SMARTINTERNZ

Credit Card Approval Prediction Using Machine Learning

Project Report

introduction

1.1 overview

Credit risk as the board in banks basically centers around deciding the probability of a customer's default or credit decay and how expensive it will end up being assuming it happens. It is important to consider major factors and predict beforehand the probability of consumers defaulting given their conditions. Which is where a machine learning model comes in handy and allows the banks and major financial institutions to predict whether the customer, they are giving the loan to, will default or not. This project builds a machine learning model with the best accuracy possible using python. First we load and view the dataset. The dataset has a combination of both mathematical and non-mathematical elements, that it contains values from various reaches, in addition to that it contains a few missing passages. We preprocess the dataset to guarantee the AI model we pick can make great expectations. After the information is looking great, some exploratory information examination is done to assemble our instincts. Finally, we will build a machine learning model that can predict if an individual's application for a credit card will be accepted. Using various tools and techniques we then try to improve the accuracy of the model. This project uses Jupyter notebook for python programming to build the machine learning model. Using Data Analysis and Machine Learning, we attempted to determine the most essential parameters for obtaining credit card acceptance in this project.

1.2 Purpose:

It uses personal information and data submitted by credit card applicants to predict the probability of future defaults and credit card borrowings. The bank is able to decide whether to issue a credit card to the applicant. Credit scores can objectively quantify the magnitude of risk.

2 LITERATURE SURVEY

2.1 Existing problem:

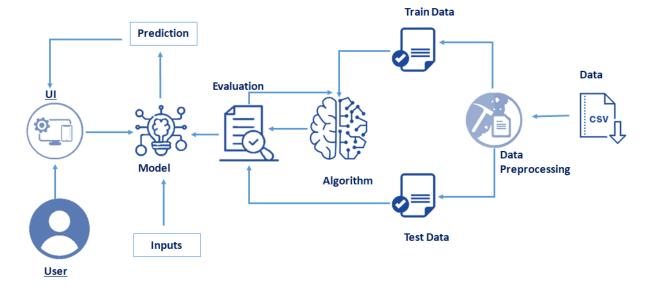
This is a prediction problem in which we need to predit whether a person eligiable for credit card or not

2.2 Proposed solution

it's means the combination of software, hardware, other products or equipment, and any and all services (including any installation, implementation, training, maintenance and support services) necessary to implement the solution described by user in its Proposal.

3.THEORITICAL ANALYSIS

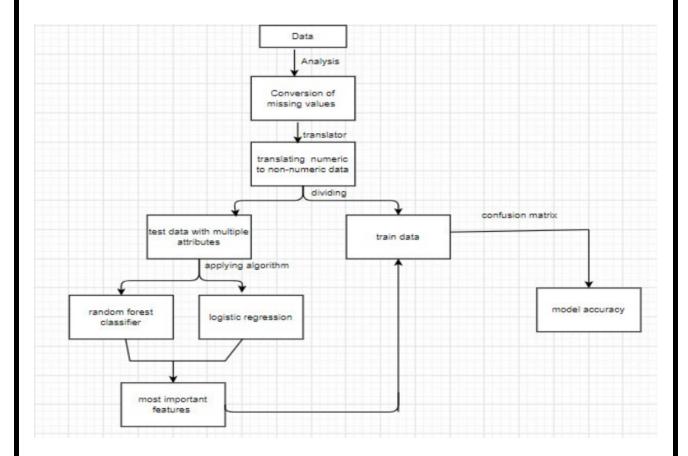
3.1 Block Diagram:



3.2 Software Requirements:

- ANACONDA NAVIGATOR
- JUPYTER NOTEBOOK
- SPIDER

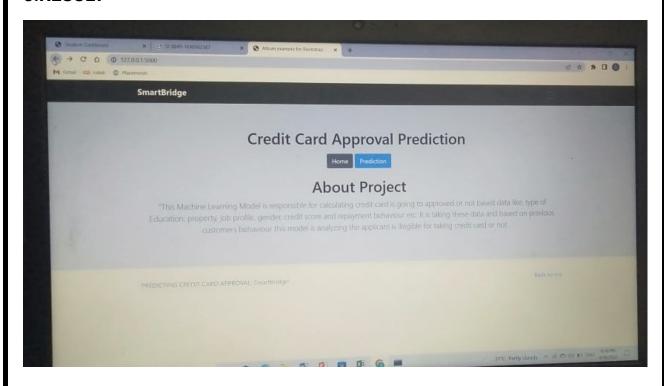
3.3 FLOW CHART

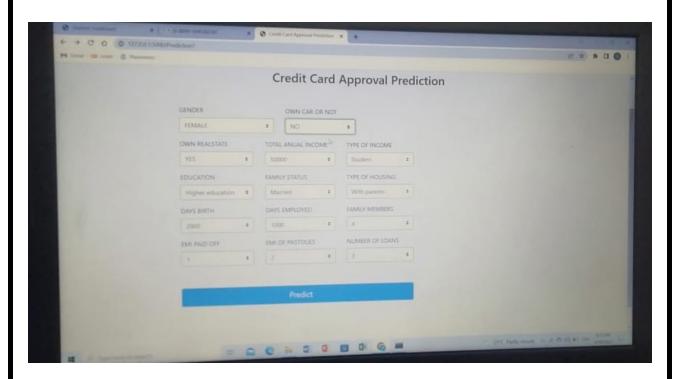


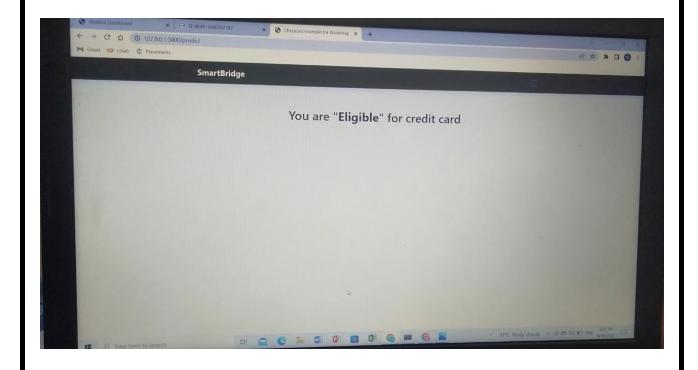
4. Project Flow

- Data Collection.
- Data Visualization
- Data Pre-processing
- Model Building
- Application Building

5.RESULT







6. ADAVANTAGES AND DISADAVANTAGES:

6.1 ADAVANTAGES

- Opportunity to build credit
- Earn rewards such as cash back or miles points
- Protection against credit card fraud
- Free credit score information
- No foreign transaction fees

6.2 DISADAVANTAGES

- Minimum due trap
- Hidden costs
- Ease of overuse
- High intrest rate

7. CONCLUSION:

Currently, factors considered are regular details related to gender, age of the consumer, his/hercredit reports and worthiness, yearly income, and the number of years he/she has been working. Further, to improve this work, various other factors or conditions can be considered like their history related to any offense and their assets which can be both physical and liquid cash. These features can improve the model to be more effective and can help the institutes to make better decisions so that they can avoid experiencing frauds and loss. Various classification algorithms can be used to build a model and compare the rates or levels of accuracy to improve the model for better use.

7. FUTURE SCOPE:

machine learning needs you to know computer programming, statistics and data evaluation, the future scope of your machine learning career can also be in **leadership** roles in automation or analytics environments

8.REFERENCE:

K. Chaudhary, J. Yadav, and B. Mallick, "A review of fraud detection techniques: Credit card,"

International Journal of Computer Applications

9.APPENDIX

9.1 source code

SOURCE CODE:

```
In [2]: import numpy as np
                    import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
                    \textbf{from} \  \, \textbf{sklearn.ensemble} \  \, \textbf{import} \  \, \textbf{RandomForestClassifier}
                    from sklearn.model_selection import train_test_split, RandomizedSearchCV from sklearn.model_selection import train_test_split, RandomizedSearchCV from sklearn.metrics import OneHotEncoder from sklearn.metrics import classification_report,confusion_matrix,f1_score from sklearn.linear_model import LogisticRegression from sklearn.ensemble import GradientBoostingClassifier
                    from sklearn.tree import DecisionTreeClassifier
       In [3]: app = pd.read_csv('application_record.csv')
credit = pd.read_csv('credit_record.csv')
       In [4]: app.head()
       Out[4]:
                                ID CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REALTY CNT_CHILDREN AMT_INCOME_TOTAL NAME_INCOME_TYPE NAME_EDUCATION_TYPE N
                     0 5008804
                                                      М
                                                                                                                             0
                                                                                                                                                 427500.0
                                                                                                                                                                                                     Higher education
                                                                                                                                                                              Working
                                                      М
                                                                                                                             0
                                                                                                                                                 427500.0
                      1 5008805
                                                                                                                                                                              Working
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                                                                                                                             0
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                      3 5008808
                                                                             Ν
                                                                                                                                                 270000.0
                                                                                                                                                              Commercial associate
                                                                                                                                                                                              Secondary / secondary special
                      4 5008809
                                                                                                                                                 270000.0 Commercial associate
print('Types of house of the people:')
print(app['NAME_HOUSING_TYPE'].value_counts())
sns.set(rc = {'figure.figsize':(15,4)})
sns.countplot(x='NAME_HOUSING_TYPE',data=app,palette ='Set2')
Types of house of the people:
House / apartment
                                         393831
With parents
                                          19077
Municipal apartment
                                          14214
 Rented apartment
                                            5974
Office apartment
                                            3922
 Co-op apartment
                                            1539
Name: NAME_HOUSING_TYPE, dtype: int64
 <AxesSubplot:xlabel='NAME_HOUSING_TYPE', ylabel='count'>
     400000
      350000
     300000
     250000
     200000
     150000
```

```
flg, ax=plt.subplots(figsize=(8,6))
sns.heatmap(app.corr(),annot=True)
<AxesSubplot:>
                                                                                                 - 1.0
                   ID
                              -0.0052 0.011 -0.005-0.0025
                                                                                                  - 0.8
                                     0.019 0.35 -0.24
                                                                0.038 -0.038 0.028 0.88
      CNT_CHILDREN
                                                                -0.034 0.0044 0.11 0.011
                                                                                                 - 0.6
 AMT_INCOME_TOTAL
                                                                0.17 -0.038 0.097 0.31
         DAYS_BIRTH
                        -0.005 0.35 0.054
                                                   -0.62
                                                                                                 - 0.4
                        0.0025-0.24 -0.14 -0.62
                                                                -0.23 0.0049-0.074 -0.23
    DAYS_EMPLOYED
                                                                                                 - 0.2
         FLAG_MOBIL
                                                                                                 - 0.0
                        -0.023 0.038 -0.034 0.17 -0.23
                                                                       0.29 -0.061 0.05
 FLAG_WORK_PHONE
                                                                                                 - -0.2
        FLAG_PHONE
                        -0.019 -0.0380.0044 -0.038 0.0049
                                                                             0.0012-0.024
         FLAG_EMAIL
                        0.033 0.028 0.11 0.097 -0.074
                                                                                    0.022
                                                                                                  -0.4
                        0.0019 0.88
                                                                 0.05 -0.024 0.022
 CNT_FAM_MEMBERS
                                                                                                   -0.6
                                                    DAYS_EMPLOYED
                                                                                      ONT FAM MEMBERS
                                       MT_INCOME_TOTAL
                                             DAYS_BIRTH
                                                           RAG_MOBIL
                                                                  LAG_WORK_PHONE
                                                                        FLAG_PHONE
                                                                               RAG_EMAIL
```

app.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 438557 entries, 0 to 438556 Data columns (total 18 columns):

#	Column	Non-Null Count	Dtype
		420557	
0	ID	438557 non-null	
1	CODE_GENDER	438557 non-null	
2	FLAG_OWN_CAR	438557 non-null	object
3	FLAG_OWN_REALTY	438557 non-null	object
4	CNT_CHILDREN	438557 non-null	int64
5	AMT_INCOME_TOTAL	438557 non-null	float64
6	NAME_INCOME_TYPE	438557 non-null	object
7	NAME_EDUCATION_TYPE	438557 non-null	object
8	NAME_FAMILY_STATUS	438557 non-null	object
9	NAME_HOUSING_TYPE	438557 non-null	object
10	DAYS_BIRTH	438557 non-null	int64
11	DAYS_EMPLOYED	438557 non-null	int64
12	FLAG_MOBIL	438557 non-null	int64
13	FLAG_WORK_PHONE	438557 non-null	int64
14	FLAG_PHONE	438557 non-null	int64
15	FLAG_EMAIL	438557 non-null	int64
16	OCCUPATION_TYPE	304354 non-null	object
17	CNT_FAM_MEMBERS	438557 non-null	float64
dtypes: float64(2), int64(8), object(8)			

memory usage: 60.2+ MB

```
def logistic reg(xtrain,xtest, ytrain, ytest):
  Ir-LogisticRegression (solver-'liblinear')
  lr.fit(xtrain, ytrain)
  vpred-lr.predict(xtest)
  print('***LogisticRegression***')
  print('Confusion matrix')
  print(confusion_matrix(ytest,ypred))
  print('Classification report')
  print(classification_report(ytest, ypred))
def random forest(xtrain, xtest, ytrain,ytest):
  rf=RandomForestClassifier()
  rf.fit(xtrain, ytrain)
  ypred-rf.predict(xtest)
  print('***RandomForestClassifier***')
  print('Confusion matrix')
  print(confusion matrix(ytest,ypred))
  print('Classification report')
  print(classification report(ytest,ypred))
def g_boosting (xtrain, xtest, ytrain, ytest):
   gb=GradientBoostingClassifier()
   gb.fit(xtrain, ytrain)
   ypred=gb.predict(xtest)
   print('***Gradient BoostingClassifier***')
   print('Confusion matrix')
   print(confusion_matrix(ytest,ypred))
   print('Classification report')
   print(classification_report(ytest, ypred))
def compare_model (xtrain,xtest, ytrain,ytest):
  logistic_reg(xtrain, xtest, ytrain,ytest)
print('-'*100)
  random_forest(xtrain, xtest, ytrain,ytest)
print('-'*100)
  g_boosting(xtrain, xtest, ytrain,ytest)
  print('-'*100)
  d_tree(xtrain, xtest, ytrain,ytest)
dt = DecisionTreeClassifier()
dt.fit(xtrain,ytrain)
ypred = dt.predict(xtest)
import pickle
pickle.dump(dt,open("model.pk1","wb"))
```

