Machine learning - Hackathon

Vehicle Insurance Prediction

IMPORT

- import numpy and pandas for numerical calculation and Data Handling & Processing.
- for Scaling , Encoding and Polinomial features for Hidden paterns: MinMaxScaler , OneHotEncoder , PolynomialFeatures , SelectKBest , f_classif.
- for Imputing na : SimpleImputer
- Under and over sampleling for imbalanced data set: RandomUnderSampler , RandomOverSampler
- For Dimentionality Reduction and as model: PCA
- test case split and Cross validation for right hyper parmeter : train_test_split , GridSearchCV
- Metrics to calculate Classification type target: accuracy_score, classification_report, confusion_matrix , f1_score , roc_auc_score.
- for Pipeline Creationa and transformimg : Pipeline , ColumnTransformer
- For chart and visuals : matplotlib.pyplot , Seaborn
- Joblib for saving the file
- Warnings to filterout unnecessary warninngs during Model Training.

Data Loading and EDA process

- Importing data from using pd.read_CSV (All train , test and Sample prediction data sets.)
- Using df.info() , df.describe() , df.shape , df.head() , train_data.isna().sum() , train_data.duplicated().sum() to get over view of data types , data size and no of columns and columns names , missing value and duplicated data informations are identified.
- Use of box plot , coorliration matrix ,scaterplot and paire plot for identifying the outliers and patters and overall relatationship and behaviour of data can we identified.
- Here we dont have any linear relation ship and poor correlation are identified ,and values are scared overlapped and doesnot follow any standard patter.
- Also unbalance Target data is identified. We need to do either undersampeling (loss of features) or oversampeling (duplication of features). We will try both the methords.

Preprocessing

- First we remove the Outlier , by using the comparison operator in train data.
- We planed to try models for both under sampled and over sampled one. First go with under sampling to train data.
- Different preprocessing was done for under sampling and oversampling ,
- Maping values as bellow as shown for under sampling
- For over sampling i have done OHE to Vehicle age and Regional_code is left as it is (since during trying the oversampled data , we have already got good results in RF and tree based alorithms, since RF can handle regional_code as it is , so we are planing to go with this .

Undersampled_Preprocessing:

```
data['Gender'] = data['Gender'].map({'Female': 0, 'Male': 1})
data['Vehicle_Damage'] = data['Vehicle_Damage'].map({'No': 0, 'Yes': 1})
data['Vehicle_Age'] = data['Vehicle_Age'].map({'< 1 Year': 0, '1-2 Year': 1 , '> 2 Years':3})
```

```
bins = [0, 10, 20, 30, 40, 52]
labels = ['1-10', '11-20', '21-30', '31-40', '41-52']
data['Region_group'] = pd.cut(data['Region_Code'], bins=bins, labels=labels)
data = data.drop(columns='Region_Code')
```

Oversampled _Preprocessing:

```
[15]: data['Gender'] = data['Gender'].map({'Female': 0, 'Male': 1})
      data['Vehicle_Damage'] = data['Vehicle_Damage'].map({'No': 0, 'Yes': 1})

[16]: data.head()

      <div> •••

[17]: encoded_data = pd.get_dummies(data,columns = ['Vehicle_Age'],drop_first =  True)
```

- Do all these steps by concat of train and test data to capture the column chages will use for testing.
- Then remove the 'id' column from the data.
- After all this split again the train and test data seperately and save as Preprocessed train nad preprocessed test data.
- NOTE : Due to Model performance time and Ohencoded colums will be used for all models we have done this before the pipeline. We will be performing scaling seperatelyin pipeline.
- Scaling should be performed to train data only , else lead to data leakage , that no the case for OHE.
- Before building pipeline do create a function for easy and fast calculation as bellow and split the data x and y based on target variable , and use train_test_split method to it.

```
def results(x_train , x_test , y_train , y_test , model):
    model.fit(x_train,y_train)
    train_predict = model.predict(x_train)
    test_predict = model.predict(x_test)
    print('Train F1_score:',f1_score(y_train , train_predict))
    print('Test F1_score:',f1_score(y_test , test_predict))
    print('Train Accuracy_score:\n',accuracy_score(y_train , train_predict))
    print('Test Accuracy_score:\n',accuracy_score(y_test , test_predict))
    print('Train confusion_matrix:\n',confusion_matrix(y_train , train_predict))
    print('Test confusion_matrix:\n',confusion_matrix(y_test , test_predict))
    print('Train Classification_Report:\n',classification_report(y_train , train_predict))
    print('Test Classification_Report:\n',classification_report(y_test , test_predict))
    print('Train score\n', roc_auc_score(y_train , train_predict))
    print('Test score\n', roc_auc_score(y_test , test_predict))
```

```
x = prepr_train.drop(columns=['Response'])
y = prepr_train['Response']
```

```
x_train , x_test , y_train , y_test = train_test_split(x , y , test_size= 0.3 , random_state= 42)
```

Models Planned To Perform

- Logistic Regression (Due to Binary target)
- Random Forest
- KNN
- Naive Bayes
- Boosting
- Voting
- Stacking

Algorithms Performed

Under Sampled Data

- Linear Regression :
  1. **LR** (Poor Performance)
  2. **LR + Polynomial Features , degree = 2** .(to analysis unseen pattern in Linear model)
  3. **LR + Polynomial Features + Select K Best + PCA** (to reduce and select important features and compressed to two using PCA.)
  4. → (Since model have no or less linear relation ship , Performance is not Good)

- Random Forest :
  1. **RF with Scaled Data + Hyper parameters .** (good compared to LR , since score is 73%).
  2. **GridsearchCV for previous model. (** Same score not much difference in score)
  3. **RF with unscaled data + hyper parameters.(** Good performance compared to Scaled data, since score is in range of 83%)
- KNN:
  1. **KNN** –(Poor Performance like LR)
- Naive Bayes:
  1. NB –(Poor Performance like LR)

- Boosting :
  1. **ADA Boost with scaled data (** performance is low even with estimator as DT).
  2. **ADA Boost with un-scaled data (** Performance is Good as like RF we used before, score 82 %)
  3. **GridSearchCV with ADA Boost and DT parameter (** No significan difference in score value as Previous score of 82 remains same)
  4. **XGB with unscaled data (** apart all booting we tried untill now has good Score of 84% with minimal difference in train and test data.)

Algorithms Performed

Over Sampled Data

- Linear Regression :
  1. **LR** (Poor Performance)
  2. **LR + Polynomial Features , degree = 2** .(to analysis unseen pattern in Linear model)
  3. **LR + Polynomial Features + Select K Best + PCA** (to reduce and select important features and compressed to two using PCA.)
  4. → (Since model have no or less linear relation ship , Performance is not Good and results are as same as under sampled data. No improvement)
- Random Forest :
  1. **RF with unscaled data + Hyper parameters (max_depth = 5,15 ,20,35,45 and diffferent leaf and split).**(Tried with different depth rate we got increaching accuracy untill 90% , Good mode).
- Boosting:
  1. **ADA Boosting with unscaled data with DT estimator: (** Model performance is very Good slightly Seams to be Overfitting.)
  2. **XGB Boosting with unscaled data with DT estimator: (** very promising Result and very Generalized Data accuracy up to 83% , both train and test as very little deviation**.)**
  3. **XGB Boosting with unscaled data with Hyper parameter : (** no significan change in Output)

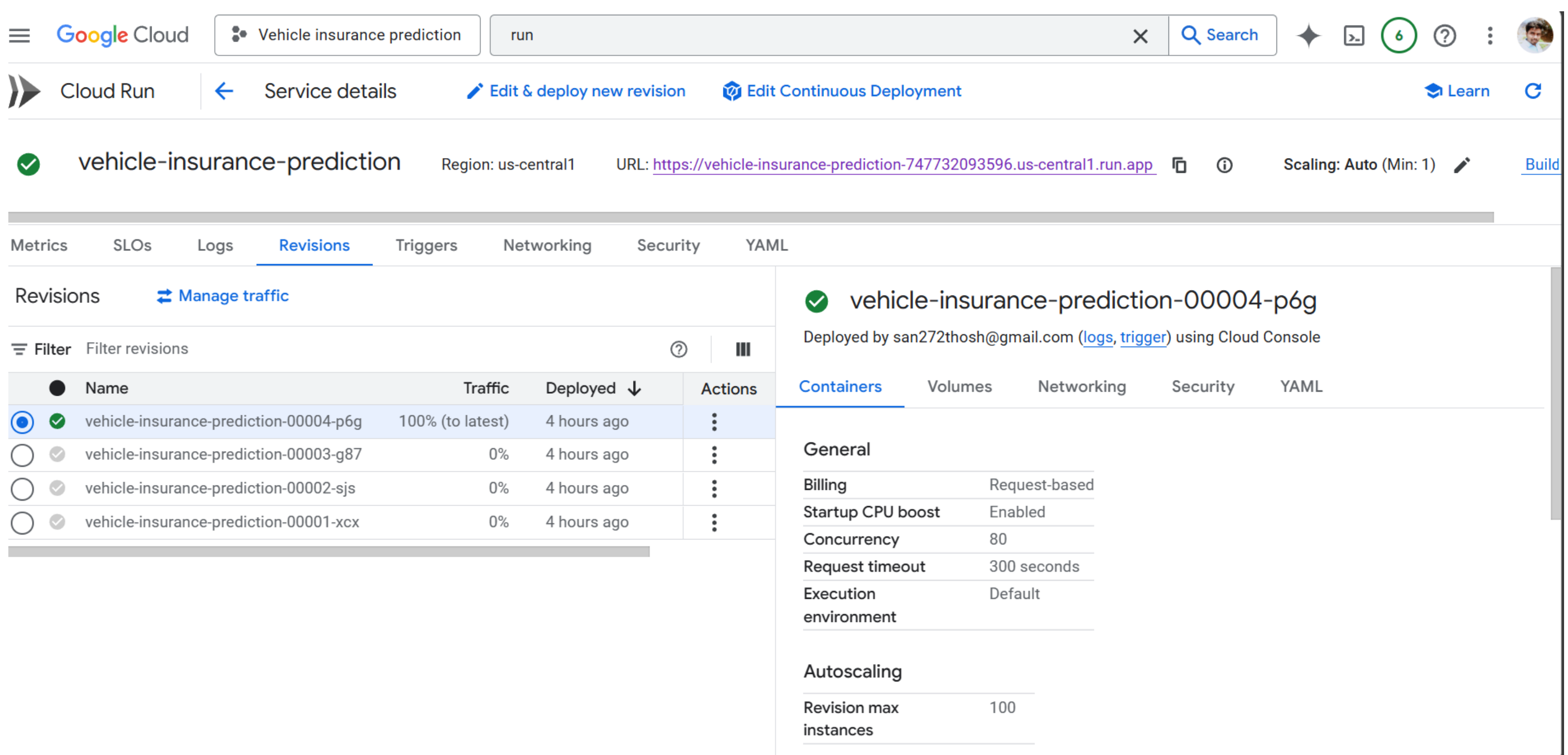
- KNN:
  1. **KNN** –(Poor Performance like LR)
- Naive Bayes:
  1. NB –(Poor Performance like LR)
- Voting:
  1. **Voting Soft (**Tried the combination of models that have predicted Good, (Random forest and XG boost). (Good results compared to all Models performed untill now) (4 models)
  2. **Voting hard(**Tried the combination of models that have predicted Good, (Random forest and XG boost). No good compared to Soft Voting. We go with Soft Voting.
  3. **Voting Soft**(tried with 6 models , no good output compared with top 4)
- Stacking:
  1. **Stacking with same models and final estimator as LR (** performance is not but no as good as voting soft , Train and test difference is high)
  2. **Stacking with same models and final estimator as XGB (** performance is not but no as good as voting soft)

Creating Webapp and Model Deployement

- After model training use PKL to save using Joblib we have imported.
- After Saving we need to create the webapp, for that we use VS-Code to create. Create a file name of webapp.py , here we use streamlit to create a custom page set up.
- Here we need to test custom input , so we create every input columns need for prediction and the inputs go throught the model and predict the output. Code file is attacked with other document.
- To run the file use code " **streamlit run weapp.py** " check weather the models is working without any error.
- Now we are colser to deploy the model in GCP , for that we nee Dockerfile and requirement.txt file, both are necessary to deploy model in a container image.
- In requirement.txt we need to specify the libraries need to perform the task and Dockerfile contains nessary information for creation a docker within GCP.
- Dockerfile consist of python version , working Directory , run commands to go through the requirements.txt and server address details and runcode that we use to run Web app.
- After Creating the all the required file , we use github as medium platform for Cloud , github platform easy to manage data changes compared to directly applying in GCP.
- In Github Create an repository for this project and save all the file (PKl file , webapp.py , requirements.txt , train_data.csv , Dockerfile).

Cloud Deployement

- After uploading in Github , Open the Google cloud platform (many cloud platform avaiable , but we use Google cloud) . Select Create new project → console Run
- Select github from platform and login to you github platform , select allow all , then select Docker. Then click ‘Create’.
- Select the accessability to Allow unathorized and give instance value as 1. than ‘create’
- Model will automatically check and gives no error as below.
- After that copy the URL and can we shared. Using this anyone can access you model.



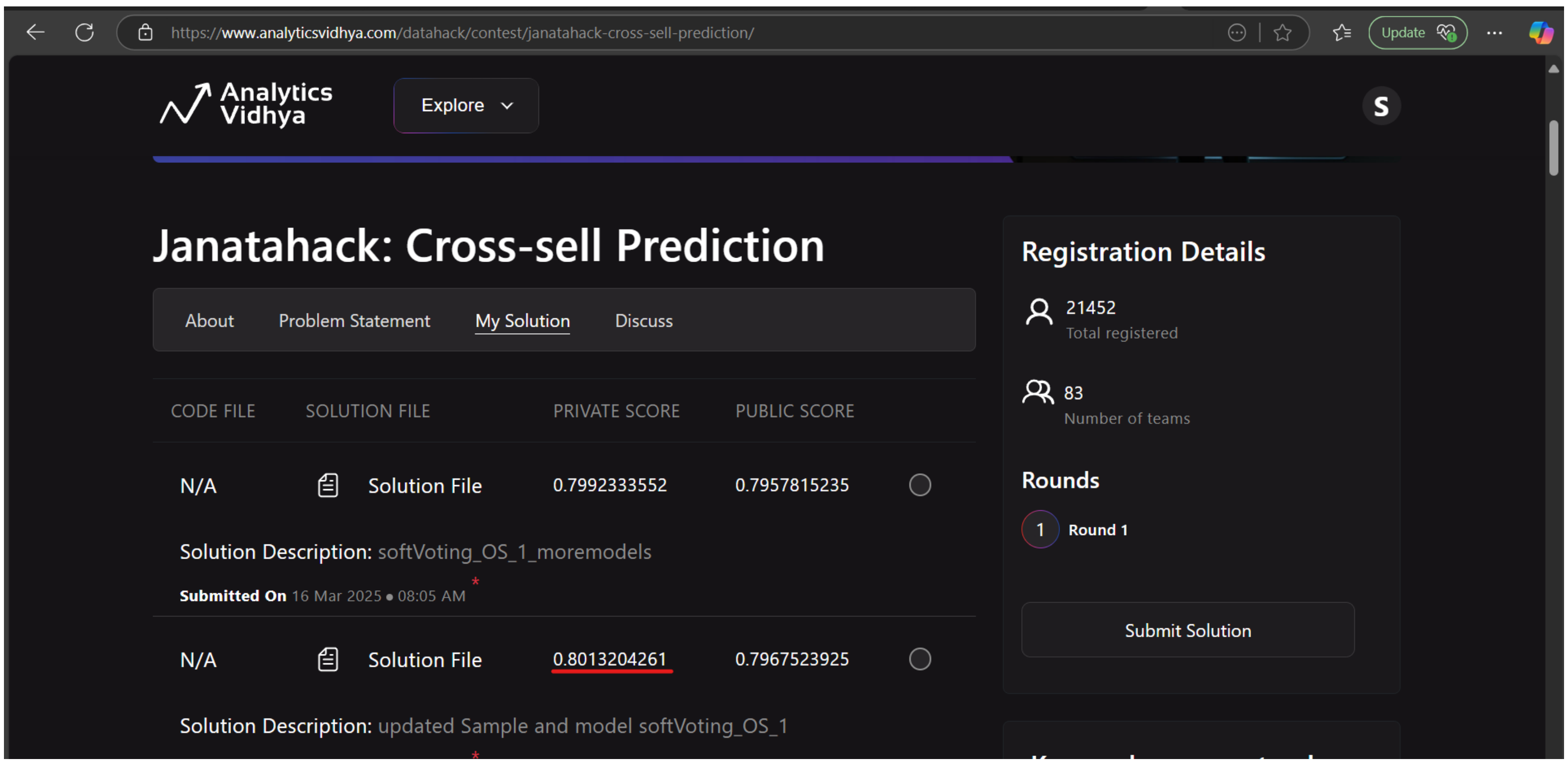
Problems Faces

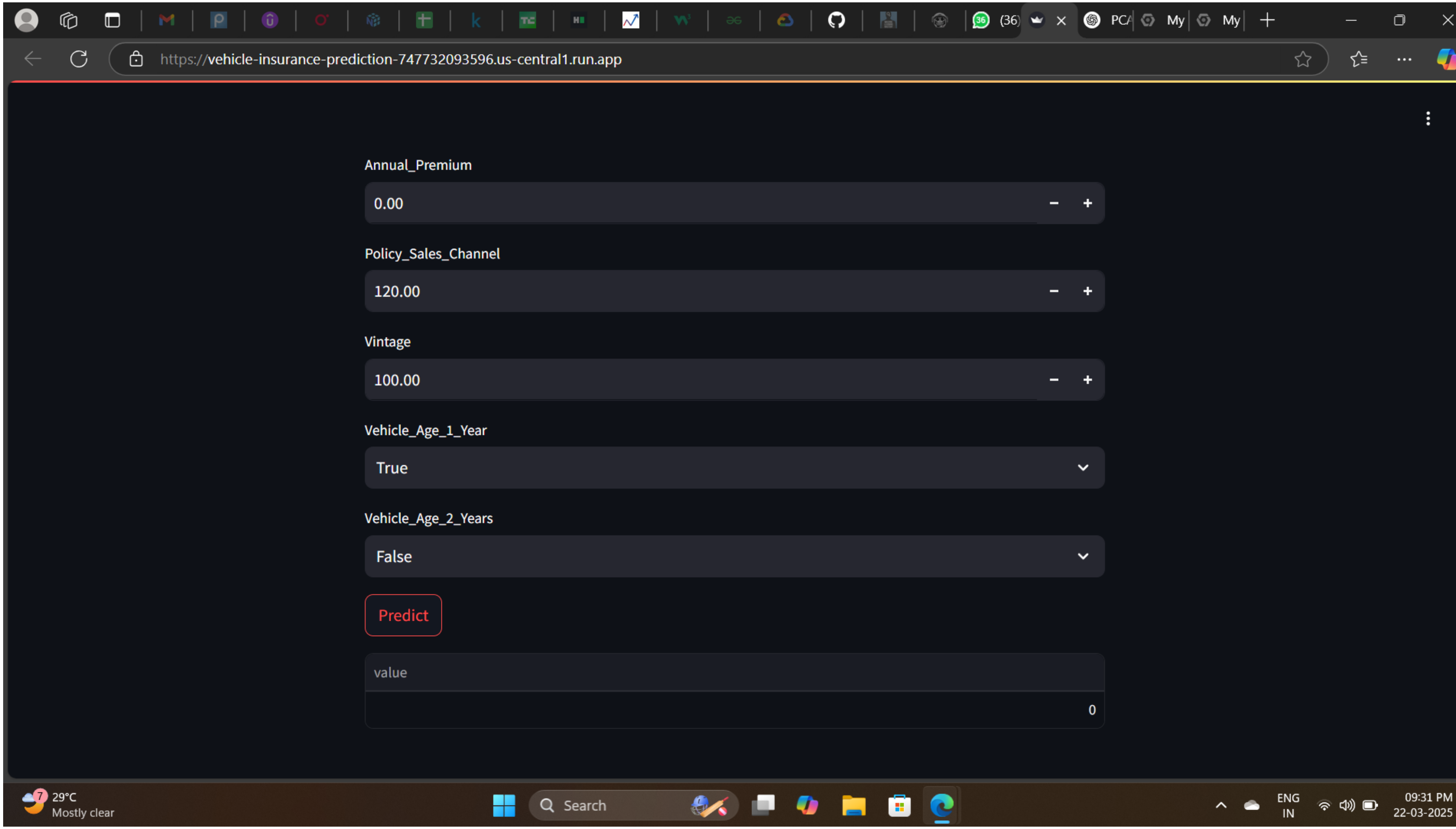
- Unable to upload the PLK file , since my file size neary 100 MB but github supports only max 25 Mb , compression take me hard time and also caused errors in GCP run.
- In option my i try to unload using Google Drive via link to maintain the orinality of the model , but not worked.
- Due to larger data size , unable to perform certain CV combinations , that took nearly more time than expected, Due to limited time i can up with this model.
- Due larger data size , GCP run didn’t predict , even thought there is no error message , worked only when i increase the memory size in GCP configration to 2GB.

Completed Model URL from GCP

https://vehicle-insurance-prediction-747732093596.us-central1.run.app

Analytics Vidhya Competition best Score:




https://vehicle-insurance-prediction-747732093596.us-central1.run.app
Annual_Premium
0.00
Policy_Sales_Channel
120.00
Vintage
100.00
Vehicle_Age_1_Year
True
Vehicle_Age_2_Years
False
Predict
value
0
29°C
Mostly clear
Search
ENG
IN
09:31 PM
22-03-2025