*****************BUILD PROJECT TIMELINE ANALYSIS***************** Analyze project timelines and cost-impacting variables to improve forecasting for new asset deployments in the RAN network. End-2-End Code

LOADING THE DATA TO THE ENVIRONMENT Relative path is used for loading the data for the ease of running the code on different systems.

```
##################### LOADING ALL THE NECESSARY PACKAGES
#####################
import os
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import warnings
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
warnings.filterwarnings("ignore")
directory = "./SiteTracker Projecttracker milestones"
##ADD RELATIVE FILEPATH
main_df = pd.read_csv(os.path.join(directory, os.listdir(directory)
[0]))
names = main_df.columns

for filename in os.listdir(directory)[1:]:
    if filename.endswith('.csv'):
        file_path = os.path.join(directory, filename)
        df = pd.read_csv(file_path,header = None,names = names)
        main_df = pd.concat([main_df,df], ignore_index=True)

print(main_df.shape)
```

```
(783343, 152)
```

DATA FILTERATION The data is filtered based on the internal meetings

Step-1 Counting the row-wise Null values for each project that is duplicated

Step-2 Consider the project that has least null values so that all the necessary data is gained

Step-3 Applying necessary filterations like Milestone_Achieved = MS13 to get all the Milestone dates, Project_Scope = In-Scope and Tech_TTO_A not equal to absurd dates

Step-4 Drop all the unnecessary columns based on the meeting

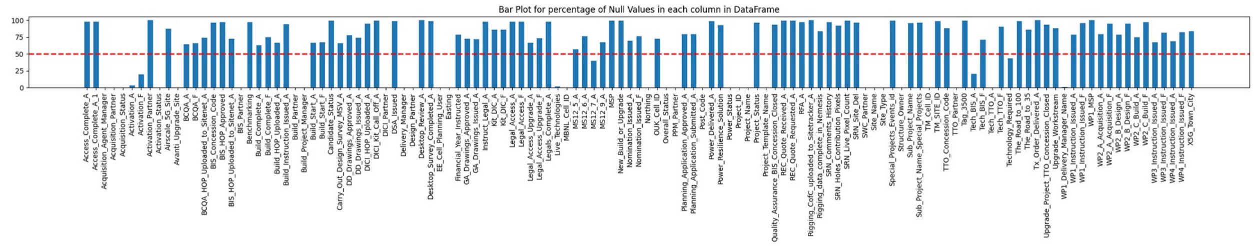
```
dupdf = main_df

dupdf['UPDATED_DATE'] =
pd.to_datetime(dupdf['UPDATED_DATE'],format='mixed',dayfirst = True)
df_sorted = dupdf.sort_values(by=['Project_ID', 'UPDATED_DATE'],
ascending=[True, False])

# Creating a new column to count non-null values across all columns
df_sorted['non_null_count'] = df_sorted.notnull().sum(axis=1)

# Sort by ProjectID and then by non_null_count to prioritize rows with
the most filled data
df_sorted = df_sorted.sort_values(by=['Project_ID', 'non_null_count'],
ascending=[True, False])

# Drop duplicates based on ProjectID, keeping the row with the most
non-null values
df_cleaned = df_sorted.drop_duplicates(subset=['Project_ID'],
keep='first')

# Drop the helper column used for counting non-null values
df_cleaned = df_cleaned[(df_cleaned['Milestone_Achieved'] == 'MS13') &
(df_cleaned['Project_Scope'] == 'In Scope') &
(df_cleaned['Tech_TTO_A'] != '1900-01-01')]

# Dropping all the columns that were discussed in the meeting
drop_columns =
['non_null_count','UPDATED_DATE','Created_Date','Upgrade_Project','Par
ent_Project','Milestone_Achieved','BT_Project','Project_Scope','Out_of
_Scope_Reason','Out_of_Scope_Comments','Date_Removed_from_Scope','TM_C
ell_ID_dup','SRN_Upgrade_Type','Created_Date','NTQ','Quality_Assurance
','Upgrade_Project_Name']
df_cleaned = df_cleaned.drop(columns=drop_columns)

# Drop all the empty columns
df_cleaned = df_cleaned.dropna(axis=1, how='all')
df_cleaned = df_cleaned.reset_index(drop=True)

cleaned_data = df_cleaned.copy()

cleaned_data.replace('01/01/1900', np.nan, inplace=True)
cleaned_data.replace('01/01/2999', np.nan, inplace=True)
cleaned_data.replace('2999-01-01', np.nan, inplace=True)
cleaned_data.replace('2999-12-31', np.nan, inplace=True)

cols_A = [col for col in cleaned_data.columns if col.endswith('_A')]
```

```
cols_F = [col for col in cleaned_data.columns if col.endswith('_F')]
common_cols = set([col[:-2] for col in cols_A]).intersection([col[:-2]
for col in cols_F])
selected_columns = [col for col in cleaned_data.columns if col[:-2] in
common_cols and (col.endswith('_A') or col.endswith('_F'))]

for col in selected_columns:
     cleaned_data[col] = pd.to_datetime(cleaned_data[col],format =
'mixed', dayfirst = True)
```

NULL DATA ANALYSIS This method takes a dataframe as input and returns the percentage of null values in each column so that the column with more null values can be further investigated and remove if necessary

```
# NULL DATA ANALYSIS
def get_null_data(df):
  null_data = {
      'Column': [],
      'Total Values': [],
      'Null Values': [],
      'Percentage of Null Values': []
  }

  for column in df.columns:
      total_values = len(df[column])  # Total length of the column
      null_values = df[column].isnull().sum()  # Number of null values
in the column
      percentage_null = (null_values / total_values) * 100  #
Percentage of null values

      # Append results to the data dictionary
      null_data['Column'].append(column)
      null_data['Total Values'].append(total_values)
      null_data['Null Values'].append(null_values)
      null_data['Percentage of Null Values'].append(percentage_null)

  # Create DataFrame from the collected data
  null_df = pd.DataFrame(null_data)

  return null_df
null_df = get_null_data(cleaned_data)
null_df = null_df.sort_values(by='Column')
plt.figure(figsize=(25, 5))
plt.bar(null_df['Column'],null_df['Percentage of Null Values'], width
= 0.6)
plt.title('Bar Plot for percentage of Null Values in each column in
DataFrame')
plt.xticks(rotation=90)
plt.axhline(y=50, color='red', linestyle='--', linewidth=2)
```

```
plt.tight_layout()
plt.show()
```



FEATURE SELECTION XGBoost is used for feature selection process.

All the "Selected columns" from the previous step including categorical variables are given as input for this model and the target column is Tech_TTO_A.

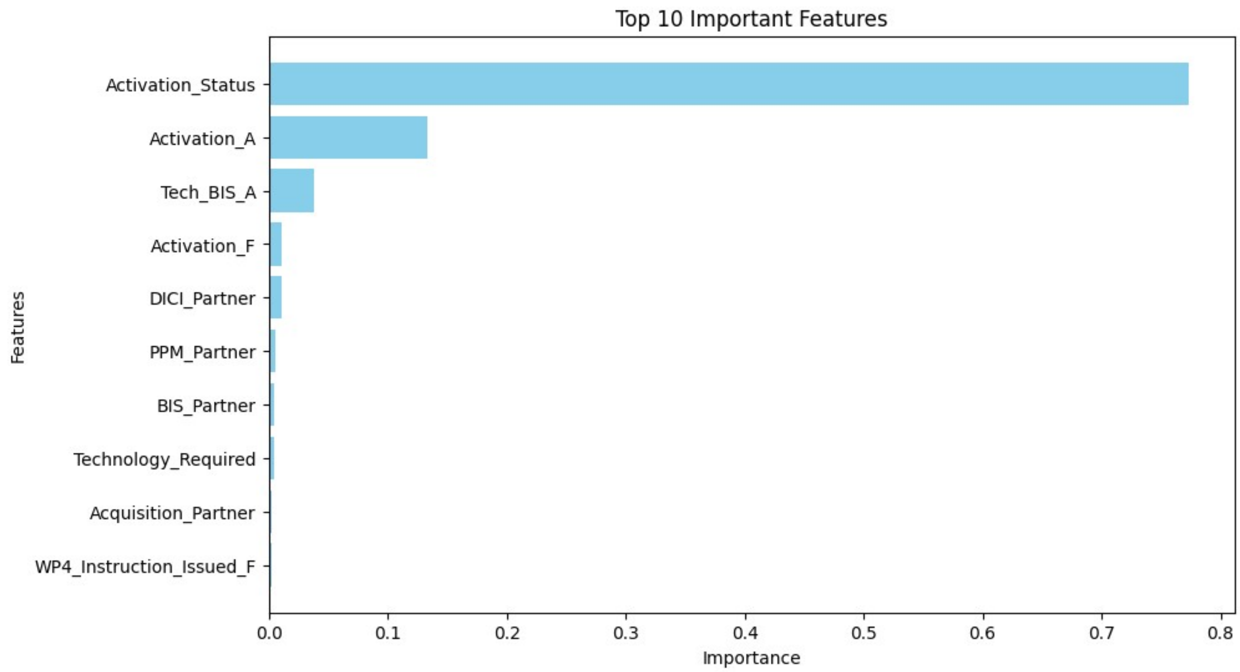
The below code shows top10 important features. Change "topN" to see top n features.

```
### Feature Selection with XG Boost
import pandas as pd
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score

df_fs = cleaned_data.copy()
df_fs = df_fs[selected_columns +
['PPM_Partner','BIS_Partner','Activation_Status','Technology_Required'
,'DICI_Partner','Acquisition_Partner','Build_Partner']]
for col in selected_columns:
    df_fs[col] = pd.to_datetime(df_fs[col])
    df_fs[col] = df_fs[col].astype('int64') // 10**9
categorical_columns = df_fs.select_dtypes(include=['object']).columns
label_encoder = LabelEncoder()
for col in categorical_columns:
  df_fs[col] = label_encoder.fit_transform(df_fs[col].astype(str))

df_fs = df_fs.fillna(df_fs.median())
#df_cleaned.dtypes

X = df_fs.drop(columns=['Tech_TTO_A'])
y = df_fs['Tech_TTO_A']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

xgb_model = xgb.XGBRegressor(objective='reg:squarederror',
random_state=42)
```

```python
xgb_model.fit(X_train, y_train)

importance = xgb_model.feature_importances_

feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importance
})

feature_importance_df =
feature_importance_df.sort_values(by='Importance', ascending=False)
topN = 10

print("Top features based on importance:")
print(feature_importance_df.head(topN))  # Display the top N features


plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'].head(topN),
feature_importance_df['Importance'].head(topN), color='skyblue')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.title('Top {a} Important Features'.format(a=topN))
plt.gca().invert_yaxis()
plt.show()

top_features = feature_importance_df['Feature'].head(topN)

X_train_top = X_train[top_features]
X_test_top = X_test[top_features]

xgb_model.fit(X_train_top, y_train)

y_pred = xgb_model.predict(X_test_top)

mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"MAE Score with top features: {mae:.4f}")
print(f"R2 Score with top features: {r2:.4f}")
```

```
Top features based on importance:
                     Feature  Importance
33         Activation_Status    0.772935
13              Activation_A    0.133094
15                 Tech_BIS_A    0.037582
12              Activation_F    0.010662
35              DICI_Partner    0.010472
31               PPM_Partner    0.005227
32               BIS_Partner    0.004443
34       Technology_Required    0.004099
```

```
36        Acquisition_Partner    0.002613
30  WP4_Instruction_Issued_F    0.002364
```




```
MAE Score with top features: 2193342.3200
R2 Score with top features: 0.8537
```

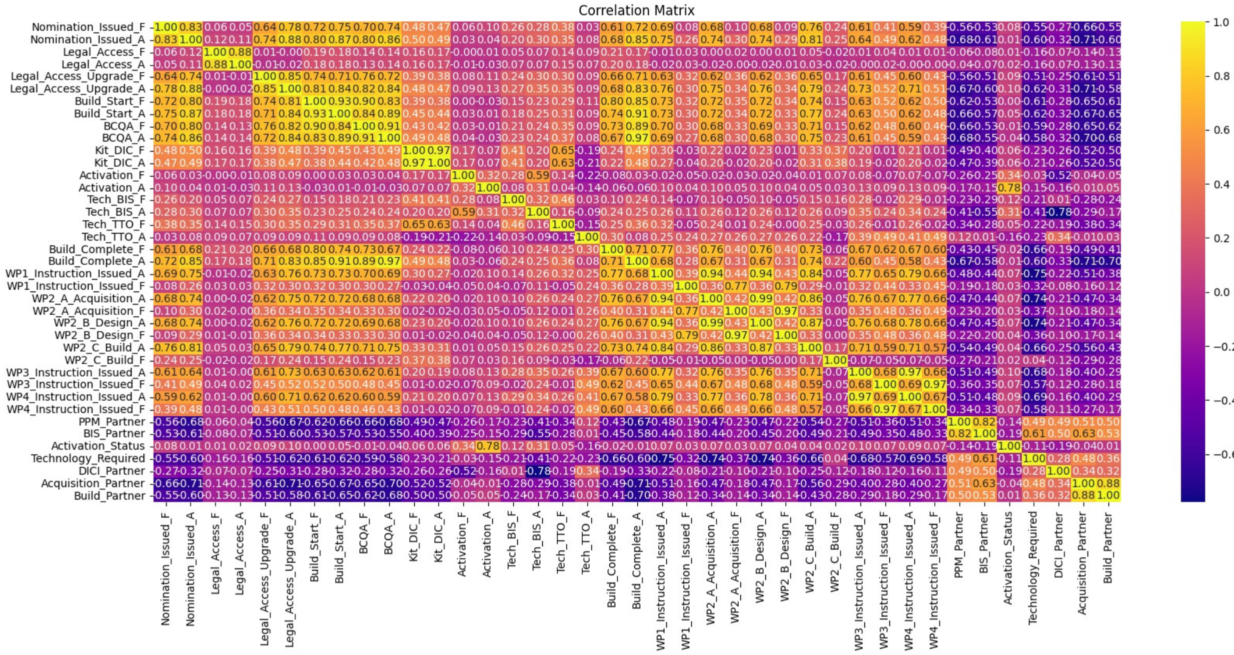
Correlation Matrix The below code shows correlation matrix where all the milestone columns are fed.

From the heatmap, we can select the collinear columns and remove them based on further investigation and analysis.

```
### CORRELATION MATRIX

cor_matrix = df_fs.corr()

corr_matrix_abs = cor_matrix.abs()

mask = np.triu(np.ones(cor_matrix.shape), k=1)

high_corr = corr_matrix_abs.where(mask == 1)

threshold = 0.8
high_corr_pairs = high_corr.stack().loc[lambda x: x > threshold]

print(high_corr_pairs)

plt.figure(figsize=(20, 8))
sns.heatmap(cor_matrix, annot=True, cmap='plasma', fmt=".2f")
```

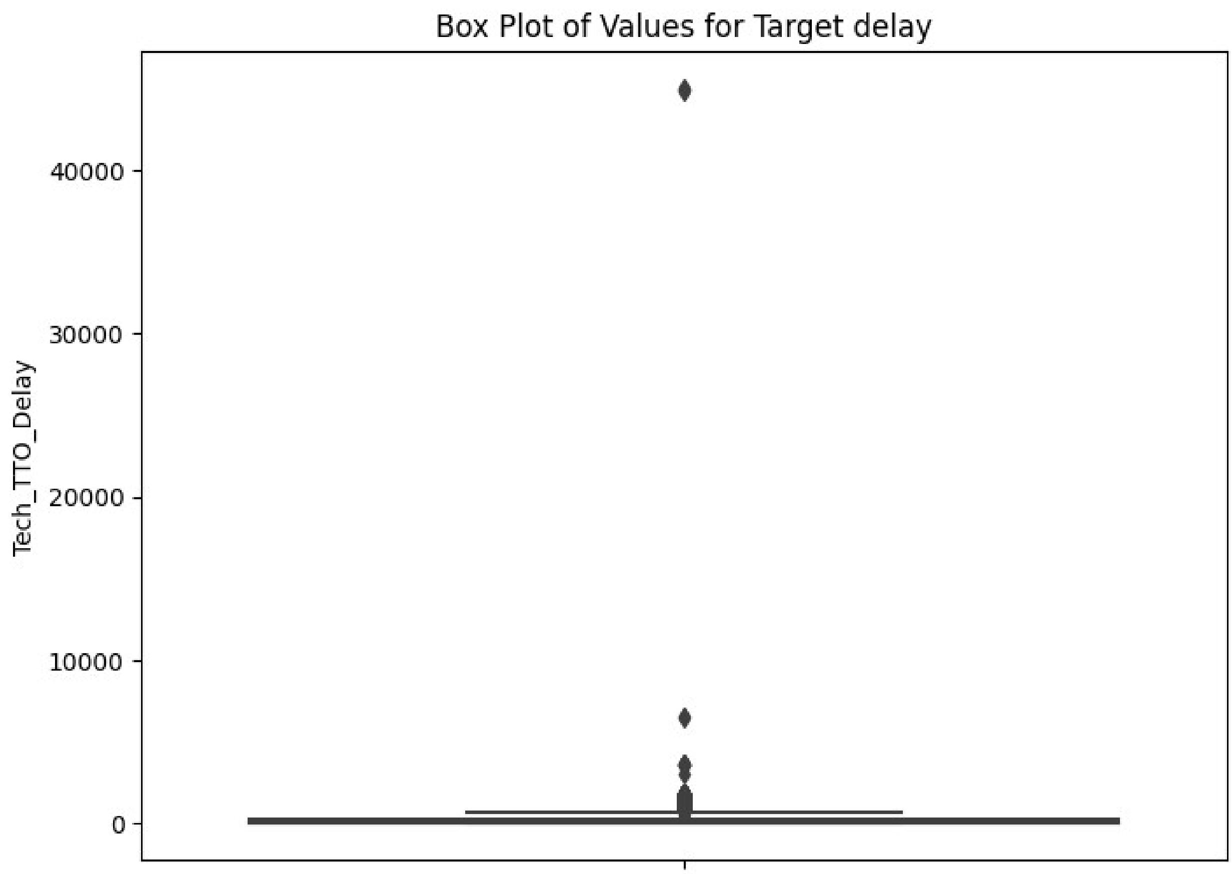
```
plt.title('Correlation Matrix')
plt.show()
```

```
Nomination_Issued_F        Nomination_Issued_A          0.831080
Nomination_Issued_A        Legal_Access_Upgrade_A       0.877028
                           Build_Start_A                0.865084
                           BCQA_F                       0.801441
                           BCQA_A                       0.855407
                           Build_Complete_A             0.845394
                           WP2_C_Build_A                0.812362
Legal_Access_F             Legal_Access_A               0.881715
Legal_Access_Upgrade_F     Legal_Access_Upgrade_A       0.851506
Legal_Access_Upgrade_A     Build_Start_F                0.806111
                           Build_Start_A                0.844338
                           BCQA_F                       0.819077
                           BCQA_A                       0.844709
                           Build_Complete_A             0.831378
Build_Start_F              Build_Start_A                0.930506
                           BCQA_F                       0.898995
                           BCQA_A                       0.826055
                           Build_Complete_A             0.852783
Build_Start_A              BCQA_F                       0.843084
                           BCQA_A                       0.889632
                           Build_Complete_A             0.914929
BCQA_F                     BCQA_A                       0.906088
                           Build_Complete_A             0.893640
BCQA_A                     Build_Complete_A             0.970438
Kit_DIC_F                  Kit_DIC_A                    0.972622
WP1_Instruction_Issued_A   WP2_A_Acquisition_A          0.935774
                           WP2_B_Design_A               0.936958
                           WP2_C_Build_A                0.844875
WP2_A_Acquisition_A        WP2_B_Design_A               0.985589
                           WP2_C_Build_A                0.862377
WP2_A_Acquisition_F        WP2_B_Design_F               0.974645
WP2_B_Design_A             WP2_C_Build_A                0.871061
WP3_Instruction_Issued_A   WP4_Instruction_Issued_A     0.967197
WP3_Instruction_Issued_F   WP4_Instruction_Issued_F     0.969228
PPM_Partner                BIS_Partner                  0.821889
Acquisition_Partner        Build_Partner                0.877050
dtype: float64
```



TARGET COLUMN ANALYSIS The target column is selected and the descriptive statistics is analysed to know the variability for handling it efficiently.

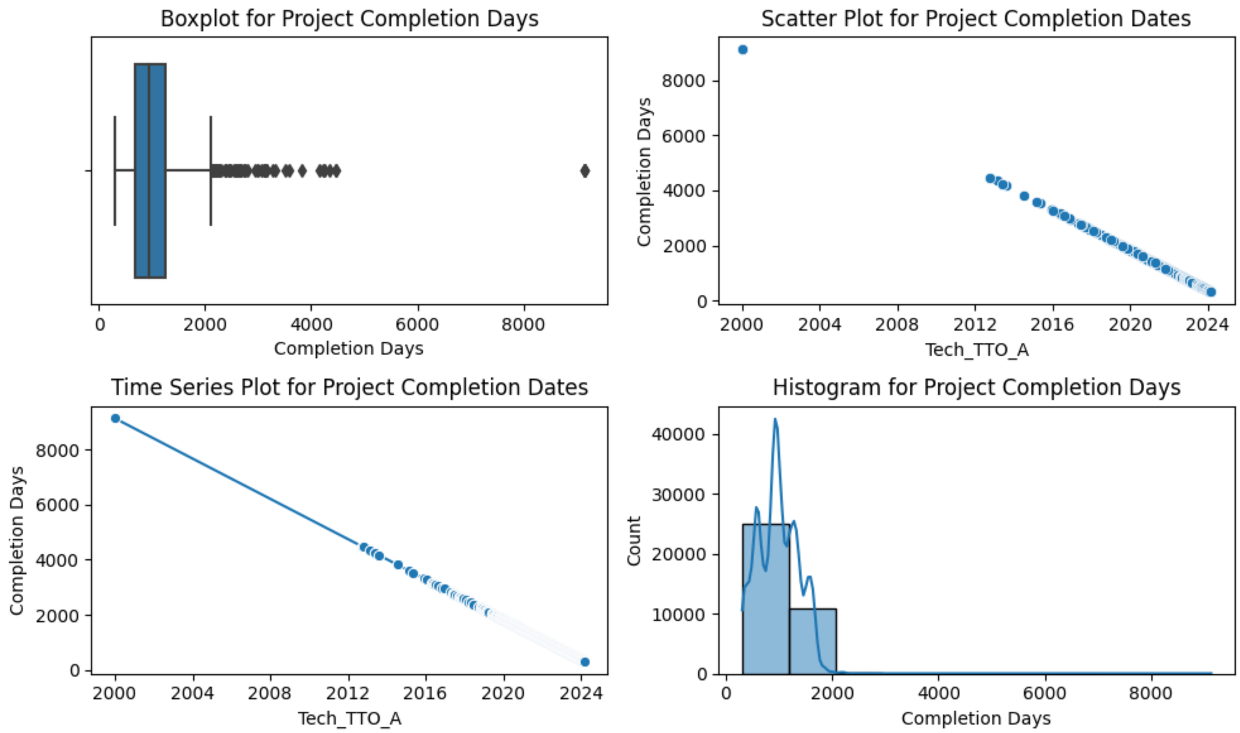
```
### Target Column Analysis
eda_target = cleaned_data[['Project_ID','Tech_TTO_A','Tech_TTO_F']]
eda_target = eda_target.dropna().reset_index(drop=True)
eda_target['Tech_TTO_Delay'] = (eda_target['Tech_TTO_A'] -
eda_target['Tech_TTO_F']).dt.days.abs()
print(eda_target.Tech_TTO_Delay.describe())
plt.figure(figsize=(8, 6))
sns.boxplot(y='Tech_TTO_Delay', data=eda_target)
plt.title('Box Plot of Values for Target delay')
plt.show()

count     3557.000000
mean       329.525162
std       1590.642618
min          0.000000
25%          3.000000
50%          9.000000
75%        252.000000
max      45054.000000
Name: Tech_TTO_Delay, dtype: float64
```



Outlier Analysis Here a reference data is used to get the number of days from project completion date from the start date of the project.

```
### Outlier Detection Analysis
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

ref_date = 'Activation_A'
cleaned_data['Completion Days'] = (cleaned_data['Tech_TTO_A'] -
cleaned_data[ref_date]).dt.days.abs()

fig, axes = plt.subplots(2, 2, figsize=(10, 6))

# Plot 1: Boxplot
sns.boxplot(x=cleaned_data['Completion Days'], ax=axes[0, 0])
axes[0, 0].set_title('Boxplot for Project Completion Days')

# Plot 2: Scatter plot
sns.scatterplot(x=cleaned_data['Tech_TTO_A'],
y=cleaned_data['Completion Days'], ax=axes[0, 1])
axes[0, 1].set_title('Scatter Plot for Project Completion Dates')
```

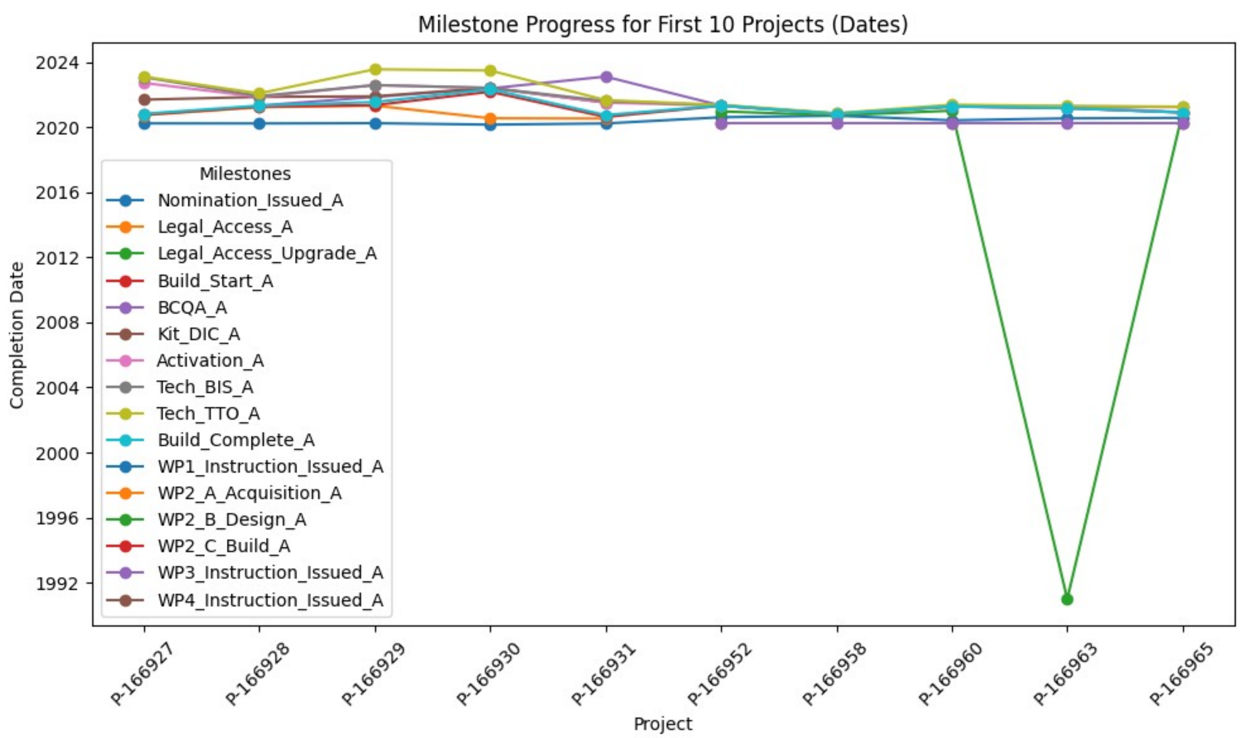
```
# Plot 3: Time series plot
sns.lineplot(x=cleaned_data['Tech_TTO_A'], y=cleaned_data['Completion
Days'], marker='o', ax=axes[1, 0])
axes[1, 0].set_title('Time Series Plot for Project Completion Dates')

# Plot 4: Histogram
sns.histplot(cleaned_data['Completion Days'], bins=10, ax=axes[1,
1],kde = True)
axes[1, 1].set_title('Histogram for Project Completion Days')

plt.tight_layout()
plt.show()
```



MILESTONE ANALYSIS All the milestone's actual dates are used for this analysis to know if there are any patters or trend during each milestone's completion.

```
### Milestone Analysis
mile_analysis = [item for item in selected_columns if
item.endswith('_A')]
mile_analysis.append('Project_ID')
mile_analysis = cleaned_data[mile_analysis].head(10)
mile_analysis.set_index('Project_ID', inplace=True)
plt.figure(figsize=(10, 6))

# Iterate over each milestone and plot it
for milestone in mile_analysis.columns:
```

```
    plt.plot(mile_analysis.index, mile_analysis[milestone],
marker='o', label=milestone)

# Add title and labels
plt.title('Milestone Progress for First 10 Projects (Dates)')
plt.xlabel('Project')
plt.ylabel('Completion Date')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45)

# Add legend
plt.legend(title='Milestones')

# Show the plot
plt.tight_layout()
plt.show()
```



NULL HANDLING FUNCTION The below function handle null values efficiently by using IterativeImputer method.

A clip() function is used for maintaining the uniformity of the data where all the dates lie between a defined range.

```
def null_imputer(df):
    reference_date = datetime(1970, 1, 1)
```

```
    for col in df.columns:
        df[col] = df[col].apply(lambda x: (x - reference_date).days if
pd.notna(x) else np.nan)

    imputer = IterativeImputer(max_iter=10, random_state=0)
    df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)

    min_ordinal = (datetime(2000, 1, 1) - reference_date).days
    max_ordinal = (datetime(2025, 1, 1) - reference_date).days

    df = df.clip(lower=min_ordinal, upper=max_ordinal)

    # Convert back to datetime after imputation using pd.to_timedelta
    for col in df.columns:
        df[col] = reference_date + pd.to_timedelta(df[col], unit='D')
    return df
```

****DATA PREPERATION FOR APPROACH 1: MILESTONE BASED DURATION CALCULATION****

Here only the Actual Milestone completion Dates are considered so that they are sorted and subtracted to get the milestone durations.

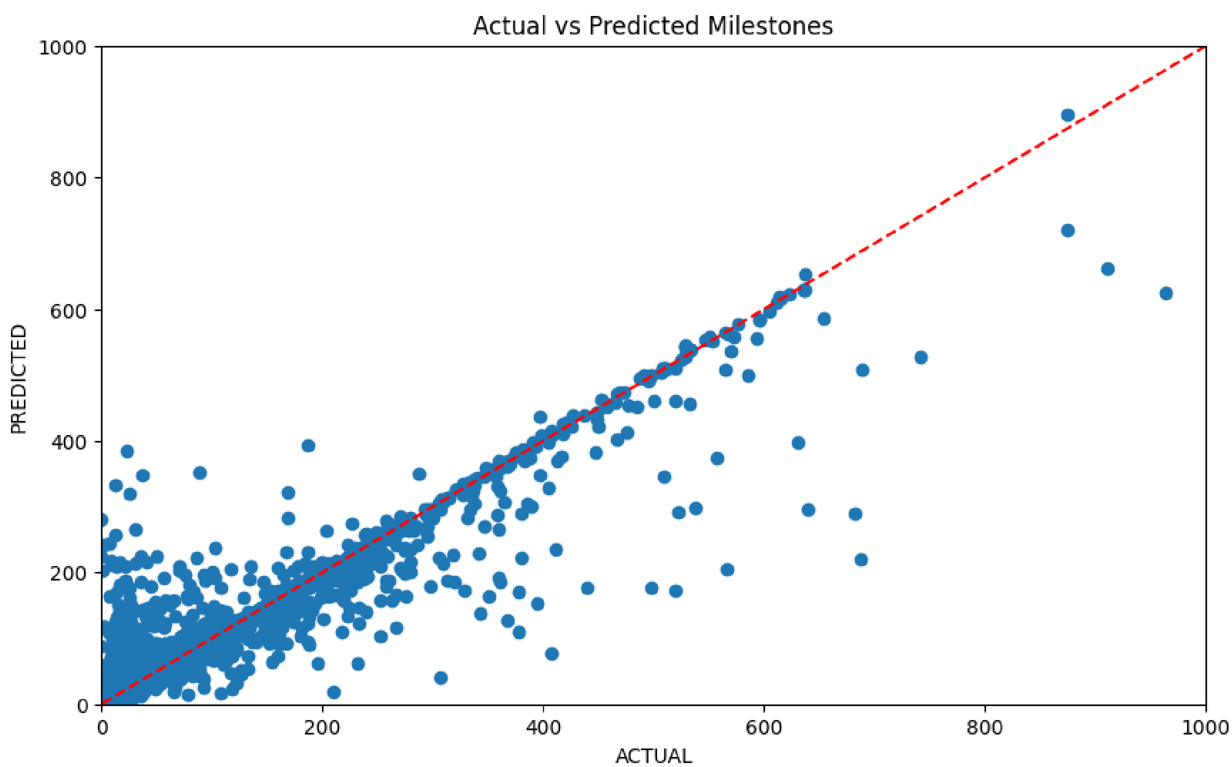
This approach is considered because the milestones are found to be non-sequential.

```
### Data for Approach-1: Milestone Based Duration Calculation
milestone_cols = [item for item in selected_columns if
item.endswith('_A')] ## To get all the Actual Dates Column names
X_milestones = cleaned_data[milestone_cols] ## Get the data from
cleaned Table
X_milestones = null_imputer(X_milestones) ## Null Handling
X_sorted = X_milestones.apply(lambda row: sorted(row), axis=1) ##
Sorting the dates row-wise (horizontally) in ascending order
X_diff = X_sorted.apply(lambda row: [(row[i] - row[i-1]).days for i in
range(1, len(row))]) ## Subtracting Nth date with (N-1)th Date to get
Duration
X_diff = pd.DataFrame(X_diff.tolist(), index=X_milestones.index) ##
Resultant Table with 13 differnces
y = (X_milestones['Tech_TTO_A'] - X_milestones.Activation_A).dt.days
### Total duration of the project is the target column
X_train, X_test, y_train, y_test = train_test_split(X_diff, y,
test_size=0.15, random_state=42) ## Splitting the data with for
training and testing randomly
```

Approach-1: Random Forest Regression Model

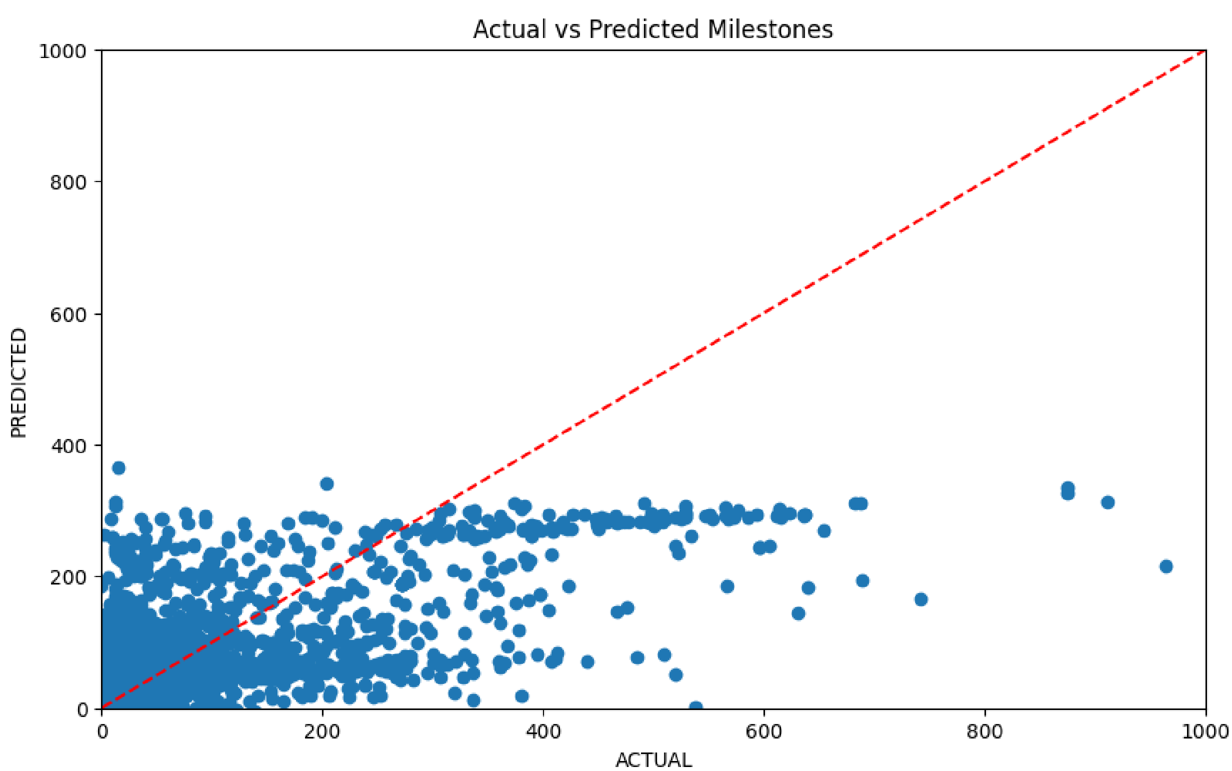
```
#RANDOM FOREST
milestone_model = RandomForestRegressor(n_estimators = 100,
random_state=42)
milestone_model.fit(X_train, y_train)
```

```
per_pred = milestone_model.predict(X_train)
y_pred_days = milestone_model.predict(X_test)
mae_days = mean_absolute_error(y_test, y_pred_days)
print("Mean Absolute Error in days: ", mae_days)
r2 = r2_score(y_test, y_pred_days)
print(f'R² Score: {r2}')

plt.figure(figsize=(10,6))
plt.scatter(y_test,y_pred_days)
min_val = min(min(y_test), min(y_pred_days))  # Get the minimum value
for the diagonal line
max_val = max(max(y_test), max(y_pred_days))  # Get the maximum value
for the diagonal line
plt.plot([min_val, max_val], [min_val, max_val], 'r--', label='Perfect
prediction (y = x)')
plt.title('Actual vs Predicted Milestones')
plt.xlabel('ACTUAL')
plt.ylabel('PREDICTED')
plt.xlim(0,1000)
plt.ylim(0,1000)
plt.show()

Mean Absolute Error in days:  10.325104244229337
R² Score: 0.8100851237775669
```



Approach-1: Linear Regression Model

```
#LINEAR REGRESSION
modellr = LinearRegression()
modellr.fit(X_train, y_train)
y_pred = modellr.predict(X_test)
print("Mean Absolute Error in days: ", mean_absolute_error(y_test,
y_pred))
r2lr = r2_score(y_test, y_pred)
print(f'R² Score: {r2lr}')
plt.figure(figsize=(10,6))
plt.scatter(y_test,y_pred)
min_val = min(min(y_test), min(y_pred))  # Get the minimum value for
the diagonal line
max_val = max(max(y_test), max(y_pred))  # Get the maximum value for
the diagonal line
plt.plot([min_val, max_val], [min_val, max_val], 'r--', label='Perfect
prediction (y = x)')
plt.title('Actual vs Predicted Milestones')
plt.xlabel('ACTUAL')
plt.ylabel('PREDICTED')
plt.xlim(0,1000)
plt.ylim(0,1000)
plt.show()

Mean Absolute Error in days:  46.89827211400531
R² Score: 0.3254888998673142
```



Approach-1: Long Short-Term Memory Model

```
import numpy as np
import pandas as pd
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

df = X_diff
scaler = MinMaxScaler()
scaled_data_X = scaler.fit_transform(df)
scaled_data_y = scaler.fit_transform(y.values.reshape(-1, 1))
X_lstm = scaled_data_X.reshape((scaled_data_X.shape[0], 1,
scaled_data_X.shape[1]))

X_train_lstm, X_test_lstm, y_train_lstm, y_test_lstm =
train_test_split(X_lstm, scaled_data_y, test_size=0.2,
random_state=42)

model = Sequential()
model.add(LSTM(50, activation='relu',
input_shape=(X_train_lstm.shape[1], X_train_lstm.shape[2])))
model.add(Dense(2))

model.compile(optimizer='adam', loss='mean_squared_error')

model.fit(X_train_lstm, y_train_lstm, epochs=100, batch_size=32,
validation_data=(X_test_lstm, y_test_lstm), verbose=2)

predicted_milestone = model.predict(X_test_lstm)
y_pred_original =
scaler.inverse_transform(np.concatenate((X_test_lstm[:, 0, :],
predicted_milestone), axis=1))[:, -1]
y_test_original =
scaler.inverse_transform(np.concatenate((X_test_lstm[:, 0, :],
y_test_lstm.reshape(-1, 1)), axis=1))[:, -1]
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score

mae = mean_absolute_error(y_test_original, y_pred_original)
mse = mean_squared_error(y_test_original, y_pred_original)
rmse = np.sqrt(mse)
r2 = r2_score(y_test_original, y_pred_original)

print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
print(f'R² Score: {r2}')
plt.figure(figsize=(10,6))
```

```
plt.scatter(y_test_original,y_pred_original)
min_val = min(min(y_test_original), min(y_pred_original))  # Get the
minimum value for the diagonal line
max_val = max(max(y_test_original), max(y_pred_original))  # Get the
maximum value for the diagonal line
plt.plot([min_val, max_val], [min_val, max_val], 'r--', label='Perfect
prediction (y = x)')
plt.title('Actual vs Predicted Milestones')
plt.xlabel('ACTUAL')
plt.ylabel('PREDICTED')
plt.xlim(0,1000)
plt.ylim(0,1000)
plt.show()
```

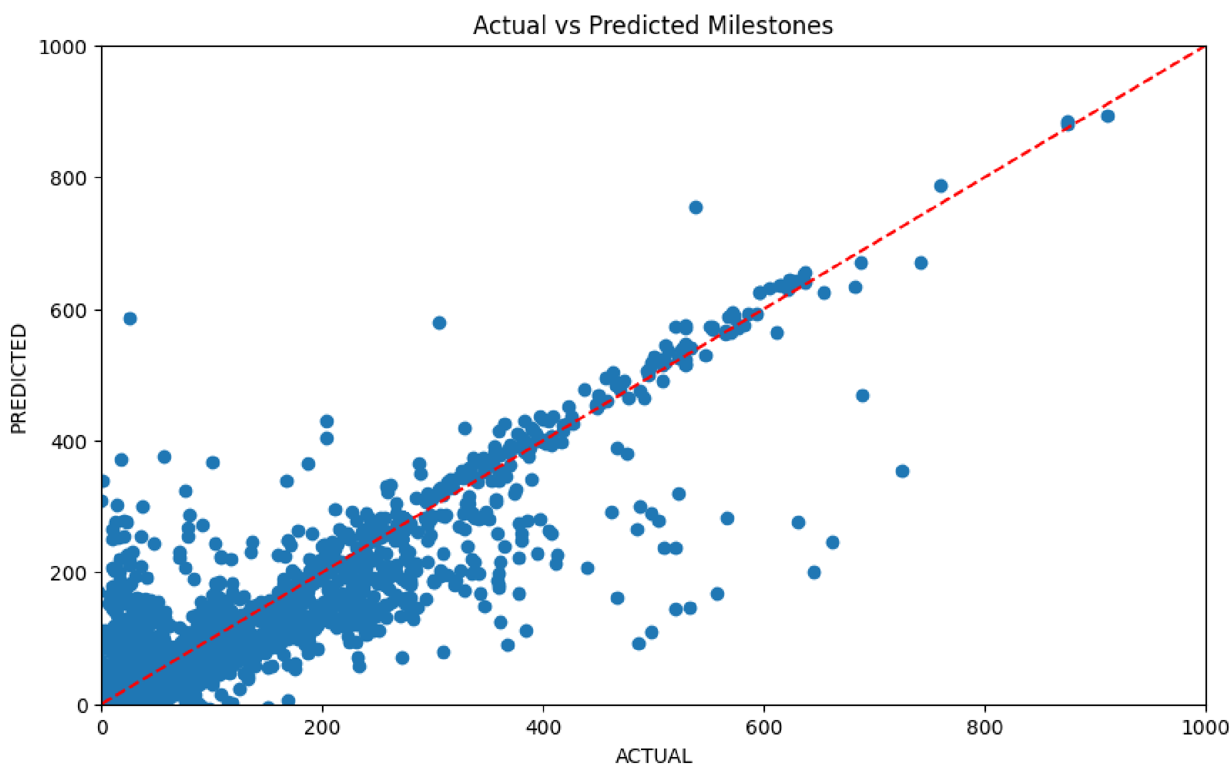
```
Epoch 1/100
896/896 - 5s - 6ms/step - loss: 0.0111 - val_loss: 7.1259e-04
Epoch 2/100
896/896 - 2s - 3ms/step - loss: 5.9581e-04 - val_loss: 5.0977e-04
Epoch 3/100
896/896 - 2s - 3ms/step - loss: 4.2422e-04 - val_loss: 3.8544e-04
Epoch 4/100
896/896 - 3s - 3ms/step - loss: 3.4144e-04 - val_loss: 3.3753e-04
Epoch 5/100
896/896 - 2s - 3ms/step - loss: 3.0638e-04 - val_loss: 3.1286e-04
Epoch 6/100
896/896 - 2s - 3ms/step - loss: 2.8485e-04 - val_loss: 2.9780e-04
Epoch 7/100
896/896 - 2s - 2ms/step - loss: 2.7186e-04 - val_loss: 2.7785e-04
Epoch 8/100
896/896 - 3s - 3ms/step - loss: 2.6191e-04 - val_loss: 2.8167e-04
Epoch 9/100
896/896 - 2s - 2ms/step - loss: 2.5681e-04 - val_loss: 2.5827e-04
Epoch 10/100
896/896 - 2s - 3ms/step - loss: 2.4700e-04 - val_loss: 2.7553e-04
Epoch 11/100
896/896 - 2s - 3ms/step - loss: 2.3985e-04 - val_loss: 2.5484e-04
Epoch 12/100
896/896 - 2s - 2ms/step - loss: 2.3481e-04 - val_loss: 2.4280e-04
Epoch 13/100
896/896 - 3s - 3ms/step - loss: 2.2934e-04 - val_loss: 2.7801e-04
Epoch 14/100
896/896 - 3s - 3ms/step - loss: 2.2451e-04 - val_loss: 2.4562e-04
Epoch 15/100
896/896 - 3s - 3ms/step - loss: 2.1933e-04 - val_loss: 2.3268e-04
Epoch 16/100
896/896 - 2s - 3ms/step - loss: 2.1496e-04 - val_loss: 2.2834e-04
Epoch 17/100
896/896 - 2s - 3ms/step - loss: 2.1137e-04 - val_loss: 2.3119e-04
Epoch 18/100
896/896 - 3s - 3ms/step - loss: 2.0724e-04 - val_loss: 2.2589e-04
```

```
Epoch 19/100
896/896 - 2s - 3ms/step - loss: 2.0371e-04 - val_loss: 2.3550e-04
Epoch 20/100
896/896 - 2s - 2ms/step - loss: 2.0195e-04 - val_loss: 2.3945e-04
Epoch 21/100
896/896 - 2s - 3ms/step - loss: 2.0052e-04 - val_loss: 2.2708e-04
Epoch 22/100
896/896 - 2s - 2ms/step - loss: 1.9786e-04 - val_loss: 2.1221e-04
Epoch 23/100
896/896 - 2s - 3ms/step - loss: 1.9543e-04 - val_loss: 2.1988e-04
Epoch 24/100
896/896 - 2s - 3ms/step - loss: 1.9065e-04 - val_loss: 2.5120e-04
Epoch 25/100
896/896 - 2s - 3ms/step - loss: 1.8891e-04 - val_loss: 2.3717e-04
Epoch 26/100
896/896 - 2s - 3ms/step - loss: 1.8754e-04 - val_loss: 2.0733e-04
Epoch 27/100
896/896 - 3s - 3ms/step - loss: 1.8543e-04 - val_loss: 2.1372e-04
Epoch 28/100
896/896 - 2s - 3ms/step - loss: 1.8370e-04 - val_loss: 2.1306e-04
Epoch 29/100
896/896 - 2s - 3ms/step - loss: 1.8294e-04 - val_loss: 2.1384e-04
Epoch 30/100
896/896 - 3s - 3ms/step - loss: 1.8140e-04 - val_loss: 1.9994e-04
Epoch 31/100
896/896 - 2s - 3ms/step - loss: 1.7847e-04 - val_loss: 2.0062e-04
Epoch 32/100
896/896 - 3s - 3ms/step - loss: 1.7767e-04 - val_loss: 3.0332e-04
Epoch 33/100
896/896 - 2s - 3ms/step - loss: 1.8582e-04 - val_loss: 1.9670e-04
Epoch 34/100
896/896 - 2s - 3ms/step - loss: 1.7216e-04 - val_loss: 2.0840e-04
Epoch 35/100
896/896 - 3s - 3ms/step - loss: 1.7329e-04 - val_loss: 2.2728e-04
Epoch 36/100
896/896 - 2s - 3ms/step - loss: 1.7282e-04 - val_loss: 2.1923e-04
Epoch 37/100
896/896 - 2s - 3ms/step - loss: 1.7053e-04 - val_loss: 1.9783e-04
Epoch 38/100
896/896 - 2s - 3ms/step - loss: 1.6986e-04 - val_loss: 2.2304e-04
Epoch 39/100
896/896 - 2s - 3ms/step - loss: 1.6973e-04 - val_loss: 1.8955e-04
Epoch 40/100
896/896 - 2s - 2ms/step - loss: 1.6734e-04 - val_loss: 2.0467e-04
Epoch 41/100
896/896 - 2s - 2ms/step - loss: 1.6600e-04 - val_loss: 2.0050e-04
Epoch 42/100
896/896 - 3s - 3ms/step - loss: 1.6840e-04 - val_loss: 1.9556e-04
Epoch 43/100
```

```
896/896 - 2s - 2ms/step - loss: 1.6451e-04 - val_loss: 1.8768e-04
Epoch 44/100
896/896 - 2s - 2ms/step - loss: 1.6334e-04 - val_loss: 1.9713e-04
Epoch 45/100
896/896 - 3s - 3ms/step - loss: 1.6268e-04 - val_loss: 1.8924e-04
Epoch 46/100
896/896 - 3s - 3ms/step - loss: 1.6540e-04 - val_loss: 1.8483e-04
Epoch 47/100
896/896 - 2s - 3ms/step - loss: 1.5964e-04 - val_loss: 1.9135e-04
Epoch 48/100
896/896 - 2s - 3ms/step - loss: 1.6184e-04 - val_loss: 1.8839e-04
Epoch 49/100
896/896 - 2s - 3ms/step - loss: 1.6188e-04 - val_loss: 1.9146e-04
Epoch 50/100
896/896 - 2s - 3ms/step - loss: 1.5998e-04 - val_loss: 1.9641e-04
Epoch 51/100
896/896 - 3s - 3ms/step - loss: 1.5893e-04 - val_loss: 2.1136e-04
Epoch 52/100
896/896 - 2s - 3ms/step - loss: 1.5700e-04 - val_loss: 1.8711e-04
Epoch 53/100
896/896 - 2s - 2ms/step - loss: 1.5567e-04 - val_loss: 1.8850e-04
Epoch 54/100
896/896 - 2s - 2ms/step - loss: 1.5677e-04 - val_loss: 1.8694e-04
Epoch 55/100
896/896 - 2s - 2ms/step - loss: 1.5433e-04 - val_loss: 2.0315e-04
Epoch 56/100
896/896 - 2s - 2ms/step - loss: 1.5441e-04 - val_loss: 2.3451e-04
Epoch 57/100
896/896 - 2s - 3ms/step - loss: 1.5439e-04 - val_loss: 1.8554e-04
Epoch 58/100
896/896 - 3s - 3ms/step - loss: 1.5275e-04 - val_loss: 1.7713e-04
Epoch 59/100
896/896 - 2s - 2ms/step - loss: 1.5218e-04 - val_loss: 1.9176e-04
Epoch 60/100
896/896 - 3s - 3ms/step - loss: 1.5238e-04 - val_loss: 1.7880e-04
Epoch 61/100
896/896 - 3s - 3ms/step - loss: 1.5025e-04 - val_loss: 1.9058e-04
Epoch 62/100
896/896 - 2s - 3ms/step - loss: 1.5001e-04 - val_loss: 1.9108e-04
Epoch 63/100
896/896 - 3s - 3ms/step - loss: 1.5214e-04 - val_loss: 1.7934e-04
Epoch 64/100
896/896 - 2s - 2ms/step - loss: 1.4879e-04 - val_loss: 1.8198e-04
Epoch 65/100
896/896 - 2s - 3ms/step - loss: 1.5078e-04 - val_loss: 1.7801e-04
Epoch 66/100
896/896 - 2s - 3ms/step - loss: 1.4821e-04 - val_loss: 1.8427e-04
Epoch 67/100
896/896 - 2s - 3ms/step - loss: 1.4833e-04 - val_loss: 1.8277e-04
```

```
Epoch 68/100
896/896 - 3s - 3ms/step - loss: 1.4880e-04 - val_loss: 1.8058e-04
Epoch 69/100
896/896 - 3s - 3ms/step - loss: 1.4620e-04 - val_loss: 2.6726e-04
Epoch 70/100
896/896 - 2s - 2ms/step - loss: 1.4731e-04 - val_loss: 1.8762e-04
Epoch 71/100
896/896 - 2s - 3ms/step - loss: 1.4756e-04 - val_loss: 1.7737e-04
Epoch 72/100
896/896 - 2s - 3ms/step - loss: 1.4799e-04 - val_loss: 1.7877e-04
Epoch 73/100
896/896 - 2s - 3ms/step - loss: 1.4355e-04 - val_loss: 1.8160e-04
Epoch 74/100
896/896 - 3s - 3ms/step - loss: 1.4453e-04 - val_loss: 1.7851e-04
Epoch 75/100
896/896 - 3s - 3ms/step - loss: 1.4611e-04 - val_loss: 1.7678e-04
Epoch 76/100
896/896 - 3s - 3ms/step - loss: 1.4478e-04 - val_loss: 1.8018e-04
Epoch 77/100
896/896 - 3s - 3ms/step - loss: 1.4376e-04 - val_loss: 1.8308e-04
Epoch 78/100
896/896 - 2s - 3ms/step - loss: 1.4231e-04 - val_loss: 1.7727e-04
Epoch 79/100
896/896 - 3s - 3ms/step - loss: 1.4419e-04 - val_loss: 1.7502e-04
Epoch 80/100
896/896 - 3s - 3ms/step - loss: 1.4305e-04 - val_loss: 1.7517e-04
Epoch 81/100
896/896 - 3s - 3ms/step - loss: 1.4308e-04 - val_loss: 1.7266e-04
Epoch 82/100
896/896 - 2s - 3ms/step - loss: 1.4196e-04 - val_loss: 1.7257e-04
Epoch 83/100
896/896 - 2s - 2ms/step - loss: 1.4144e-04 - val_loss: 1.8540e-04
Epoch 84/100
896/896 - 2s - 2ms/step - loss: 1.4250e-04 - val_loss: 2.0310e-04
Epoch 85/100
896/896 - 3s - 3ms/step - loss: 1.4049e-04 - val_loss: 1.7361e-04
Epoch 86/100
896/896 - 2s - 3ms/step - loss: 1.4228e-04 - val_loss: 1.7248e-04
Epoch 87/100
896/896 - 3s - 3ms/step - loss: 1.4137e-04 - val_loss: 2.1344e-04
Epoch 88/100
896/896 - 2s - 3ms/step - loss: 1.4135e-04 - val_loss: 1.7476e-04
Epoch 89/100
896/896 - 2s - 3ms/step - loss: 1.3779e-04 - val_loss: 1.7337e-04
Epoch 90/100
896/896 - 2s - 3ms/step - loss: 1.3915e-04 - val_loss: 2.1367e-04
Epoch 91/100
896/896 - 2s - 3ms/step - loss: 1.3997e-04 - val_loss: 1.7435e-04
Epoch 92/100
```

```
896/896 - 2s - 3ms/step - loss: 1.3923e-04 - val_loss: 1.8286e-04
Epoch 93/100
896/896 - 2s - 3ms/step - loss: 1.3807e-04 - val_loss: 1.7542e-04
Epoch 94/100
896/896 - 2s - 3ms/step - loss: 1.3763e-04 - val_loss: 1.7418e-04
Epoch 95/100
896/896 - 2s - 2ms/step - loss: 1.3794e-04 - val_loss: 1.8751e-04
Epoch 96/100
896/896 - 3s - 3ms/step - loss: 1.3900e-04 - val_loss: 1.7467e-04
Epoch 97/100
896/896 - 2s - 2ms/step - loss: 1.3658e-04 - val_loss: 1.8045e-04
Epoch 98/100
896/896 - 3s - 3ms/step - loss: 1.3737e-04 - val_loss: 1.7430e-04
Epoch 99/100
896/896 - 2s - 2ms/step - loss: 1.3776e-04 - val_loss: 1.7583e-04
Epoch 100/100
896/896 - 3s - 3ms/step - loss: 1.3697e-04 - val_loss: 1.8200e-04
224/224 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
Mean Absolute Error: 23.74179641753051
Mean Squared Error: 2747.9337185656527
Root Mean Squared Error: 52.420737485900105
R² Score: 0.7559334369802996
```



****DATA PREPERATION FOR APPROACH 2: FORECASTED DATE AND DELAY-BASED PREDICTION****

Here both the Actual and Forecasted Milestone completion Dates are considered so that they are subtracted to get the milestone delays.

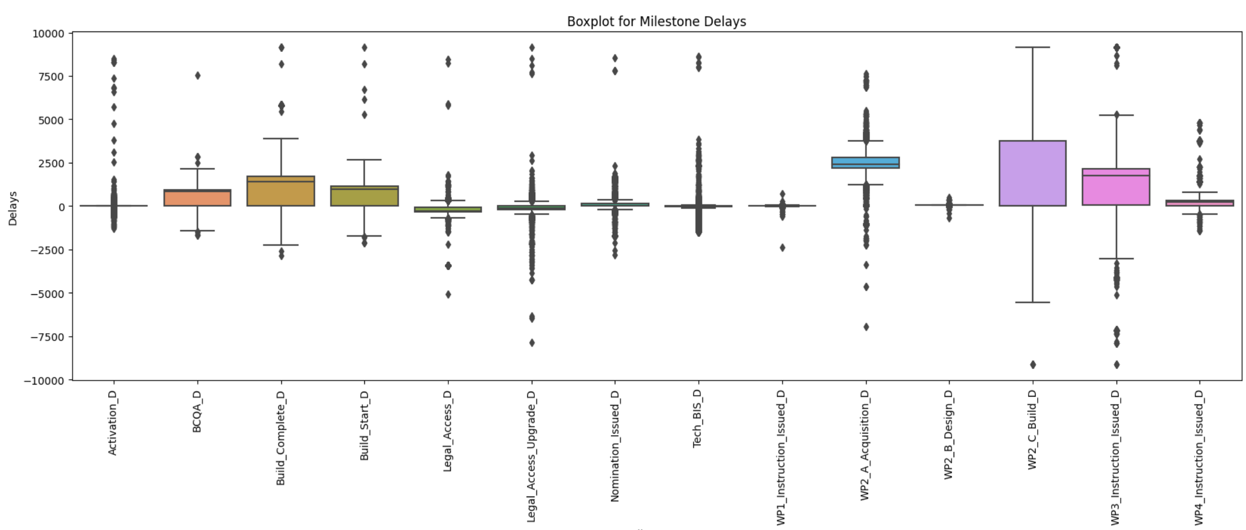
This approach is considered because the milestones delays play a major role in project completion

```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
df = cleaned_data
df = df.drop(columns = 'Project_ID')
df.replace('2999-01-01', np.nan, inplace=True)
df.replace('01/01/2999', np.nan, inplace=True)
df = df[df['Tech_TTO_A'] >= '31/12/2019']

milestones =
["Activation","BCQA","Build_Complete","Build_Start","Legal_Access","Te
ch_TTO","Legal_Access_Upgrade","Nomination_Issued","Tech_BIS","WP1_Ins
truction_Issued","WP2_A_Acquisition","WP2_B_Design","WP2_C_Build","WP3
_Instruction_Issued","WP4_Instruction_Issued"]  # Example milestones
(non-sequential)
cols = []
for milestone in milestones:
    #Add forecasted dates and delays for each milestone to the feature
list
   cols.append(f'{milestone}_A')
   cols.append(f'{milestone}_F')
df = df[cols]## Considering both Actual and Forecatsed columns

df = null_imputer(df) ## Null Handling
milestones =
["Activation","BCQA","Build_Complete","Build_Start","Legal_Access","Le
gal_Access_Upgrade","Nomination_Issued","Tech_BIS","WP1_Instruction_Is
sued","WP2_A_Acquisition","WP2_B_Design","WP2_C_Build","WP3_Instructio
n_Issued","WP4_Instruction_Issued"]  # Example milestones (non-
sequential)
for milestone in milestones:
    df[f'{milestone}_D'] = (df[f'{milestone}_A'] -
df[f'{milestone}_F']).dt.days ## Actual - Forecast = Delay
    # Prepare features and target
features = []

for milestone in milestones:
    # Add forecasted dates and delays for each milestone to the
feature list
    features.append(f'{milestone}_F')
    features.append(f'{milestone}_D')
```

```
# Create the feature matrix X
X = df[features]

# Convert forecasted dates to numeric values (timestamps)
for feature in features:
    if '_F' in feature:
        X[feature] = pd.to_datetime(X[feature]).apply(lambda x:
x.timestamp())

# The target variable is the actual project end date (e.g., milestone
X)
y = pd.to_datetime(df['Tech_TTO_A']).apply(lambda x: x.timestamp())
# Split data 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)
```

DELAY ANALYSIS An analysis is done on the delays of each milestone below to check which milestone has more number of delays

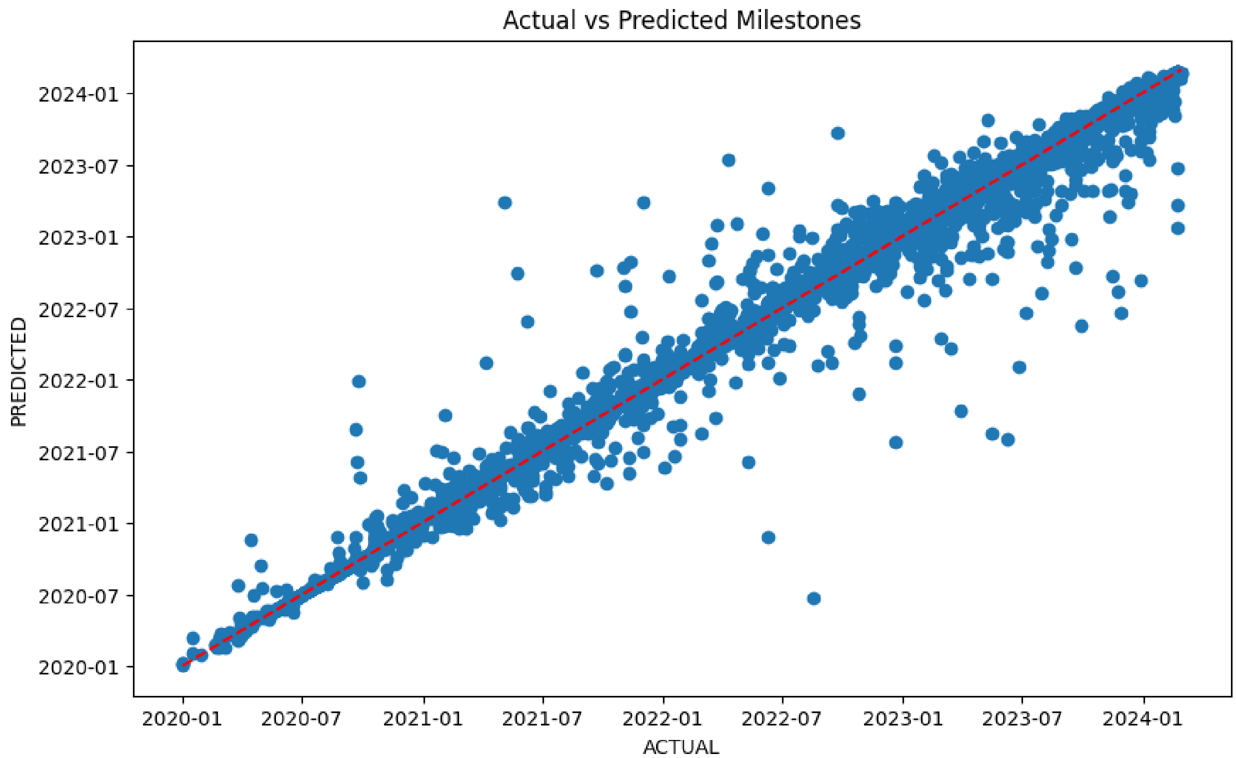
```
### Delay Analysis
delay_analysis = [item for item in df.columns if item.endswith('_D')]
delay_analysis = df[delay_analysis]
data_melted = delay_analysis.melt(var_name='Milestones',
value_name='Delays')
plt.figure(figsize=(20, 6))
sns.boxplot(x='Milestones', y='Delays', data=data_melted)
plt.title('Boxplot for Milestone Delays')
plt.xticks(rotation=90)
plt.show()
```



Approach-2: Random Forest Regression Model

```
# Initialize the RandomForestRegressor for Approach 2
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model
rf_model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = rf_model.predict(X_test)

# Convert predicted and actual timestamps back to dates
y_pred_dates = pd.to_datetime(y_pred, unit='s')  # Convert predicted
timestamps to dates
y_test_dates = pd.to_datetime(y_test, unit='s')  # Convert actual
timestamps to dates

# Evaluate model performance
mae = np.mean(np.abs(y_test_dates - y_pred_dates))
print(f"Mean Absolute Error (MAE): {mae}")
r21 = r2_score(y_test_dates, y_pred_dates)
print(f'R² Score: {r21}')
# Example: Print predicted vs actual end dates for comparison
print("Predicted End Dates vs Actual End Dates")
#print(pd.DataFrame({'Predicted End Date': y_pred_dates, 'Actual End
Date': y_test_dates}))
import matplotlib.pyplot as plt
plt.figure(figsize=(10,6))
plt.scatter(y_test_dates,y_pred_dates)
min_val = min(min(y_test_dates), min(y_pred_dates))  # Get the minimum
value for the diagonal line
max_val = max(max(y_test_dates), max(y_pred_dates))  # Get the maximum
value for the diagonal line
plt.plot([min_val, max_val], [min_val, max_val], 'r--', label='Perfect
prediction (y = x)')
plt.title('Actual vs Predicted Milestones')
plt.xlabel('ACTUAL')
plt.ylabel('PREDICTED')
plt.show()
```

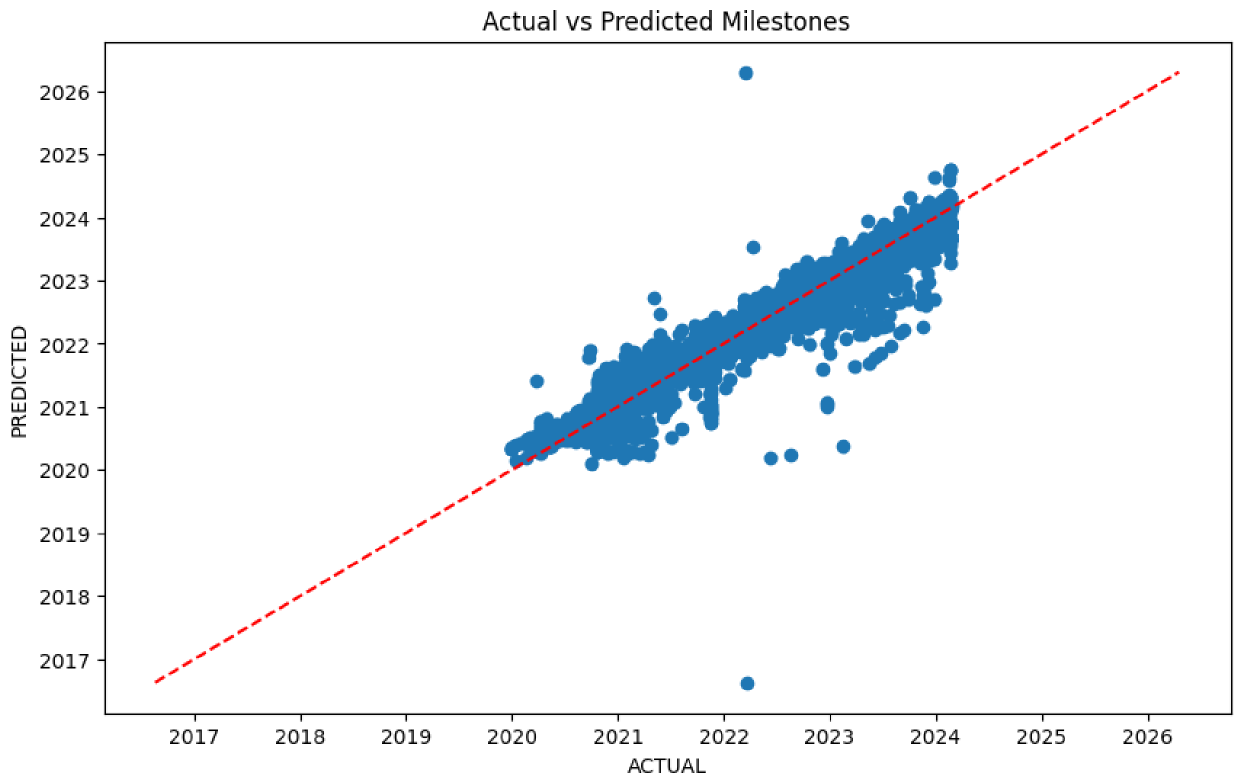
```
Mean Absolute Error (MAE): 13 days 23:21:32.801799269
R² Score: 0.9847422054347027
Predicted End Dates vs Actual End Dates
```



Approach-2: Linear Regression Model

```
#LINEAR REGRESSION
modellr_a2 = LinearRegression()
modellr_a2.fit(X_train, y_train)
y_pred_a2 = modellr_a2.predict(X_test)

y_pred_dates_a2 = pd.to_datetime(y_pred_a2, unit='s')  # Convert
predicted timestamps to dates
y_test_dates_a2 = pd.to_datetime(y_test, unit='s')

mae_a2 = np.mean(np.abs(y_test_dates_a2 - y_pred_dates_a2))
print(f"Mean Absolute Error (MAE): {mae_a2}")
r2lr_a2 = r2_score(y_test_dates_a2, y_pred_dates_a2)
print(f'R² Score: {r2lr_a2}')
plt.figure(figsize=(10,6))
plt.scatter(y_test_dates_a2,y_pred_dates_a2)
min_val = min(min(y_test_dates_a2), min(y_pred_dates_a2))  # Get the
minimum value for the diagonal line
max_val = max(max(y_test_dates_a2), max(y_pred_dates_a2))  # Get the
maximum value for the diagonal line
plt.plot([min_val, max_val], [min_val, max_val], 'r--', label='Perfect
prediction (y = x)')
plt.title('Actual vs Predicted Milestones')
plt.xlabel('ACTUAL')
```

```
plt.ylabel('PREDICTED')
plt.show()

Mean Absolute Error (MAE): 45 days 17:11:37.351539866
R² Score: 0.9469749647781145
```



Approach-2: Long Short-Term Memory (LSTM) Model

```
import numpy as np
import pandas as pd
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

df_lstm_a2 = X
y_a2 = y
scaler_a2 = MinMaxScaler()
scaled_data_X_a2 = scaler_a2.fit_transform(df_lstm_a2)
scaled_data_y_a2 = scaler_a2.fit_transform(y_a2.values.reshape(-1, 1))
X_lstm_a2 = scaled_data_X_a2.reshape((scaled_data_X_a2.shape[0], 1,
scaled_data_X_a2.shape[1]))

X_train_lstm_a2, X_test_lstm_a2, y_train_lstm_a2, y_test_lstm_a2 =
train_test_split(X_lstm_a2, scaled_data_y_a2, test_size=0.2,
```

```
random_state=42)

model_a2 = Sequential()
model_a2.add(LSTM(50, activation='relu',
input_shape=(X_train_lstm_a2.shape[1], X_train_lstm_a2.shape[2])))
model_a2.add(Dense(1))

model_a2.compile(optimizer='adam', loss='mean_squared_error')

model_a2.fit(X_train_lstm_a2, y_train_lstm_a2, epochs=100,
batch_size=32, validation_data=(X_test_lstm_a2, y_test_lstm_a2),
verbose=2)

predicted_milestone_a2 = model_a2.predict(X_test_lstm_a2)
y_pred_original_a2 =
scaler_a2.inverse_transform(np.concatenate((X_test_lstm_a2[:, 0, :],
predicted_milestone_a2), axis=1))[:, -1]
y_test_original_a2 =
scaler_a2.inverse_transform(np.concatenate((X_test_lstm_a2[:, 0, :],
y_test_lstm_a2.reshape(-1, 1)), axis=1))[:, -1]
y_pred_original_a2 = pd.to_datetime(y_pred_original_a2, unit='s')  #
Convert predicted timestamps to dates
y_test_original_a2 = pd.to_datetime(y_test_original_a2, unit='s')

mae_a2_lstm = np.abs(y_test_original_a2 - y_pred_original_a2).mean()
print(f"Mean Absolute Error (MAE): {mae_a2_lstm}")
r2lr_a2_lstm = r2_score(y_test_original_a2, y_pred_original_a2)
print(f'R² Score: {r2lr_a2_lstm}')
plt.figure(figsize=(10,6))
plt.scatter(y_test_original_a2,y_pred_original_a2)
min_val = min(min(y_test_original_a2), min(y_pred_original_a2))  # Get
the minimum value for the diagonal line
max_val = max(max(y_test_original_a2), max(y_pred_original_a2))  # Get
the maximum value for the diagonal line
plt.plot([min_val, max_val], [min_val, max_val], 'r--', label='Perfect
prediction (y = x)')
plt.title('Actual vs Predicted Milestones')
plt.xlabel('ACTUAL')
plt.ylabel('PREDICTED')
plt.show()
```

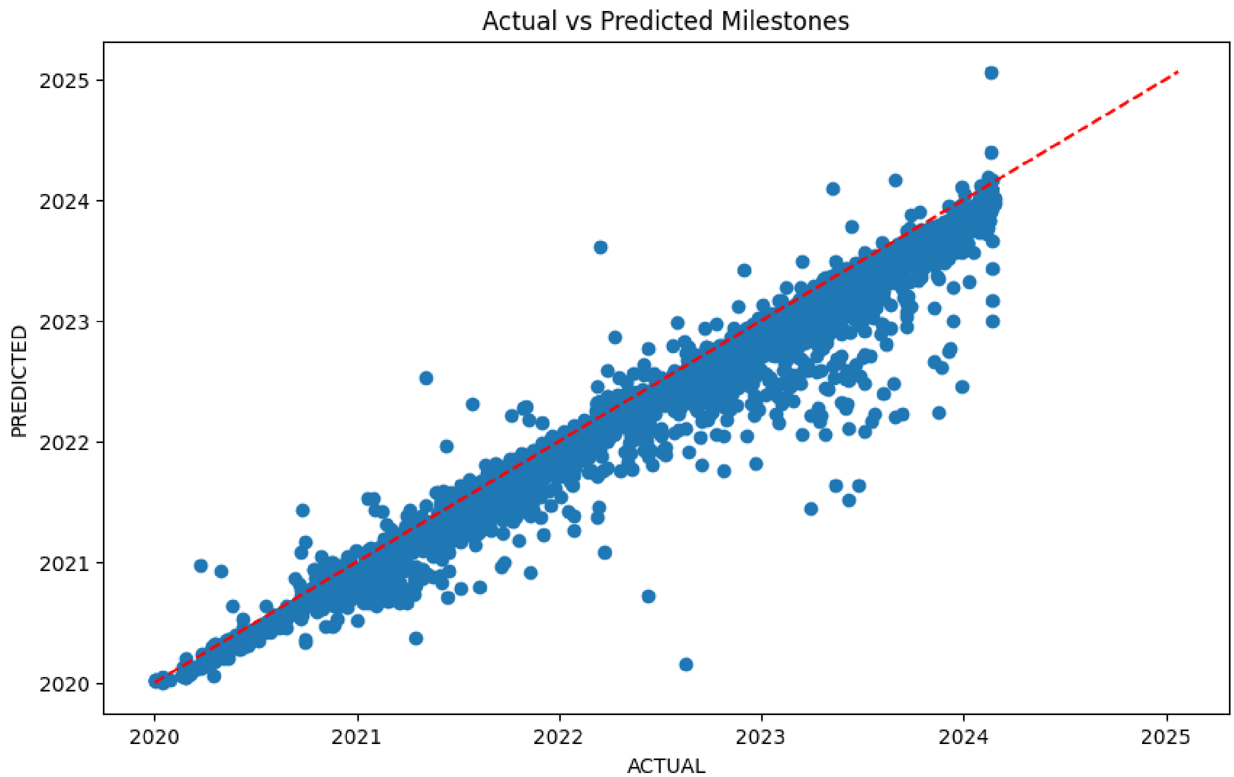
```
Epoch 1/100
890/890 - 4s - 5ms/step - loss: 0.0316 - val_loss: 0.0122
Epoch 2/100
890/890 - 2s - 2ms/step - loss: 0.0091 - val_loss: 0.0077
Epoch 3/100
890/890 - 2s - 2ms/step - loss: 0.0064 - val_loss: 0.0055
Epoch 4/100
890/890 - 2s - 2ms/step - loss: 0.0049 - val_loss: 0.0046
Epoch 5/100
```

```
890/890 - 2s - 2ms/step - loss: 0.0041 - val_loss: 0.0040
Epoch 6/100
890/890 - 2s - 2ms/step - loss: 0.0036 - val_loss: 0.0038
Epoch 7/100
890/890 - 2s - 2ms/step - loss: 0.0032 - val_loss: 0.0040
Epoch 8/100
890/890 - 3s - 3ms/step - loss: 0.0030 - val_loss: 0.0037
Epoch 9/100
890/890 - 2s - 2ms/step - loss: 0.0028 - val_loss: 0.0029
Epoch 10/100
890/890 - 2s - 2ms/step - loss: 0.0026 - val_loss: 0.0030
Epoch 11/100
890/890 - 2s - 2ms/step - loss: 0.0025 - val_loss: 0.0043
Epoch 12/100
890/890 - 2s - 2ms/step - loss: 0.0023 - val_loss: 0.0023
Epoch 13/100
890/890 - 2s - 2ms/step - loss: 0.0022 - val_loss: 0.0029
Epoch 14/100
890/890 - 2s - 2ms/step - loss: 0.0022 - val_loss: 0.0023
Epoch 15/100
890/890 - 2s - 2ms/step - loss: 0.0021 - val_loss: 0.0026
Epoch 16/100
890/890 - 2s - 2ms/step - loss: 0.0020 - val_loss: 0.0019
Epoch 17/100
890/890 - 2s - 2ms/step - loss: 0.0020 - val_loss: 0.0022
Epoch 18/100
890/890 - 3s - 3ms/step - loss: 0.0019 - val_loss: 0.0018
Epoch 19/100
890/890 - 2s - 2ms/step - loss: 0.0019 - val_loss: 0.0035
Epoch 20/100
890/890 - 2s - 2ms/step - loss: 0.0018 - val_loss: 0.0020
Epoch 21/100
890/890 - 2s - 2ms/step - loss: 0.0018 - val_loss: 0.0018
Epoch 22/100
890/890 - 2s - 2ms/step - loss: 0.0018 - val_loss: 0.0022
Epoch 23/100
890/890 - 3s - 3ms/step - loss: 0.0018 - val_loss: 0.0030
Epoch 24/100
890/890 - 2s - 2ms/step - loss: 0.0017 - val_loss: 0.0018
Epoch 25/100
890/890 - 2s - 2ms/step - loss: 0.0017 - val_loss: 0.0020
Epoch 26/100
890/890 - 2s - 2ms/step - loss: 0.0017 - val_loss: 0.0018
Epoch 27/100
890/890 - 2s - 2ms/step - loss: 0.0017 - val_loss: 0.0017
Epoch 28/100
890/890 - 2s - 2ms/step - loss: 0.0017 - val_loss: 0.0016
Epoch 29/100
890/890 - 2s - 2ms/step - loss: 0.0017 - val_loss: 0.0016
```

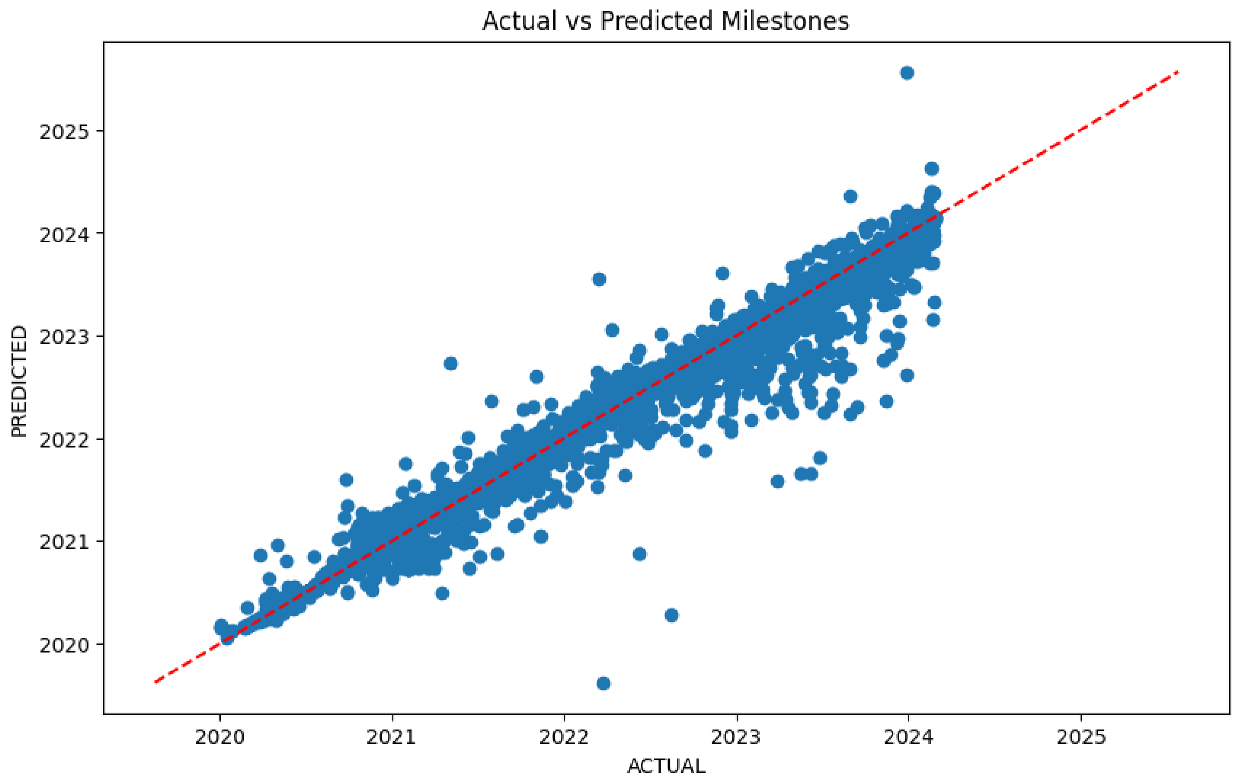
```
Epoch 30/100
890/890 - 2s - 2ms/step - loss: 0.0016 - val_loss: 0.0023
Epoch 31/100
890/890 - 2s - 2ms/step - loss: 0.0016 - val_loss: 0.0016
Epoch 32/100
890/890 - 2s - 2ms/step - loss: 0.0016 - val_loss: 0.0016
Epoch 33/100
890/890 - 2s - 2ms/step - loss: 0.0016 - val_loss: 0.0016
Epoch 34/100
890/890 - 2s - 2ms/step - loss: 0.0016 - val_loss: 0.0015
Epoch 35/100
890/890 - 2s - 2ms/step - loss: 0.0016 - val_loss: 0.0015
Epoch 36/100
890/890 - 2s - 2ms/step - loss: 0.0015 - val_loss: 0.0017
Epoch 37/100
890/890 - 2s - 2ms/step - loss: 0.0015 - val_loss: 0.0014
Epoch 38/100
890/890 - 2s - 2ms/step - loss: 0.0015 - val_loss: 0.0020
Epoch 39/100
890/890 - 2s - 2ms/step - loss: 0.0015 - val_loss: 0.0015
Epoch 40/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0016
Epoch 41/100
890/890 - 2s - 2ms/step - loss: 0.0015 - val_loss: 0.0015
Epoch 42/100
890/890 - 2s - 2ms/step - loss: 0.0015 - val_loss: 0.0027
Epoch 43/100
890/890 - 2s - 2ms/step - loss: 0.0015 - val_loss: 0.0016
Epoch 44/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0016
Epoch 45/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0015
Epoch 46/100
890/890 - 3s - 3ms/step - loss: 0.0014 - val_loss: 0.0014
Epoch 47/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0015
Epoch 48/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0013
Epoch 49/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0023
Epoch 50/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0015
Epoch 51/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0014
Epoch 52/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0013
Epoch 53/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0014
Epoch 54/100
```

```
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0014
Epoch 55/100
890/890 - 3s - 3ms/step - loss: 0.0014 - val_loss: 0.0015
Epoch 56/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0016
Epoch 57/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0016
Epoch 58/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0014
Epoch 59/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0021
Epoch 60/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0018
Epoch 61/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0033
Epoch 62/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0014
Epoch 63/100
890/890 - 3s - 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 64/100
890/890 - 3s - 3ms/step - loss: 0.0013 - val_loss: 0.0015
Epoch 65/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0015
Epoch 66/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 67/100
890/890 - 3s - 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 68/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0018
Epoch 69/100
890/890 - 2s - 2ms/step - loss: 0.0014 - val_loss: 0.0014
Epoch 70/100
890/890 - 3s - 3ms/step - loss: 0.0013 - val_loss: 0.0027
Epoch 71/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0014
Epoch 72/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 73/100
890/890 - 2s - 3ms/step - loss: 0.0013 - val_loss: 0.0015
Epoch 74/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 75/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0014
Epoch 76/100
890/890 - 2s - 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 77/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 78/100
890/890 - 2s - 3ms/step - loss: 0.0012 - val_loss: 0.0016
```

```
Epoch 79/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 80/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 81/100
890/890 - 3s - 3ms/step - loss: 0.0013 - val_loss: 0.0014
Epoch 82/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0015
Epoch 83/100
890/890 - 2s - 3ms/step - loss: 0.0012 - val_loss: 0.0013
Epoch 84/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0014
Epoch 85/100
890/890 - 3s - 3ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 86/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0013
Epoch 87/100
890/890 - 3s - 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 88/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 89/100
890/890 - 2s - 2ms/step - loss: 0.0013 - val_loss: 0.0025
Epoch 90/100
890/890 - 3s - 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 91/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0014
Epoch 92/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0017
Epoch 93/100
890/890 - 2s - 3ms/step - loss: 0.0012 - val_loss: 0.0013
Epoch 94/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 95/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0016
Epoch 96/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0011
Epoch 97/100
890/890 - 3s - 3ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 98/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 99/100
890/890 - 2s - 3ms/step - loss: 0.0013 - val_loss: 0.0013
Epoch 100/100
890/890 - 2s - 2ms/step - loss: 0.0012 - val_loss: 0.0022
223/223 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
Mean Absolute Error (MAE): 46 days 19:22:12.937680880
R² Score: 0.962170584500898
```

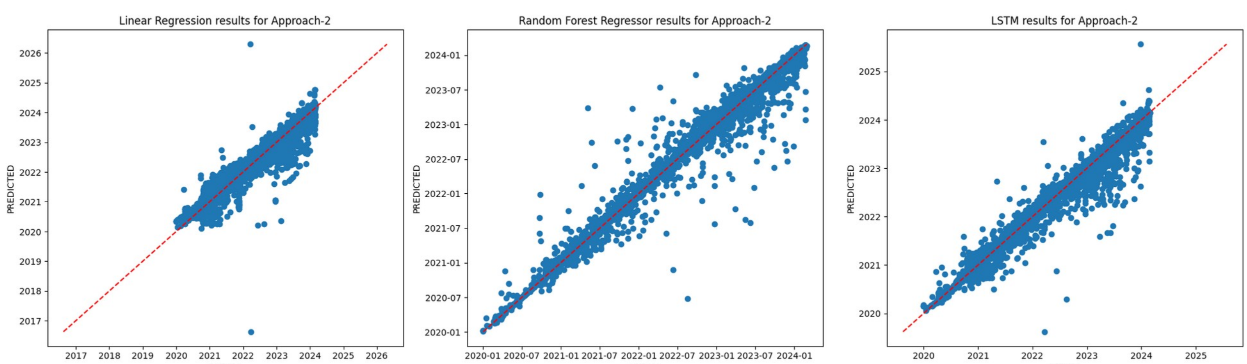



```
Mean Absolute Error (MAE): 25 days 14:17:29.663424186
R² Score: 0.9759402140385585
```




```
## Resultant plots for Approach-2

import matplotlib.pyplot as plt

# Assuming y_test, y_pred, y_pred_days, y_test_original,
y_pred_original are defined

# Create subplots (1 row, 3 columns)
fig, axes = plt.subplots(1, 3, figsize=(20, 6))

# Plot 1: Linear Regression results for Approach-1
axes[0].scatter(y_test_dates_a2, y_pred_dates_a2)
axes[0].set_title('Linear Regression results for Approach-2')
min_val = min(min(y_test_dates_a2), min(y_pred_dates_a2))  # Get the
minimum value for the diagonal line
max_val = max(max(y_test_dates_a2), max(y_pred_dates_a2))  # Get the
maximum value for the diagonal line
axes[0].plot([min_val, max_val], [min_val, max_val], 'r--',
label='Perfect prediction (y = x)')
axes[0].set_xlabel('ACTUAL')
axes[0].set_ylabel('PREDICTED')

# Plot 2: Random Forest Regressor results for Approach-1
axes[1].scatter(y_test_dates, y_pred_dates)
axes[1].set_title('Random Forest Regressor results for Approach-2')
min_val = min(min(y_test_dates), min(y_pred_dates))  # Get the minimum
```

```
value for the diagonal line
max_val = max(max(y_test_dates), max(y_pred_dates))  # Get the maximum
value for the diagonal line
axes[1].plot([min_val, max_val], [min_val, max_val], 'r--',
label='Perfect prediction (y = x)')
axes[1].set_xlabel('ACTUAL')
axes[1].set_ylabel('PREDICTED')

# Plot 3: LSTM results for Approach-1
axes[2].scatter(y_test_original_a2, y_pred_original_a2)
axes[2].set_title('LSTM results for Approach-2')
min_val = min(min(y_test_original_a2), min(y_pred_original_a2))  # Get
the minimum value for the diagonal line
max_val = max(max(y_test_original_a2), max(y_pred_original_a2))  # Get
the maximum value for the diagonal line
axes[2].plot([min_val, max_val], [min_val, max_val], 'r--',
label='Perfect prediction (y = x)')
axes[2].set_xlabel('ACTUAL')
axes[2].set_ylabel('PREDICTED')

# Adjust layout
plt.tight_layout()

# Show the plots
plt.show()
```



****PREDICTIONS FOR NEW DATA****

Previously we have considered only Milestone_Achieved = MS13 records so now for predicting let us consider Milestone_Achieved = MS12 so that "Tech_TTO_A" column will be empty

```
new_data = main_df

new_data['UPDATED_DATE'] =
pd.to_datetime(dupdf['UPDATED_DATE'],format='mixed',dayfirst = True)
new_data = dupdf.sort_values(by=['Project_ID', 'UPDATED_DATE'],
ascending=[True, False])
```

```
# Creating a new column to count non-null values across all columns
new_data['non_null_count'] = new_data.notnull().sum(axis=1)

# Sort by ProjectID and then by non_null_count to prioritize rows with
the most filled data
new_data = new_data.sort_values(by=['Project_ID', 'non_null_count'],
ascending=[True, False])

# Drop duplicates based on ProjectID, keeping the row with the most
non-null values
new_data = new_data.drop_duplicates(subset=['Project_ID'],
keep='first')

# Drop the helper column used for counting non-null values
new_data = new_data[(new_data['Milestone_Achieved'] == 'MS12') &
(new_data['Project_Scope'] == 'In Scope')]

# Dropping all the columns that were discussed in the meeting
drop_columns_new =
['non_null_count','UPDATED_DATE','Created_Date','Upgrade_Project','Par
ent_Project','Milestone_Achieved','BT_Project','Project_Scope','Out_of
_Scope_Reason','Out_of_Scope_Comments','Date_Removed_from_Scope','TM_C
ell_ID_dup','SRN_Upgrade_Type','Created_Date','NTQ','Quality_Assurance
','Upgrade_Project_Name']
new_data = new_data.drop(columns=drop_columns_new)

# Drop all the empty columns
new_data = new_data.dropna(axis=1, how='all')
new_data = new_data.reset_index(drop=True)

new_data_for_pred = new_data.copy()

new_data_for_pred.replace('01/01/1900', np.nan, inplace=True)
new_data_for_pred.replace('01/01/2999', np.nan, inplace=True)
new_data_for_pred.replace('2999-01-01', np.nan, inplace=True)
new_data_for_pred.replace('2999-12-31', np.nan, inplace=True)

cols_A_new = [col for col in new_data_for_pred.columns if
col.endswith('_A')]
cols_F_new = [col for col in new_data_for_pred.columns if
col.endswith('_F')]
common_cols_new = set([col[:-2] for col in
cols_A]).intersection([col[:-2] for col in cols_F])
selected_columns_new = [col for col in new_data_for_pred.columns if
col[:-2] in common_cols_new and (col.endswith('_A') or
col.endswith('_F'))]

for col in selected_columns_new:
     new_data_for_pred[col] =
```

```
pd.to_datetime(new_data_for_pred[col],format = 'mixed', dayfirst =
True)
```

****SINCE RANDOM FOREST PERFORMED WELL IN APPROACH 2 LET US USE THAT MODEL****

Inputs required are ["Project_ID","Activation","BCQA","Build_Complete","Build_Start","Legal_Access","Legal_Access_Upgrade","Nomination_Issued","Tech_BIS" ,"WP1_Instruction_Issued","WP2_A_Acquisition","WP2_B_Design","WP2_C_Build","WP3_Instruction_Issued","WP4_Instruction_Issued"]

```
def new_data_preprocess(data,model):
    df = data
    df = df.drop(columns = 'Project_ID')
    df.replace('2999-01-01', np.nan, inplace=True)
    df.replace('01/01/2999', np.nan, inplace=True)
    milestones =
["Activation","BCQA","Build_Complete","Build_Start","Legal_Access","Le
gal_Access_Upgrade","Nomination_Issued","Tech_BIS","WP1_Instruction_Is
sued","WP2_A_Acquisition","WP2_B_Design","WP2_C_Build","WP3_Instructio
n_Issued","WP4_Instruction_Issued"]
    cols = []
    for milestone in milestones:
        cols.append(f'{milestone}_A')
        cols.append(f'{milestone}_F')
    df = df[cols]
    df = null_imputer(df) ## Null Handling
    for milestone in milestones:
        df[f'{milestone}_D'] = (df[f'{milestone}_A'] -
df[f'{milestone}_F']).dt.days ## Actual - Forecast = Delay

    features = []
    for milestone in milestones:
    # Add forecasted dates and delays for each milestone to the
feature list
        features.append(f'{milestone}_F')
        features.append(f'{milestone}_D')
    df = df[features]

    # Convert forecasted dates to numeric values (timestamps)
    for feature in df.columns:
        if '_F' in feature:
            df[feature] = pd.to_datetime(df[feature]).apply(lambda x:
x.timestamp())
    model = eval(model)
    predictions = model.predict(df)
    predictions = pd.to_datetime(predictions, unit='s').date
    data['Tech_TTO_Predictions'] = predictions
```

```python
    return data[['Project_ID','Tech_TTO_Predictions']]
    #return predictions
```

****NOTE: BEFORE RUNNING THIS METHOD, PLEASE RUN THE RANDOM FOREST REGRESSOR MODEL CELL****

```python
dats = new_data_preprocess(new_data_for_pred,'rf_model')
dats
```

```
    Project_ID Tech_TTO_Predictions
0     P-167292           2023-11-21
1     P-171956           2024-01-18
2     P-172040           2024-01-25
3     P-172061           2024-01-18
4     P-172068           2024-01-18
..         ...                  ...
541   P-275282           2024-02-14
542   P-275315           2024-02-14
543   P-275409           2023-10-31
544   P-275410           2023-10-31
545   P-276957           2023-10-13

[546 rows x 2 columns]
```