765
  Accuracy: 0.710
  F1 Score: 0.709
  Precision: 0.710
  Recall: 0.710
--------------------------------------------------
```

Berdasarkan data yang diperoleh, kita dapat membandingkan performa model berdasarkan metrik yang telah dihitung (AUC, Accuracy, F1 Score, Precision, dan Recall). Dua model dengan performa terbaik adalah:

Gradient Boosted Tree (GBT):

AUC: 0.783 (tertinggi di antara semua model). Akurasi, F1 Score, Precision, dan Recall juga relatif lebih baik dibanding model lain.

Random Forest (RF):

AUC: 0.772 (tertinggi kedua). Performa keseluruhan lebih unggul daripada Logistic Regression dan Multilayer Perceptron.

```
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

# Evaluator
evaluator = BinaryClassificationEvaluator(labelCol=label_col, metricName="areaUnderROC")

# Hyperparameter tuning untuk Random Forest
rf = RandomForestClassifier(featuresCol="features", labelCol=label_col)
rf_param_grid = ParamGridBuilder() \
    .addGrid(rf.numTrees, [50, 100]) \
    .addGrid(rf.maxDepth, [5, 10]) \
    .build()

rf_cv = CrossValidator(estimator=rf,
                       estimatorParamMaps=rf_param_grid,
                       evaluator=evaluator,
                       numFolds=3)  # 3-fold cross-validation
```

```
rf_pipeline = Pipeline(stages=[assembler, rf_cv])
# Ambil sampel data yang lebih kecil untuk pelatihan
smaller_training_data = training_data.sample(fraction=0.1, seed=42)
smaller_testing_data = testing_data.sample(fraction=0.1, seed=42)

rf_model = rf_pipeline.fit(smaller_training_data)

# Evaluasi ulang dengan model yang telah dituning
rf_predictions = rf_model.transform(smaller_testing_data)
rf_auc = evaluator.evaluate(rf_predictions)


# Hyperparameter tuning untuk Gradient Boosted Tree
gbt = GBTClassifier(featuresCol="features", labelCol=label_col)
gbt_param_grid = ParamGridBuilder() \
    .addGrid(gbt.maxIter, [50]) \
    .addGrid(gbt.maxDepth, [5]) \
    .addGrid(gbt.stepSize, [0.1]) \
    .build()

gbt_cv = CrossValidator(estimator=gbt,
                        estimatorParamMaps=gbt_param_grid,
                        evaluator=evaluator,
                        numFolds=3)  # 3-fold cross-validation

gbt_pipeline = Pipeline(stages=[assembler, gbt_cv])
gbt_model = gbt_pipeline.fit(smaller_training_data)

gbt_predictions = gbt_model.transform(smaller_testing_data)
gbt_auc = evaluator.evaluate(gbt_predictions)
```