AI-DRIVEN EXPLORATION AND PREDICTION OF COMPANY REGISTRATION TRENDS WITH REGISTRAR OF COMPANIES (ROC)

Project Title: ROC Company Analysis

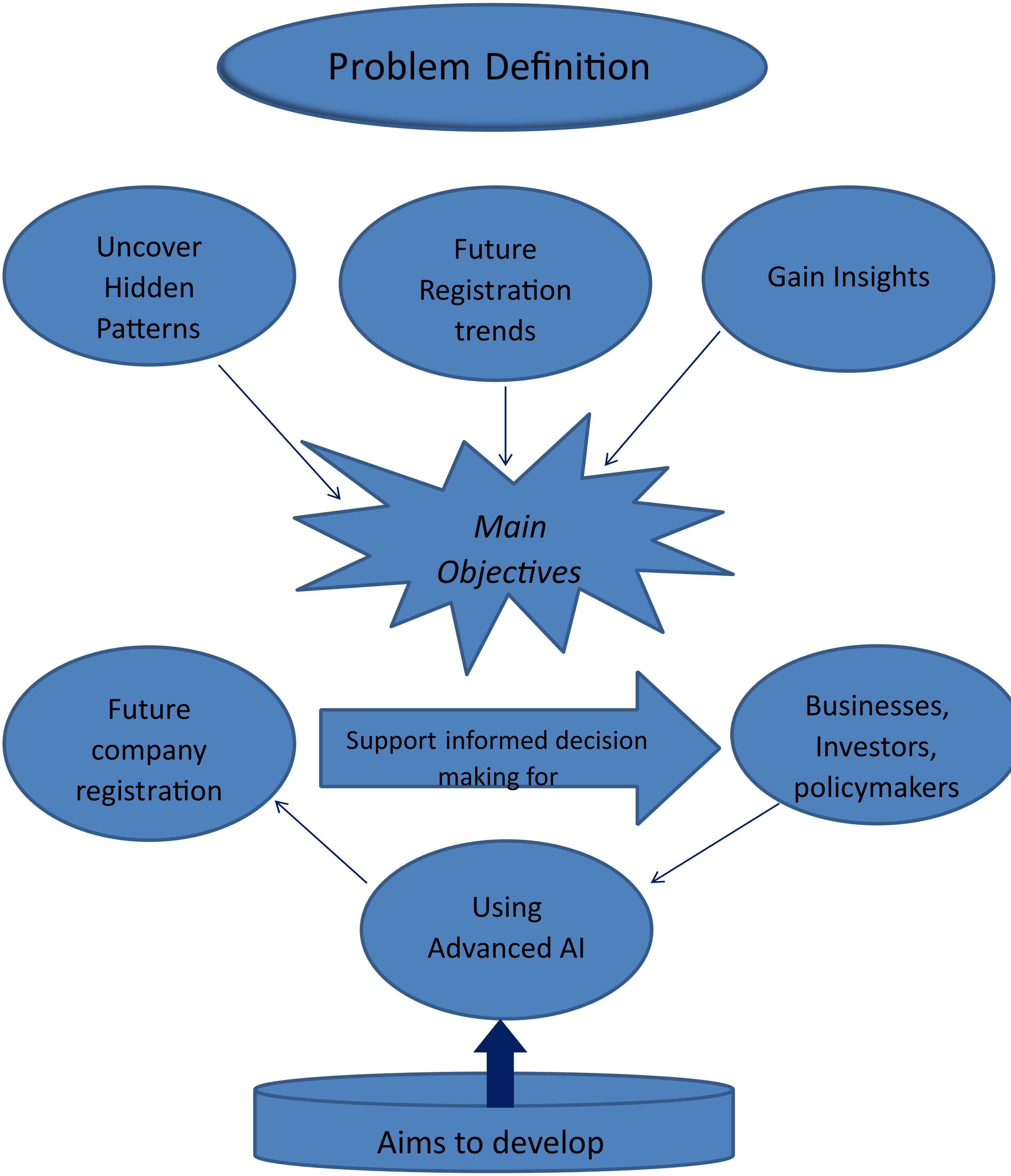
Project Summary:

In this document, we can clearly see about above project in this document. And discuss about problem definition, scope of project, vision of project, phase of projects, detail about team members, what will we do, how it will be complete, requirements, problem analysis and conclusion.

The AI-driven analysis aims to uncover hidden patterns, discover valuable insights into the company landscape, and forecast future registration trends. By applying cutting-edge AI algorithms, the study seeks to identify unique characteristics and relationships among registered companies, enabling a more sophisticated understanding of the business ecosystem in Tamil Nadu

Development Platform: Google Colab Jupyter notebook

Dataset Link: https://tn.data.gov.in/resource/company-master-data-tamil-nadu-upto-28th-february-2019

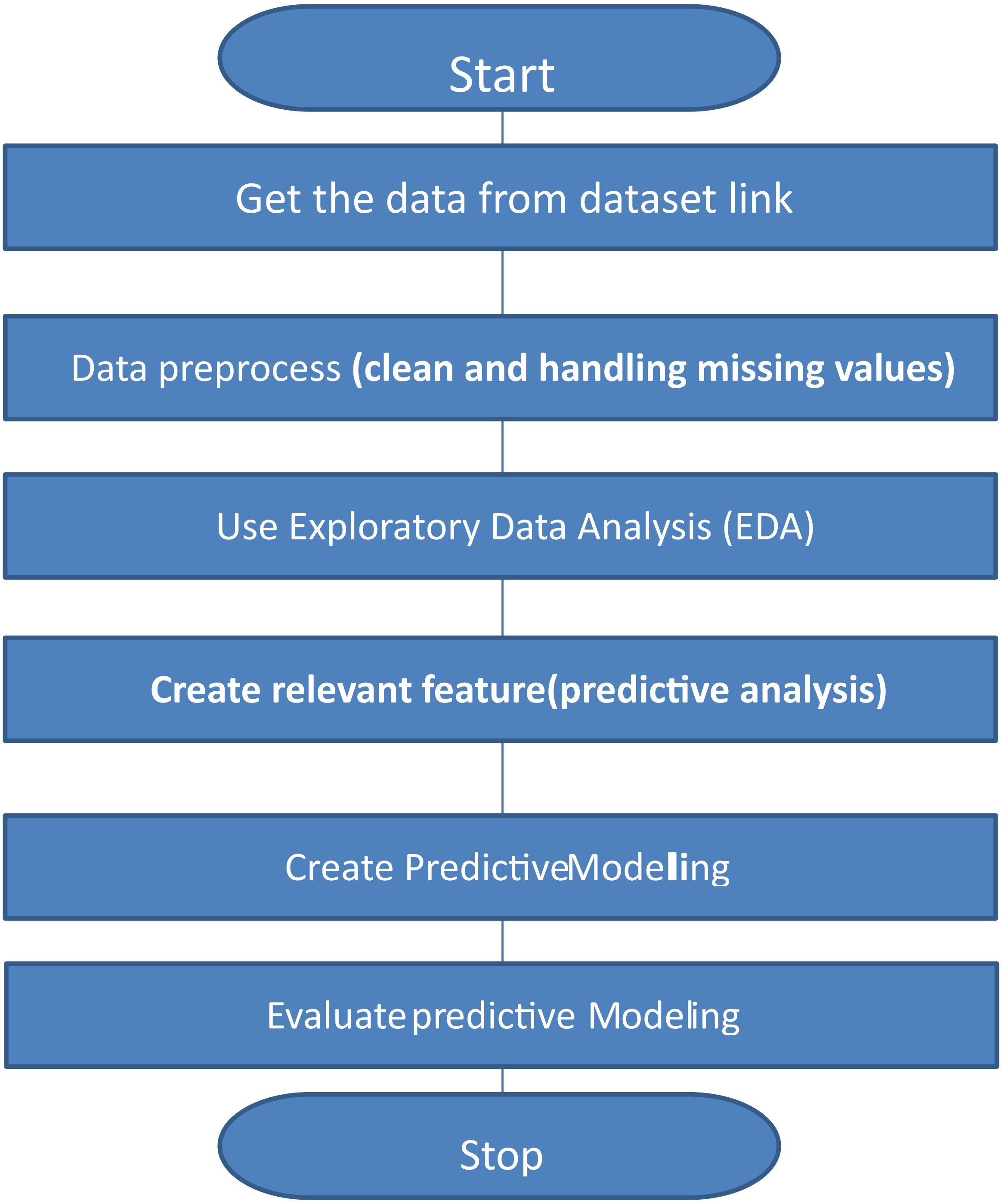

Problem Definition
Uncover Hidden Patterns
Future Registration trends
Gain Insights
Main Objectives
Future company registration
Support informed decision making for
Businesses, Investors, policymakers
Using Advanced AI
Aims to develop

Milestone of Project:

PHASE NO	NAME OF PHASE	DESCRIPTION	DATE OF COMPLETION
1	Problem definition and design thinking	Create algorithm to prepare the data and determine how to evaluate the future analysis.	01/10/2023
2	Innovation	Use Ensembling methods for improved predictive accuracy	10/10/2023
3	Development part 1	Exploration and prediction project by loading the data, Preprocessing the dataset.	17/10/2023
4	Development part 2	Performing the EDA, Feature Engineering, predictive model	27/10/2023

Design Thinking:

In the project summary, I declared my dataset. In this, I would be clean and preprocess the data, evaluate the predictive model.



PROCESS AND DATA:

1. *Data Collection: Gather historical stock prices, trading volumes, and relevant financial data. Sources could include financial databases, APIs, or web scraping tools.*
2. *Data Pre-processing: Clean the data, handle missing values, and perform feature engineering. This step might involve normalization, scaling, or transforming the data to make it suitable for the chosen model.*
3. *Feature Selection: Choose relevant features that might affect stock prices, such as historical prices, trading volumes, news sentiment, economic indicators, and company-specific information.*
4. *Model Selection: Select an appropriate machine learning algorithm such as linear regression, decision trees, random forests, or deep learning models like recurrent neural networks (RNNs) or long short-term memory networks (LSTMs).*
5. *Training the Model: Use a portion of the data to train the model, adjusting parameters and hyper parameters to optimize performance.*
6. *Model Evaluation: Assess the model's performance using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), or Root Mean Squared Error (RMSE) on a validation dataset.*
7. *Testing the Model: Apply the trained model to a separate test dataset to evaluate its predictive power.*
8. *Iterate and Refine: Fine-tune the model by iterating on the pre-processing steps, feature selection, and model selection to improve predictive accuracy.*

Program:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
%matplotlib inline
import seaborn as sns
from IPython.display import HTML
from sklearn.preprocessing import LabelEncoder
from collections import Counter
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score,
StratifiedKFold, learning_curve, train_test_split
```

```
#Get the data
df = pd.read_csv('/Data_Gov_Tamil_Nadu.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11370 entries, 0 to 11369
Data columns (total 17 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   CORPORATE_IDENTIFICATION_NUMBER         11370 non-null  object 
 1   COMPANY_NAME                            11370 non-null  object 
 2   COMPANY_STATUS                          11369 non-null  object 
 3   COMPANY_CLASS                           11058 non-null  object 
 4   COMPANY_CATEGORY                        11058 non-null  object 
 5   COMPANY_SUB_CATEGORY                    11058 non-null  object 
 6   DATE_OF_REGISTRATION                    11331 non-null  object 
 7   REGISTERED_STATE                        11369 non-null  object 
 8   AUTHORIZED_CAP                          11369 non-null  float64
 9   PAIDUP_CAPITAL                          11369 non-null  float64
 10  INDUSTRIAL_CLASS                        11059 non-null  float64
 11  PRINCIPAL_BUSINESS_ACTIVITY_AS_PER_CIN  11369 non-null  object 
 12  REGISTERED_OFFICE_ADDRESS               11357 non-null  object 
 13  REGISTRAR_OF_COMPANIES                  11346 non-null  object 
 14  EMAIL_ADDR                              7924 non-null   object 
 15  LATEST_YEAR_ANNUAL_RETURN               5554 non-null   object 
 16  LATEST_YEAR_FINANCIAL_STATEMENT         5577 non-null   object 
dtypes: float64(3), object(14)
memory usage: 1.5+ MB
```

CodeText

```
#check Duplicate Data
print(df.duplicated().sum())

0
```

```
#date and time is converted object in to datetime64
df['DATE_OF_REGISTRATION'] =
pd.to_datetime(df['DATE_OF_REGISTRATION'])
df['day_of_week'] =
df['DATE_OF_REGISTRATION'].dt.day_name()
df['month'] = df['DATE_OF_REGISTRATION'].dt.month
df['year'] = df['DATE_OF_REGISTRATION'].dt.year
print(df['DATE_OF_REGISTRATION'])
```

```
0        1961-01-12
1        2002-02-28
2        1982-01-03
3        2002-02-28
4        2002-02-28
            ...
11365    2004-10-12
11366    2005-05-30
11367    2005-10-06
11368    2005-09-16
11369    2002-02-28
Name: DATE_OF_REGISTRATION, Length: 11370, dtype: datetime64[ns]
```

```
#checking the missing values
print(df.isnull().sum())
```

```
CORPORATE_IDENTIFICATION_NUMBER            0
COMPANY_NAME                               0
COMPANY_STATUS                             1
COMPANY_CLASS                            312
COMPANY_CATEGORY                         312
COMPANY_SUB_CATEGORY                     312
DATE_OF_REGISTRATION                      39
REGISTERED_STATE                           1
AUTHORIZED_CAP                             1
PAIDUP_CAPITAL                             1
INDUSTRIAL_CLASS                         311
PRINCIPAL_BUSINESS_ACTIVITY_AS_PER_CIN     1
REGISTERED_OFFICE_ADDRESS                 13
REGISTRAR_OF_COMPANIES                    24
EMAIL_ADDR                              3446
LATEST_YEAR_ANNUAL_RETURN               5816
LATEST_YEAR_FINANCIAL_STATEMENT         5793
day_of_week                               39
month                                     39
dtype: int64
```

```
# fill missing values in column with their most repeated
```

```
df['COMPANY_CLASS'].fillna(df['COMPANY_CLASS'].mode()
[0], inplace=True)
df['COMPANY_CATEGORY'].fillna(df['COMPANY_CATEGORY'].
mode()[0], inplace=True)
df['COMPANY_SUB_CATEGORY'].fillna(df['COMPANY_SUB_CAT
EGORY'].mode()[0], inplace=True)
df['DATE_OF_REGISTRATION'].fillna(df['DATE_OF_REGISTR
ATION'].mode()[0], inplace=True)
df['INDUSTRIAL_CLASS'].fillna(df['INDUSTRIAL_CLASS'].
mode()[0], inplace=True)
df['REGISTERED_OFFICE_ADDRESS'].fillna(df['REGISTERED
_OFFICE_ADDRESS'].mode()[0], inplace=True)
df['REGISTRAR_OF_COMPANIES'].fillna(df['REGISTRAR_OF_
COMPANIES'].mode()[0], inplace=True)
df['EMAIL_ADDR'].fillna(df['EMAIL_ADDR'].mode()[0],
inplace=True)
df['LATEST_YEAR_ANNUAL_RETURN'].fillna(df['LATEST_YEA
R_ANNUAL_RETURN'].mode()[0], inplace=True)
df['LATEST_YEAR_FINANCIAL_STATEMENT'].fillna(df['LATE
ST_YEAR_FINANCIAL_STATEMENT'].mode()[0],
inplace=True)
```

```
# interpolate missing values using linear
interpolation
df['COMPANY_CLASS'].interpolate(inplace=True)
df['COMPANY_CATEGORY'].interpolate(inplace=True)
df['COMPANY_SUB_CATEGORY'].interpolate(inplace=True)
df['INDUSTRIAL_CLASS'].interpolate(inplace=True)
df['REGISTERED_OFFICE_ADDRESS'].interpolate(inplace=T
rue)
df['REGISTRAR_OF_COMPANIES'].interpolate(inplace=True
)
df['EMAIL_ADDR'].interpolate(inplace=True)
df['LATEST_YEAR_ANNUAL_RETURN'].interpolate(inplace=T
rue)
df['LATEST_YEAR_FINANCIAL_STATEMENT'].interpolate(inp
lace=True)
```

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

```
CORPORATE_IDENTIFICATION_NUMBER           0
COMPANY_NAME                              0
COMPANY_STATUS                            1
COMPANY_CLASS                             0
COMPANY_CATEGORY                          0
COMPANY_SUB_CATEGORY                      0
DATE_OF_REGISTRATION                      0
REGISTERED_STATE                          1
AUTHORIZED_CAP                            1
PAIDUP_CAPITAL                            1
INDUSTRIAL_CLASS                          0
PRINCIPAL_BUSINESS_ACTIVITY_AS_PER_CIN    1
REGISTERED_OFFICE_ADDRESS                 0
REGISTRAR_OF_COMPANIES                    0
EMAIL_ADDR                                0
LATEST_YEAR_ANNUAL_RETURN                 0
LATEST_YEAR_FINANCIAL_STATEMENT           0
day_of_week                               0
month                                     0
```

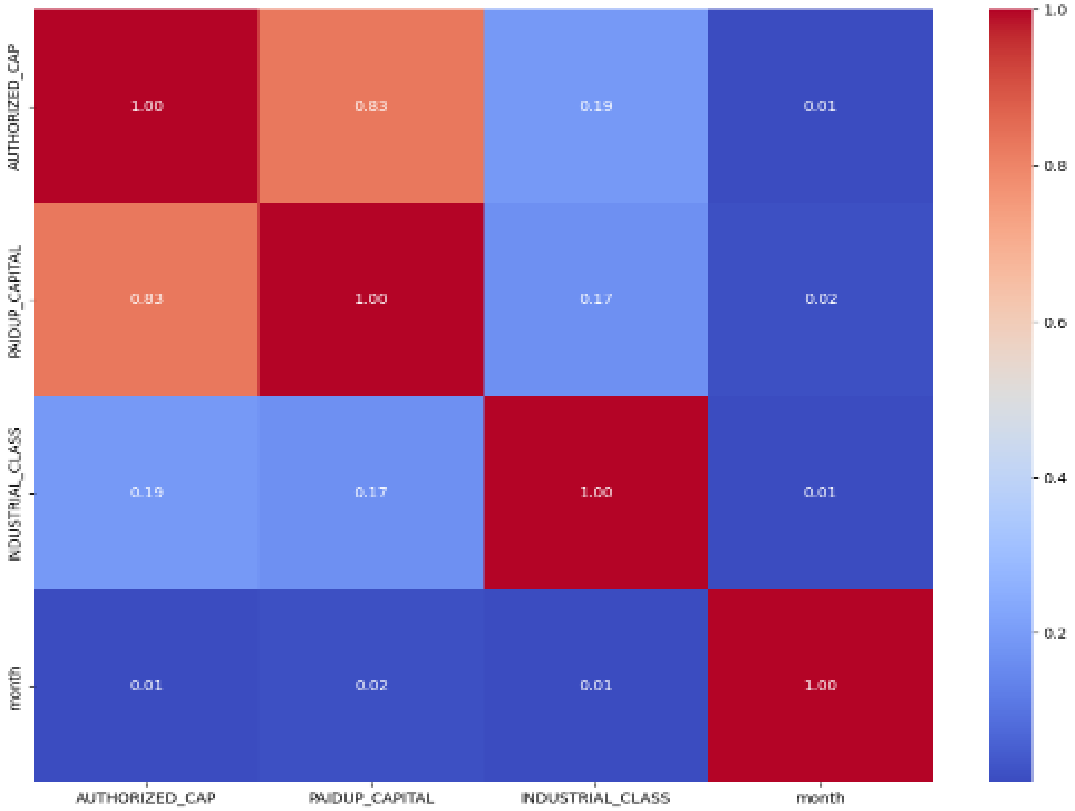
```
df.describe()
```

	AUTHORIZED_CAP	PAIDUP_CAPITAL	INDUSTRIAL_CLASS	month
count	3.855000e+03	3.855000e+03	3545.000000	3817.000000
mean	1.314988e+08	6.410010e+07	9533.436389	6.510086
std	1.504842e+09	9.001206e+08	19209.718669	3.483183
min	0.000000e+00	0.000000e+00	0.000000	1.000000
25%	2.000000e+05	1.000000e+04	1110.000000	3.000000
50%	1.000000e+06	1.000000e+05	1119.000000	6.000000
75%	5.000000e+06	1.128000e+06	1132.000000	10.000000
max	5.363000e+10	4.789458e+10	99999.000000	12.000000

Exploratory Data Analysis:

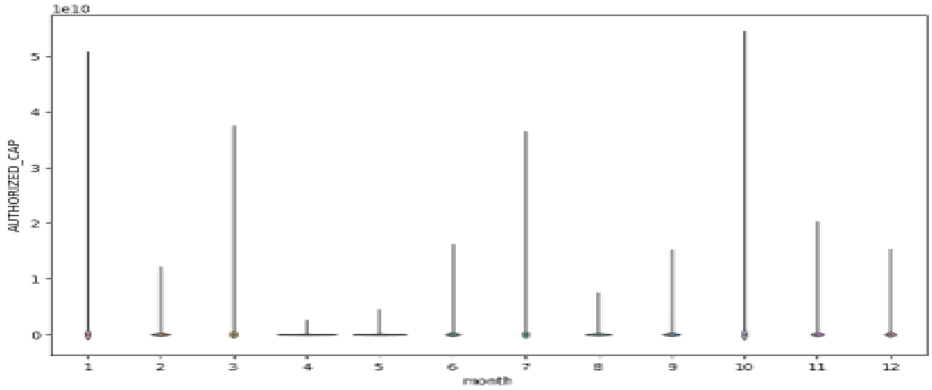
Correlation is one or more variables are related **to each other. It also helps to find the feature importance and clean the dataset before i start Modeling**

```
plt.figure(figsize=(13,10))
sns.heatmap(df.corr(),annot=True, fmt = ".2f", cmap =
"coolwarm")
```



```
# Explore AUTHORIZED_CAP vs month
plt.figure(figsize=(10,6))
sns.violinplot(data=df, x="month",
y="AUTHORIZED_CAP",
               split=True, inner="quart",
linewidth=1)
```

```
<Axes: xlabel='month', ylabel='AUTHORIZED_CAP'>
```




```python
# Explore INDUSTRIAL_CLASS vs month

plt.figure(figsize=(13,6))
g = sns.kdeplot(df["INDUSTRIAL_CLASS"][df["month"] ==
1],
      color="Red", shade = True)
g = sns.kdeplot(df["INDUSTRIAL_CLASS"][df["month"] ==
0],
      ax =g, color="Green", shade= True)
g.set_xlabel("INDUSTRIAL_CLASS")
g.set_ylabel("Frequency")
```

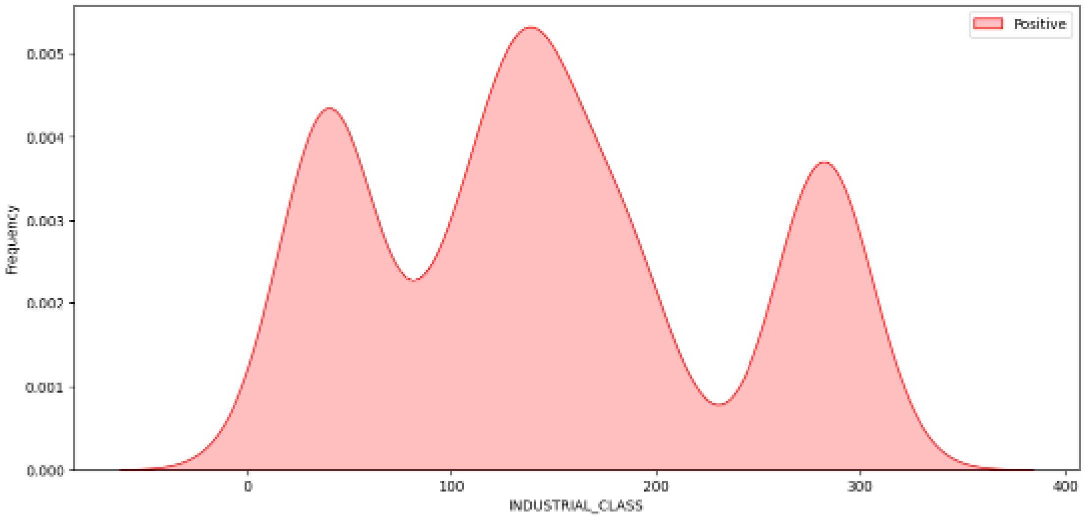
```
<ipython-input-42-98c727c289db>:3: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  g = sns.kdeplot(df["INDUSTRIAL_CLASS"][df["month"] == 1],
<ipython-input-42-98c727c289db>:5: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  g = sns.kdeplot(df["INDUSTRIAL_CLASS"][df["month"] == 0],
<matplotlib.legend.Legend at 0x7a286f08bc10>
```



Feature Engineering

Till now, i explored the dataset, did missing value corrections and data visualization. Next, i have started feature engineering. Feature engineering is useful to improve the performance of machine learning algorithms and is often considered as applied machine learning.

Outlier Detection:

```
# feature engineering (detect outliers)
```

```
def detect_outliers(df,n,features):
    outlier_indices = []
    for col in features:
        Q1 = np.percentile(df[col], 25)
        Q3 = np.percentile(df[col],75)
        IQR = Q3 - Q1

        # outlier step
        outlier_step = 1.5 * IQR

        # Determine a list of indices of outliers for feature col
        outlier_list_col = df[(df[col] < Q1 - outlier_step) | (df[col] > Q3 + outlier_step )].index

        # append the found outlier indices for col to the list of outlier indices
        outlier_indices.extend(outlier_list_col)

    # select observations containing more than 2 outliers
    outlier_indices = Counter(outlier_indices)
```

```
    multiple_outliers = list( k for k, v in
outlier_indices.items() if v > n )

    return multiple_outliers

# detect outliers from numeric features
outliers_to_drop = detect_outliers(df, 2
,['COMPANY_CLASS','AUTHORIZED_CAP',
'PAIDUP_CAPITAL','INDUSTRIAL_CLASS','month' ])
```

```
#remove outliers
df.drop(df.loc[outliers_to_drop].index, inplace=True)
```

Modeling

In this sections, i tried different models and compare the accuracy for each. Then, i performed Hyperparameter Tuning on Models that has high accuracy.

Before i split the dataset i need to transform the data into quantile using `sklearn.preprocessing`.

```
#  model evaluation
x = df[['year']]
y = df['COMPANY_CLASS']
x_train, x_test, y_train, y_test =
train_test_split(x, y, test_size=0.2,
random_state=42)
```

```
model= RandomForestRegressor(n_estimators=100,
random_state=42)
model.fit(x_train, y_train)
```

RandomForestRegressor

```
RandomForestRegressor(random_state=42)
```

```
#prediction model
y_pred = model.predict(x_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 294077005.65764993
```

```
#future trends
future_years = pd.DataFrame({'year':[2023, 2024,
2025,2026]})
future_registrations = model.predict(future_years)
print(f"prediction registrations for 2023:
{future_registrations[0]}")
print(f"prediction registrations for 2024:
{future_registrations[1]}")
print(f"prediction registrations for 2025:
{future_registrations[2]}")
```

```
prediction registrations for 2023: 1105.5193812083571
prediction registrations for 2024: 1105.5193812083571
prediction registrations for 2025: 1105.5193812083571
```

Hyperparameter Tuning

```
def analyze_grid_result(grid_result):

    print("Tuned hyperparameters: (best parameters)
", grid_result.best_params_)
    print("Accuracy :", grid_result.best_score_)

    means =
grid_result.cv_results_["mean_test_score"]
    stds = grid_result.cv_results_["std_test_score"]
    for mean, std, params in zip(means, stds,
grid_result.cv_results_["params"]):
        print("%0.3f (+/-%0.03f) for %r" % (mean, std
* 2, params))
```

```
    print()
    print("Detailed classification report:")
    y_true, y_pred = y_test,
grid_result.predict(x_test)
    print(classification_report(y_true, y_pred))
    print()
```

```
#logistic regression
model = LogisticRegression(solver='liblinear')
solvers = ['newton-cg', 'liblinear']
penalty = ['l2']
c_values = [100, 10, 1.0, 0.1, 0.01]
# Define grid search
grid = dict(solver = solvers, penalty = penalty, C =
c_values)
cv = StratifiedKFold(n_splits = 50, random_state = 1,
shuffle = True)
grid_search = GridSearchCV(estimator = model,
param_grid = grid, cv = cv, scoring = 'accuracy',
error_score = 0)
logi_result = grid_search.fit(x_train, y_train)
# Logistic Regression Hyperparameter Result
analyze_grid_result(logi_result)
```

```
# Test predictions
```

```
y_pred = logi_result.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
                   precision    recall  f1-score   support

                    Private       0.82      0.94      0.88       596
Private(One Person Company)       0.00      0.00      0.00         2
                     Public       0.59      0.28      0.38       173

                   accuracy                           0.79       771
                  macro avg       0.47      0.41      0.42       771
```

Conclusion:

Certainly, here concluding the project documentation for AIdriven exploration and prediction of company registration trends with registrar of companies, we summarize the key finding , insights and implication derived from our AI-driven exploration and prediction trends are achieved their own and future prediction will executed successful when above all done.