

To,

IITD-AIA Foundation on Smart Manufacturing

Subject: Weekly Progress Report for Week-6th

Respected sir,

Following is the required progress report to the best of my knowledge considering relevant topics to be covered:

1. *Linear Regression Implimentastion .*

2. *Logistic Regression for classification .*

3. *Support Vector Machines.*

4. *Decision tree classification.*

5. *Ensemble Learning.*

6. *Model Selection Techniques.*

Day wise work done explanati on of the week.

Day 11, July

Explored on Linear Regression implimentastion

Code:

```
import numpy as np
```

```
import pandas as pd import os
```

```
from sklearn.linear_model import LinearRegression
```

```
from sklearn.preprocessing import OneHotEncoder, StandardScaler
```

```
import warnings
```

```
import matplotlib.pyplot as plt
```

```
%matplotlib inline
```

```
for dirname,filenames in os.walk('/kaggle/input'):
```

```
    for filename in filenames:
```

```
        print (os.path.join(dirname, filename))
```

```
data = pd.read_csv("C:\Users\Nandan\Desktop\fsm\AC-Piston-Checks-main\data\de
```

```
data.head()
```

```
data.shape
```

```
print(data["image_path"].unique())
```

```
print(data['target'].unique())
```

```
##check missing or null values
```

```
data.isnull().sum()
```

```
data.describe() data.head()
```

```
import seaborn as sns
```

```
sns.pairplot(data)
```

```
numeric_data = data.select_dtypes (include=[np.number])
```

```
# Calculate the correlation matrix
```

```
corrmat = numeric_data.corr()
```

```
top_corr_features = corrmat. index
```

```
plt.figure(figsize=(5, 5))
```

```
# Plot heat map
```

```
g= sns.heatmap(numeric_data[top_corr_features].corr(), annot=True, cmap="RdY1Gn")
```

```
plt.show()
```

Reference:

<https://www.kaggle.com/s/1517530>

<https://www.youtube.com/watch?v=nOYW31rrkig&pp=ygUnaW5kZXBlbmRlbnQgYW5kIGRlcGVuZGVudCBmZWFOdXJlIGluIG1s>

Day 12 , July

Logistic Regression for classification

Steps:

It predicts categories based on given features.

The algorithm learns from data to calculate probabilities of category membership.

It uses a sigmoid function to model the relationship between features and probabilities.

During training, the algorithm adjusts parameters to minimize prediction errors.

The trained model can be used to classify new instances by applying a threshold to probabilities.

Evaluation metrics like accuracy, precision, and recall can assess the model's performance.

Logistic regression can handle binary classification and can be extended to multi-class problems

Reference:

<https://www.kaggle.com/code/faressayah/logistic-regression-for-binary-classification-task>

[https://www.youtube.com/watch?](https://www.youtube.com/watch?v=zM4VZR0px8E&pp=ygUmTG9naXN0aWMgUmVncmVzc2lvbiBmb3IgY2xhc3NpZmljYXRpb24%3D)

[v=zM4VZR0px8E&pp=ygUmTG9naXN0aWMgUmVncmVzc2lvbiBmb3IgY2xhc3NpZmljYXRpb24%3D](https://www.youtube.com/watch?v=zM4VZR0px8E&pp=ygUmTG9naXN0aWMgUmVncmVzc2lvbiBmb3IgY2xhc3NpZmljYXRpb24%3D)

Day 13, July

Support Vector Machines

Steps:

1. Preprocess the Data.

2. Split the Data into training and testing sets.
3. Choose the SVM type (classification or regression).
4. Select a kernel function (linear, polynomial, RBF, sigmoid, etc.).
5. Train the SVM model.
6. Tune the hyperparameters.
7. Evaluate the model's performance.
8. Make predictions on new data.

Reference:

<https://www.kaggle.com/discussions/getting-started/124508>

https://www.youtube.com/watch?v=5pZ-_MSM0rU&pp=ygUwIFN1cHBvcnQgIFN1cHBvcnQgVmVjdG9yIE1hY2hpbmVzVmVjdG9yIE1hY2hpbmVz

Day 14 ,july

Decision tree classification .

It splits the data based on feature values and assigns class labels to the resulting leaf nodes.

Steps:

- 1 Data preparation
- 2 Feature selection
- 3 Tree construction
- 4 Stopping criteria
- 5 Pruning (optional)
- 6 Prediction
- 7 Evaluation

Example code for decision tree classification

using Python's scikit-learn library:

```
# Import the necessary libraries
```

```
from sklearn.datasets import load_iris
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.metrics import accuracy_score
```

```
# Load the dataset
```

```
iris = load_iris()
```

```
X = iris.data
```

```
y = iris.target
```

```
# Split the dataset 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)
```

```
# Create an instance of the DecisionTreeClassifier
```

```
clf = DecisionTreeClassifier()
```

```
# Train the classifier using the training data
```

```
clf.fit(X_train, y_train)
```

```
# Make predictions on the testing data
```

```
y_pred = clf.predict(X_test)
```

```
# Calculate the accuracy of the model
```

```
accuracy = accuracy_score(y_test, y_pred)
```

```
print("Accuracy:", accuracy)
```

Reference:

<https://www.youtube.com/watch?v=ynTCUngbFHA&pp=ygUcRGVjaXNpb24gdHJlZSBjbGFzc2lmaWNhdGlvbg%3D%3D>

<https://www.kaggle.com/rishidamarla/decision-tree-classification>

Day 15 , July :

Ensemble Learning.

Ensemble learning combines multiple models to improve prediction accuracy and robustness. It trains different models, combines their predictions, and produces a more accurate final result

Steps :

1. Train multiple models (base learners).
2. Combine their predictions.
3. Obtain the final ensemble prediction.
4. Achieve improved accuracy and robustness

2) Ensemble Techniques

-
- 2.1 Max Voting / Voting Classifier
-
- 2.2 Averaging
-
- 2.3 Weighted Averaging
-
- 2.4 Stacking
-
- 2.5 Blending

-
- 2.6 Bagging
-
- 2.7 Boosting

Reference:

<https://www.kaggle.com/code/pavansanagapati/ensemble-learning-techniques-tutorial>

<https://www.youtube.com/watch?v=KIOeZ5cFZ50&pp=ygURRW5zZW1ibGUgTGVhcm5pbmc%3D>

Day 16 , July ;

Model Selection Techniques .

These techniques help in determining which model will likely generalize well to new, unseen data.

Steps :

Define the problem and evaluation criteria. Preprocess data and engineer features. Select candidate models. Split data into training, validation, and test sets. Train and evaluate models on training and validation sets. Compare model performance using metrics. Select best-performing model. Assess selected model using test set.

Reference:

https://medium.com/international-school-of-ai-data-science/use-these-methods-to-select-features-for-ml-model-1450e068ebdc?source=search_post-----0-----

<https://www.kaggle.com/code/apapiu/regularized-linear-models>

<https://www.youtube.com/watch?v=yN7ypxC7838&pp=ygUbIG1vZGVsIHNIbGVjdGlvb0ZWNobmlxdWVz>