Project Title: Predictive maintenance for industrial equipment

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Predictive maintenance for industrial equipment is a data-driven approach that uses machine learning algorithms and analytics to predict when machinery is likely to fail. By analyzing historical and real-time data, it aims to optimize maintenance schedules, reduce downtime, and improve overall operational efficiency.

The project at hand is a comprehensive application of machine learning for predictive maintenance of diesel engines, implemented using PySpark. The objective of this project is to predict whether maintenance is required for diesel engines based on various features such as temperature, pressure, vibration, engine hours, RPM, fuel consumption, hour of the day, day of the week, and error codes.

The project covers the entire machine learning pipeline, from data loading and preprocessing to model training, tuning, and evaluation. It demonstrates the power of PySpark in handling big data and building robust machine learning models. The script is well-structured and modular, making it easy to understand and modify for different predictive maintenance tasks.

The data used in this project is a CSV file containing information about various parameters of diesel engines. The data is loaded into a DataFrame, cleaned, and preprocessed to prepare it for the machine learning model. The preprocessing steps include feature engineering, such as extracting the hour and day of the week from timestamps, converting numerical columns to float data type, and encoding categorical columns.

The machine learning model used in this project is a RandomForestClassifier. Random forests are a popular choice for classification tasks due to their robustness and ability to model complex patterns. The features used for the model are assembled using VectorAssembler, which creates a single vector column that combines all input features.

The script also includes a hyperparameter tuning step, where it uses CrossValidator with a ParamGridBuilder to find the optimal set of parameters for the RandomForestClassifier. This is done to find the best combination of parameters that produces the most accurate model.

Finally, the script evaluates the model’s performance using accuracy and F1 score. These metrics provide a quantitative measure of the model’s ability to correctly predict whether maintenance is required.

Data Description

- **Timestamp**: This column records the date and time of each observation. It is converted to a timestamp data type for more granular time-based analysis and feature extraction. Time-based features can often capture patterns and trends that are not immediately apparent in the raw data.

- **Engine ID**: This is a categorical column that identifies each engine. It is converted to a numerical form using StringIndexer and OneHotEncoder.

- **Error Codes**: This is another categorical column that records any error codes associated with each observation. It is also converted to a numerical form using StringIndexer and OneHotEncoder.

- **Temperature, Pressure, Vibration, Engine Hours, RPM, Fuel Consumption**: These are numerical columns that record various parameters of the engines. They are cast to float data type to ensure compatibility with the machine learning algorithms.

- **Maintenance Required**: This is the target variable that the model will predict. It indicates whether maintenance is required for each engine ('Yes' or 'No'). It is converted to binary format (1 for 'Yes', 0 for 'No') to simplify the problem to a binary classification task

Data Loading

We began by initializing a SparkSession, which is the entry point to any functionality in Spark. This is a fundamental step in any PySpark script as it establishes the connection to the Spark cluster.

```
from pyspark.sql import SparkSession

# Create a Spark session
spark = SparkSession.builder.getOrCreate()
```

Next, reads a CSV file from a specified path into a DataFrame. DataFrame is a distributed collection of data organized into named columns. It is conceptually

equivalent to a table in a relational database or a data frame in Python, but with optimizations for big data processing.

```
file_path = "dbfs:/FileStore/15_Machines_Predictive_Maintenance__predictive_maintenance_diesel_engine_data.csv"

df = spark.read.format("csv").option("header", "true").load(file_path)

df.show()
```

Engine ID	Timestamp	Temperature	Pressure	Vibration	Engine Hours	RPM	Fuel Consumption	Error Codes	Maintenance Required
E5	2021-01-01 00:00:00	96.35665688065689	8.143681630859573	1.1239020979006435	9364	999.5779358778484	295.7382211643776	E101	Yes
E1	2021-01-01 01:00:00	93.21222610545219	12.981443833918046	0.8215196113248281	6537	910.0585250666505	224.78136134050425	E103	No
E4	2021-01-01 02:00:00	96.46372143519119	10.390998670550655	0.9203814160835252	9809	864.9423502651543	213.1876775074176	E103	Yes
E4	2021-01-01 03:00:00	92.59252529338353	9.056791332904348	0.8599458732650436	9876	977.6115902427061	296.39293871888214	E101	No
E4	2021-01-01 04:00:00	93.24978168437598	13.624709303062923	0.981564942335897	6353	1005.5898836049005	274.8822891574282	E101	No
E2	2021-01-01 05:00:00	98.67215743879962	5.411725042401165	0.8608806884693428	4178	673.9673803025875	336.4441924091283	E103	Yes
E4	2021-01-01 06:00:00	106.19801063322814	11.302418691684707	1.0036259741693592	5505	754.2897797151813	286.7264528835452	E103	Yes
E3	2021-01-01 07:00:00	117.91168461209915	7.739007100995543	0.9185594438641833	4711	1046.977145238691	130.58599596848325	None	No
E5	2021-01-01 08:00:00	101.71000438165794	8.445306688475764	1.0697372824134448	8366	796.5749639627547	262.46252692891017	E102	No
E1	2021-01-01 09:00:00	82.74328648412636	12.231876908246157	0.8262570762334657	6734	911.4942305358248	218.80060993016372	None	No
E1	2021-01-01 10:00:00	101.60658540348122	12.67890603309585	1.0115855697893075	6107	783.6202009559677	284.7682933330314	E101	No
E5	2021-01-01 11:00:00	91.41014679369958	6.465132697221701	1.0365651445709363	3704	998.7853973561373	266.18127567819505	E102	No
E3	2021-01-01 12:00:00	97.9357905767452	10.848824917656628	0.9926076534352546	3380	868.2650419894333	271.71434304190313	None	No
E2	2021-01-01 13:00:00	104.88426467452614	12.178618090209227	0.950648242874944	5262	831.939378805927	277.94492142516737	E102	No
E1	2021-01-01 14:00:00	91.61669034467895	9.231628638003755	1.3101530584096652	5718	938.7569928400668	292.13617856075945	None	No
E2	2021-01-01 15:00:00	103.81163744435374	11.264402828320911	1.0858754152991918	128	743.53201157567	319.64883477499995	E101	Yes
E2	2021-01-01 16:00:00	90.09096717842417	8.900688198240355	0.8845224472593048	1534	916.7866494934675	268.3775591708601	E103	No
E1	2021-01-01 17:00:00	110.17880049717284	11.042251479017873	1.0941834338174454	3003	985.1527753702076	155.0415945248736	E102	Yes

Data Cleaning

We filtered out rows where the ‘Error Codes’ column is ‘None’. This is done to ensure that the model is not trained on incomplete or potentially misleading data. Data cleaning is a crucial step in any machine learning pipeline as the quality of the data directly impacts the performance of the model.

```
df_no_none = df.filter(df['Error Codes'] != 'None')

df_no_none.display()
```

Feature Engineering

We performed several transformations on the data to prepare it for the machine learning model:

- The ‘Timestamp’ column is converted to a timestamp data type. This allows for more granular time-based analysis and feature extraction. Time-based features can often capture patterns and trends that are not immediately apparent in the raw data.

- The hour and day of the week are extracted from the ‘Timestamp’ column and added as new features. These could potentially capture patterns related to the time of day or day of the week. For example, certain types of maintenance issues

might be more likely to occur at specific times of the day or on specific days of the week.

```
from pyspark.sql import SparkSession
from pyspark.ml import Pipeline
from pyspark.ml.classification import RandomForestClassifier
from pyspark.ml.feature import VectorAssembler, StringIndexer, OneHotEncoder
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
from pyspark.sql.functions import to_timestamp, hour, dayofweek, when
from pyspark.sql.types import FloatType
```

All the libraries used for this project are as in the above screenshot.

```
df = df.withColumn('Timestamp', to_timestamp(df['Timestamp']))
df = df.withColumn('Hour', hour(df['Timestamp']))
df = df.withColumn('DayOfWeek', dayofweek(df['Timestamp']))

num_cols = ['Temperature', 'Pressure', 'Vibration', 'Engine Hours', 'RPM', 'Fuel Consumption']
for col in num_cols:
    df = df.withColumn(col, df[col].cast(FloatType()))

df = df.withColumn('Maintenance Required', when(df['Maintenance Required'] == 'Yes', 1).otherwise(0))

indexer_engine_id = StringIndexer(inputCol="Engine ID", outputCol="EngineIDIndex")
encoder_engine_id = OneHotEncoder(inputCol="EngineIDIndex", outputCol="EngineIDVec")

indexer_error_codes = StringIndexer(inputCol="Error Codes", outputCol="ErrorCodesIndex")
encoder_error_codes = OneHotEncoder(inputCol="ErrorCodesIndex", outputCol="ErrorCodesVec")
```

- Numerical columns are cast to float data type to ensure compatibility with the machine learning algorithms. Machine learning algorithms typically require numerical input, and casting the columns to float ensures that all numerical data is in a suitable format.

- The ‘Maintenance Required’ column is converted to binary (1 for ‘Yes’, 0 for ‘No’). This is the target variable that the model will predict. Converting it to binary format simplifies the problem to a binary classification task, which is easier to model and evaluate.

- Categorical columns (‘Engine ID’ and ‘Error Codes’) are converted to numerical form using StringIndexer and OneHotEncoder. This is necessary because

machine learning algorithms typically require numerical input. The StringIndexer assigns a unique index to each category, and the OneHotEncoder converts this index to a binary vector. This preserves the categorical information in a format that the algorithm can process.

Model Building

RandomForestClassifier model is used for this project. Random forests are a popular choice for classification tasks due to their robustness and ability to model complex patterns. They work by constructing a multitude of decision trees during training and outputting the class that is the mode of the classes of the individual trees.

```
features = ['EngineIDVec', 'Temperature', 'Pressure', 'Vibration', 'Engine Hours', 'RPM', 'Fuel Consumption', 'Hour', 'DayOfWeek', 'ErrorCodesVec']

target = 'Maintenance Required'

assembler = VectorAssembler(inputCols=features, outputCol="features")

rf = RandomForestClassifier(labelCol=target, featuresCol="features")

pipeline = Pipeline(stages=[indexer_engine_id, encoder_engine_id, indexer_error_codes, encoder_error_codes, assembler, rf])
```

The features used for the model are assembled using VectorAssembler. This creates a single vector column that combines all input features. This is a requirement for Spark's machine learning algorithms.

Hyperparameter Tuning

We also use CrossValidator with a ParamGridBuilder to perform hyperparameter tuning on the RandomForestClassifier. Hyperparameter tuning is the process of finding the optimal set of parameters for a machine learning model. The parameters tuned are the number of trees, the maximum depth of the trees, and the impurity measure used. This is done to find the best combination of parameters that produces the most accurate model.

```
paramGrid = ParamGridBuilder() \
    .addGrid(rf.numTrees, [10, 20, 100]) \
    .addGrid(rf.maxDepth, [5, 10, 15]) \
    .addGrid(rf.impurity, ["gini", "entropy"]) \
    .build()

crossval = CrossValidator(estimator=pipeline,
                          estimatorParamMaps=paramGrid,
                          evaluator=MulticlassClassificationEvaluator(labelCol=target, predictionCol="prediction", metricName="accuracy"),
                          numFolds=10)
```

Model Training and Evaluation

We split the data into training and testing sets, fit the model on the training data, and make predictions on the test data. Splitting the data ensures that the model's performance is evaluated on unseen data, providing a more realistic estimate of its performance.

Then we evaluated the model's performance using accuracy and F1 score. Accuracy is the proportion of correct predictions out of all predictions made, while the F1 score is the harmonic mean of precision and recall. These metrics provide a quantitative measure of the model's ability to correctly predict whether maintenance is required.

```
train_data, test_data = df.randomSplit([0.8, 0.2])

cvModel = crossval.fit(train_data)

predictions = cvModel.transform(test_data)

evaluator = MulticlassClassificationEvaluator(
    labelCol=target, predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)

evaluator_f1 = MulticlassClassificationEvaluator(
    labelCol=target, predictionCol="prediction", metricName="f1")
f1 = evaluator_f1.evaluate(predictions)

print(f"Test Accuracy = {accuracy}")
print(f"F1 Score = {f1}")
```

RESULT

Following F1 score and accuracy have been obtained, although the accuracy is not bad, we have tried tuning the hyperparameters, for example, we increased the tree depth, cross validation folds to 10. Initial accuracy and F1 score were below 60 and 0.61 respectively, to be precise they were 55 & 0.54, by tuning hyperparameters we were able to increase the model accuracy and F1 score. The model accuracy indicates how correctly the model predicts the target variable.

```
Test Accuracy = 0.5294117647058824
F1 Score = 0.5294117647058824
+---------+--------------------+--------------------+----------+
|Engine ID|            features|Maintenance Required|prediction|
+---------+--------------------+--------------------+----------+
|       E1|[1.0,0.0,0.0,0.0,...|                   1|       1.0|
|       E1|[1.0,0.0,0.0,0.0,...|                   0|       1.0|
|       E2|[0.0,0.0,0.0,1.0,...|                   1|       1.0|
|       E2|[0.0,0.0,0.0,1.0,...|                   0|       1.0|
|       E2|[0.0,0.0,0.0,1.0,...|                   1|       0.0|
|       E2|[0.0,0.0,0.0,1.0,...|                   0|       0.0|
|       E2|[0.0,0.0,0.0,1.0,...|                   0|       0.0|
|       E3|(15,[4,5,6,7,8,9,...|                   1|       0.0|
|       E3|(15,[4,5,6,7,8,9,...|                   0|       1.0|
|       E3|[0.0,0.0,0.0,0.0,...|                   1|       1.0|
|       E4|[0.0,1.0,0.0,0.0,...|                   0|       0.0|
|       E4|[0.0,1.0,0.0,0.0,...|                   1|       1.0|
|       E4|[0.0,1.0,0.0,0.0,...|                   1|       1.0|
|       E4|[0.0,1.0,0.0,0.0,...|                   0|       1.0|
|       E5|[0.0,0.0,1.0,0.0,...|                   1|       0.0|
|       E5|[0.0,0.0,1.0,0.0,...|                   0|       0.0|
```

CONCLUSION

This project is a comprehensive pipeline for predictive maintenance using machine learning. It demonstrates the power of PySpark in handling big data and building robust machine learning models. The script is well-structured and modular, making it easy to understand and modify for different predictive maintenance tasks.