Deep Learning with Keras and Tensorflow

House Loan Data Analysis Course-end Project 1

For safe and secure lending experience, it's important to analyze the past data. In this project, you have to build a deep learning model to predict the chance of default for future loans using the historical data. As you will see, this dataset is highly imbalanced and includes a lot of features that make this problem more challenging.

Objective: Create a model that predicts whether or not an applicant will be able to repay a loan using historical data.

Domain: Finance

Analysis to be done: Perform data preprocessing and build a deep learning prediction model.

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

In [2]:
```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

In [3]:
```
import pandas as pd
import sklearn
import numpy as np
import matplotlib.pyplot as plt
import os
import warnings
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
from sklearn.datasets import make_blobs
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
```

In console type

Adding Path setx PATH "%PATH%;C:\path\to\Anaconda3\" conda update conda pip install plotly pip install --upgrade pip on terminal

conda install -c conda-forge cufflinks-py pip install lightgbm

In [4]:
```
from sklearn.metrics import accuracy_score
from sklearn.linear_model import SGDClassifier
import plotly.offline as py
import plotly.graph_objs as go
from plotly.offline import init_notebook_mode, iplot
from sklearn.model_selection import train_test_split
init_notebook_mode(connected=True)
```

In [5]:
```
import cufflinks as cf
cf.go_offline()
import pickle
import gc
```

In [6]:
```
import lightgbm as lgb
warnings.filterwarnings('ignore')
```

Load the dataset that is given to you Loading the dataset

In [7]:
```
import csv
# csv file name
house_loan = pd.read_csv(r'D:\OneDrive\Knowledge Center\AI - ML\Masters in Artif
```

In [8]:
```
house_loan.describe()
```

Out[8]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CRED
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+(
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+(
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+(
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+(
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+(
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+(
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+(
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+(

8 rows × 106 columns

In [9]:
```
house_loan.columns
```

Out[9]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
       'AMT_CREDIT', 'AMT_ANNUITY',
       ...
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object', length=122)
```

In [10]:
```
print(house_loan.head())
```

```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0               Y             0          202500.0    406597.5      24700.5
1               N             0          270000.0   1293502.5      35698.5
2               Y             0           67500.0    135000.0       6750.0
3               Y             0          135000.0    312682.5      29686.5
4               Y             0          121500.0    513000.0      21865.5

   ...  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20 FLAG_DOCUMENT_21  \
0  ...                0                0                0                0
1  ...                0                0                0                0
2  ...                0                0                0                0
3  ...                0                0                0                0
4  ...                0                0                0                0

  AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                       0.0
1                        0.0                       0.0
2                        0.0                       0.0
3                        NaN                       NaN
4                        0.0                       0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 122 columns]
```

In [11]:
```
house_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

Check for null values in the dataset

In [12]:
```
null_values = house_loan.isnull()
null_count = house_loan.isnull().sum()
```

In [13]:
```
print(null_values, null_count)
```

```
        SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  \
0            False   False               False        False         False
1            False   False               False        False         False
2            False   False               False        False         False
3            False   False               False        False         False
4            False   False               False        False         False
...            ...     ...                 ...          ...           ...
307506       False   False               False        False         False
307507       False   False               False        False         False
307508       False   False               False        False         False
307509       False   False               False        False         False
307510       False   False               False        False         False

        FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
0                 False         False             False       False
1                 False         False             False       False
2                 False         False             False       False
3                 False         False             False       False
4                 False         False             False       False
...                 ...           ...               ...         ...
307506            False         False             False       False
307507            False         False             False       False
307508            False         False             False       False
307509            False         False             False       False
307510            False         False             False       False

        AMT_ANNUITY  ...  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  \
0             False  ...             False             False
1             False  ...             False             False
2             False  ...             False             False
3             False  ...             False             False
4             False  ...             False             False
...             ...  ...               ...               ...
307506        False  ...             False             False
307507        False  ...             False             False
307508        False  ...             False             False
307509        False  ...             False             False
307510        False  ...             False             False

        FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
0                  False             False                       False
1                  False             False                       False
2                  False             False                       False
3                  False             False                        True
4                  False             False                       False
...                  ...               ...                         ...
307506             False             False                        True
307507             False             False                        True
307508             False             False                       False
307509             False             False                       False
307510             False             False                       False

        AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
0                           False                       False
1                           False                       False
2                           False                       False
3                            True                        True
4                           False                       False
...                           ...                         ...
307506                       True                        True
```

```
307507                         True                          True
307508                        False                         False
307509                        False                         False
307510                        False                         False

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
0                           False                      False
1                           False                      False
2                           False                      False
3                            True                       True
4                           False                      False
...                           ...                        ...
307506                       True                       True
307507                       True                       True
307508                      False                      False
307509                      False                      False
307510                      False                      False

        AMT_REQ_CREDIT_BUREAU_YEAR
0                            False
1                            False
2                            False
3                             True
4                            False
...                            ...
307506                        True
307507                        True
307508                       False
307509                       False
307510                       False

[307511 rows x 122 columns] SK_ID_CURR                        0
TARGET                            0
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
                               ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 122, dtype: int64
```

In [14]:

```
null_count
```

Out[14]:

```
SK_ID_CURR                        0
TARGET                            0
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
                               ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 122, dtype: int64
```

In [15]:
```
#Instead of dropping null values house_loan = house_loan.dropna() filling it up
# fill null values with mean
# fill missing values in numeric columns with mean
for col in house_loan.select_dtypes(include=['int64', 'float64']).columns:
    house_loan[col] = house_loan[col].fillna(house_loan[col].mean())

# fill missing values in non-numeric columns with most frequent value
for col in house_loan.select_dtypes(exclude=['int64', 'float64']).columns:
    house_loan[col] = house_loan[col].fillna(house_loan[col].mode()[0])
```

In [16]:
```
null_count = house_loan.isnull().sum()
null_count
```

Out[16]:
```
SK_ID_CURR                    0
TARGET                        0
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
                             ..
AMT_REQ_CREDIT_BUREAU_DAY     0
AMT_REQ_CREDIT_BUREAU_WEEK    0
AMT_REQ_CREDIT_BUREAU_MON     0
AMT_REQ_CREDIT_BUREAU_QRT     0
AMT_REQ_CREDIT_BUREAU_YEAR    0
Length: 122, dtype: int64
```

Print percentage of default to payer of the dataset for the TARGET column Assuming the defaulters as 1 and 0

In [17]:
```
defaulters=(house_loan.TARGET==1).sum()
payers=(house_loan.TARGET==0).sum()
print(defaulters, payers)
print((defaulters/payers)*100)
```

```
24825 282686
8.781828601345662
```

In [18]:
```
#Percentage of defaulters
print((defaulters*100/(defaulters+payers)))
```

```
8.072881945686495
```

Basic cleaning of data. REmovinf duplicate, filling up NaN or null and encoding for analysis

In [19]:
```
from sklearn.preprocessing import LabelEncoder
```

In [20]:
```
le = LabelEncoder()
#select non-numeric columns
non_numeric_columns = house_loan.select_dtypes(exclude=['int64', 'float64']).col
```

In [21]:
```
# create a dictionary to store the LabelEncoder objects for each column
le_dict = {}

for col in non_numeric_columns:
    le = LabelEncoder()
    house_loan[col] = le.fit_transform(house_loan[col])
    le_dict[col] = le
```

```
# print the encoded DataFrame
print(house_loan)

# print the original values for each encoded number
for col, le in le_dict.items():
    print(f"{col}:")
    for class_, label in enumerate(le.classes_):
        print(f"{class_}: {label}")
```

```
        SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  \
0           100002       1                   0            1             0
1           100003       0                   0            0             0
2           100004       0                   1            1             1
3           100006       0                   0            0             0
4           100007       0                   0            1             0
...            ...     ...                 ...          ...           ...
307506      456251       0                   0            1             0
307507      456252       0                   0            0             0
307508      456253       0                   0            0             0
307509      456254       1                   0            0             0
307510      456255       0                   0            0             0

        FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
0                     1             0          202500.0    406597.5
1                     0             0          270000.0   1293502.5
2                     1             0           67500.0    135000.0
3                     1             0          135000.0    312682.5
4                     1             0          121500.0    513000.0
...                 ...           ...               ...         ...
307506                0             0          157500.0    254700.0
307507                1             0           72000.0    269550.0
307508                1             0          153000.0    677664.0
307509                1             0          171000.0    370107.0
307510                0             0          157500.0    675000.0

        AMT_ANNUITY  ...  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  \
0           24700.5  ...                 0                 0
1           35698.5  ...                 0                 0
2            6750.0  ...                 0                 0
3           29686.5  ...                 0                 0
4           21865.5  ...                 0                 0
...             ...  ...               ...               ...
307506      27558.0  ...                 0                 0
307507      12001.5  ...                 0                 0
307508      29979.0  ...                 0                 0
307509      20205.0  ...                 0                 0
307510      49117.5  ...                 0                 0

        FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
0                      0                 0                    0.000000
1                      0                 0                    0.000000
2                      0                 0                    0.000000
3                      0                 0                    0.006402
4                      0                 0                    0.000000
...                  ...               ...                         ...
307506                 0                 0                    0.006402
307507                 0                 0                    0.006402
307508                 0                 0                    1.000000
307509                 0                 0                    0.000000
307510                 0                 0                    0.000000

        AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
0                           0.000                    0.000000
1                           0.000                    0.000000
2                           0.000                    0.000000
3                           0.007                    0.034362
4                           0.000                    0.000000
...                           ...                         ...
307506                      0.007                    0.034362
```

```
307507                 0.007                    0.034362
307508                 0.000                    0.000000
307509                 0.000                    0.000000
307510                 0.000                    0.000000

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
0                        0.000000                   0.000000
1                        0.000000                   0.000000
2                        0.000000                   0.000000
3                        0.267395                   0.265474
4                        0.000000                   0.000000
...                           ...                        ...
307506                   0.267395                   0.265474
307507                   0.267395                   0.265474
307508                   1.000000                   0.000000
307509                   0.000000                   0.000000
307510                   2.000000                   0.000000

        AMT_REQ_CREDIT_BUREAU_YEAR
0                         1.000000
1                         0.000000
2                         0.000000
3                         1.899974
4                         0.000000
...                            ...
307506                    1.899974
307507                    1.899974
307508                    1.000000
307509                    0.000000
307510                    1.000000

[307511 rows x 122 columns]
NAME_CONTRACT_TYPE:
0: Cash loans
1: Revolving loans
CODE_GENDER:
0: F
1: M
2: XNA
FLAG_OWN_CAR:
0: N
1: Y
FLAG_OWN_REALTY:
0: N
1: Y
NAME_TYPE_SUITE:
0: Children
1: Family
2: Group of people
3: Other_A
4: Other_B
5: Spouse, partner
6: Unaccompanied
NAME_INCOME_TYPE:
0: Businessman
1: Commercial associate
2: Maternity leave
3: Pensioner
4: State servant
5: Student
```

```
6: Unemployed
7: Working
NAME_EDUCATION_TYPE:
0: Academic degree
1: Higher education
2: Incomplete higher
3: Lower secondary
4: Secondary / secondary special
NAME_FAMILY_STATUS:
0: Civil marriage
1: Married
2: Separated
3: Single / not married
4: Unknown
5: Widow
NAME_HOUSING_TYPE:
0: Co-op apartment
1: House / apartment
2: Municipal apartment
3: Office apartment
4: Rented apartment
5: With parents
OCCUPATION_TYPE:
0: Accountants
1: Cleaning staff
2: Cooking staff
3: Core staff
4: Drivers
5: HR staff
6: High skill tech staff
7: IT staff
8: Laborers
9: Low-skill Laborers
10: Managers
11: Medicine staff
12: Private service staff
13: Realty agents
14: Sales staff
15: Secretaries
16: Security staff
17: Waiters/barmen staff
WEEKDAY_APPR_PROCESS_START:
0: FRIDAY
1: MONDAY
2: SATURDAY
3: SUNDAY
4: THURSDAY
5: TUESDAY
6: WEDNESDAY
ORGANIZATION_TYPE:
0: Advertising
1: Agriculture
2: Bank
3: Business Entity Type 1
4: Business Entity Type 2
5: Business Entity Type 3
6: Cleaning
7: Construction
8: Culture
9: Electricity
```

```
10: Emergency
11: Government
12: Hotel
13: Housing
14: Industry: type 1
15: Industry: type 10
16: Industry: type 11
17: Industry: type 12
18: Industry: type 13
19: Industry: type 2
20: Industry: type 3
21: Industry: type 4
22: Industry: type 5
23: Industry: type 6
24: Industry: type 7
25: Industry: type 8
26: Industry: type 9
27: Insurance
28: Kindergarten
29: Legal Services
30: Medicine
31: Military
32: Mobile
33: Other
34: Police
35: Postal
36: Realtor
37: Religion
38: Restaurant
39: School
40: Security
41: Security Ministries
42: Self-employed
43: Services
44: Telecom
45: Trade: type 1
46: Trade: type 2
47: Trade: type 3
48: Trade: type 4
49: Trade: type 5
50: Trade: type 6
51: Trade: type 7
52: Transport: type 1
53: Transport: type 2
54: Transport: type 3
55: Transport: type 4
56: University
57: XNA
FONDKAPREMONT_MODE:
0: not specified
1: org spec account
2: reg oper account
3: reg oper spec account
HOUSETYPE_MODE:
0: block of flats
1: specific housing
2: terraced house
WALLSMATERIAL_MODE:
0: Block
1: Mixed
```

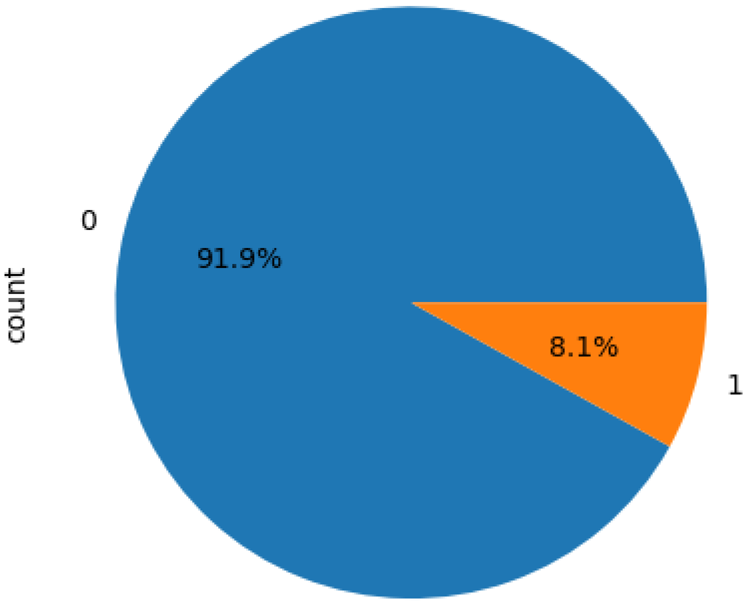
```
2: Monolithic
3: Others
4: Panel
5: Stone, brick
6: Wooden
EMERGENCYSTATE_MODE:
0: No
1: Yes
```

Anotehr method # create a label (category) encoder object fit and transform the non-numeric columns in the DataFrame house_loan[non_numeric_columns] = house_loan[non_numeric_columns].apply(le.fit_transform) print(house_loan)

Balance the dataset if the data is imbalanced The autogenerated column is SK_ID_CURR Checking and removing duplicate entries

In [28]:
```
house_loan.TARGET.value_counts().plot(kind='pie',autopct='%1.1f%%')
without_id=[column for column in house_loan.columns if column!='SK_ID_CURR']
na=house_loan[house_loan.duplicated(subset=without_id,keep=False)]
print("Duplicates are: ",na.shape[0])
```

```
Duplicates are:  0
```



house_loan.TARGET.value_counts().plot(kind='pie',autopct='%1.1f%%') without_id=[column for column in house_loan.columns if column!='SK_ID_CURR'] na=house_loan[house_loan.duplicated(subset=without_id,keep=False)] print("Duplicates are: ",na.shape[0])

Checking for balance. An imbalance between the number of paid and unpaid home loans. This could bias the model towards predicting the class that has more instances. To prevent this, a common technique is to undersample the majority class or oversample the minority class to achieve a balanced dataset. After undersampling, the datasets of the two classes are concatenated using pd.concat() to form a new balanced dataset normalised_home_loan. This dataset is then used for further analysis or model training. The pie chart at the end visualizes the distribution of the two classes in the balanced dataset.

In [32]:
```
shuffled_data=house_loan.sample(frac=1,random_state=3)
unpaid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==1]
paid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==0]
```

In [33]:
```
unpaid_home_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 24825 entries, 207339 to 196006
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int32(16), int64(41)
memory usage: 21.8 MB
```

In [34]:
```
paid_home_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 282686 entries, 260810 to 71530
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int32(16), int64(41)
memory usage: 248.0 MB
```

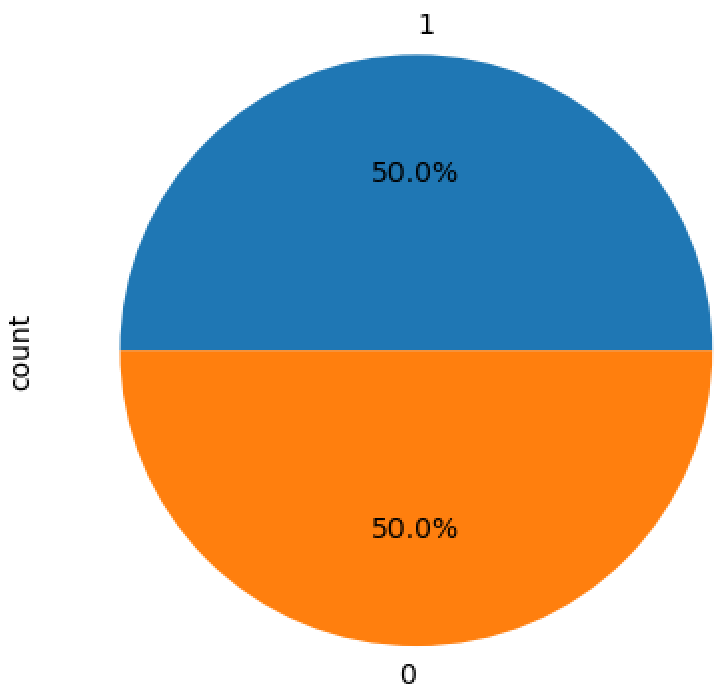
In [35]:
```
paid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==0].sample(n=24825, ran
```

Ploting the balanced data or imbalanced data

In [36]:
```
import matplotlib.pyplot as plt
```

In [37]:
```
normalised_home_loan=pd.concat([unpaid_home_loan,paid_home_loan])
normalised_home_loan.TARGET.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

Out[37]: <Axes: ylabel='count'>



Now that we have encoded, lets check the best features different method

using univariate methodsklearn.feature_selection requires all values in X to be non-negative. This is because the Chi-squared statistic is a sum of squares, which can't be calculated with negative values. Using mutual information which can handle both positive and negative values: It is slow. The code however for refernece are:

In [29]:
```
from sklearn.feature_selection import SelectKBest, mutual_info_classif
X = house_loan.drop('TARGET', axis=1)  # independent columns
y = house_loan['TARGET']  # target column
```

In [30]:
```
# apply SelectKBest class to extract top 10 best features
bestfeatures = SelectKBest(score_func=mutual_info_classif, k=10)
fit = bestfeatures.fit(X, y)
```

In [31]:
```
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)
# concatenate two dataframes for better visualization
featureScores = pd.concat([dfcolumns, dfscores], axis=1)
featureScores.columns = ['Specs', 'Score']  # naming the dataframe columns

print(featureScores.nlargest(10, 'Score'))  # print 10 best features
```

```
                 Specs     Score
21           FLAG_MOBIL  0.080002
24     FLAG_CONT_MOBILE  0.059899
96      FLAG_DOCUMENT_3  0.056605
22       FLAG_EMP_PHONE  0.056169
4       FLAG_OWN_REALTY  0.055875
85   FONDKAPREMONT_MODE  0.053577
14    NAME_HOUSING_TYPE  0.052065
88   WALLSMATERIAL_MODE  0.043359
61      COMMONAREA_MODE  0.040748
75      COMMONAREA_MEDI  0.040420
```

In [38]:
```
import tensorflow as tf
```

In [39]:
```
normalised_home_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 49650 entries, 207339 to 139806
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int32(16), int64(41)
memory usage: 43.6 MB
```

In [40]:
```
normalised_home_loan.head
```

Out[40]:
```
<bound method NDFrame.head of         SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  C
ODE_GENDER  FLAG_OWN_CAR  \
207339      340318       1                   0          0            0
8756        110186       1                   0          1            1
230344      366811       1                   0          0            0
178329      306645       1                   0          1            1
55586       164407       1                   0          1            0
...            ...     ...                 ...        ...          ...
303856      452050       0                   0          0            0
140173      262532       0                   0          0            0
44575       151640       0                   1          0            0
106175      223189       0                   0          0            0
139806      262117       0                   0          0            0

        FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
207339                0             0          112500.0    405000.0
8756                  0             0          135000.0    544491.0
230344                1             0          112500.0    225000.0
178329                1             0          157500.0    595273.5
55586                 0             0          157500.0    521451.0
...                 ...           ...               ...         ...
303856                1             0          180000.0    314100.0
140173                0             0          202500.0    490495.5
44575                 0             0          180000.0    315000.0
106175                1             0          180000.0    207396.0
139806                1             0          243000.0     67500.0

        AMT_ANNUITY  ...  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  \
207339      21969.0  ...                 0                 0
8756        17563.5  ...                 0                 0
230344      17905.5  ...                 0                 0
178329      29083.5  ...                 0                 0
55586       35406.0  ...                 0                 0
...             ...  ...               ...               ...
303856      17167.5  ...                 0                 0
140173      46701.0  ...                 0                 0
44575       15750.0  ...                 0                 0
106175      13383.0  ...                 0                 0
139806       7267.5  ...                 0                 0

        FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
207339                 0                 0                    0.000000
8756                   0                 0                    0.000000
230344                 0                 0                    0.006402
178329                 0                 0                    0.006402
55586                  0                 0                    0.000000
...                  ...               ...                         ...
303856                 0                 0                    0.000000
140173                 0                 0                    0.000000
44575                  0                 0                    0.000000
106175                 0                 0                    0.000000
139806                 0                 0                    0.000000

        AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
207339                      0.000                    0.000000
8756                        0.000                    0.000000
230344                      0.007                    0.034362
178329                      0.007                    0.034362
55586                       0.000                    0.000000
...                           ...                         ...
```

```
303856                 0.000                    0.000000
140173                 0.000                    0.000000
44575                  0.000                    0.000000
106175                 0.000                    0.000000
139806                 0.000                    0.000000

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
207339                   0.000000                   0.000000
8756                     0.000000                   0.000000
230344                   0.267395                   0.265474
178329                   0.267395                   0.265474
55586                    0.000000                   0.000000
...                           ...                        ...
303856                   0.000000                   0.000000
140173                   0.000000                   0.000000
44575                    0.000000                   0.000000
106175                   0.000000                   0.000000
139806                   0.000000                   0.000000

        AMT_REQ_CREDIT_BUREAU_YEAR
207339                    3.000000
8756                      0.000000
230344                    1.899974
178329                    1.899974
55586                     1.000000
...                            ...
303856                    6.000000
140173                    2.000000
44575                     1.000000
106175                    2.000000
139806                    3.000000

[49650 rows x 122 columns]>
```

In [41]:
```
normalised_home_loan.dropna(axis=0)
normalised_home_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 49650 entries, 207339 to 139806
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int32(16), int64(41)
memory usage: 43.6 MB
```

In [42]:
```
normalised_home_loan.isnull().sum()
```

Out[42]:
```
SK_ID_CURR                    0
TARGET                        0
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
                             ..
AMT_REQ_CREDIT_BUREAU_DAY     0
AMT_REQ_CREDIT_BUREAU_WEEK    0
AMT_REQ_CREDIT_BUREAU_MON     0
AMT_REQ_CREDIT_BUREAU_QRT     0
AMT_REQ_CREDIT_BUREAU_YEAR    0
Length: 122, dtype: int64
```

In [43]:
```
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_DAY))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_WEEK))
```

```
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_MON))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_QRT))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_YEAR))
```

```
[0.         0.00700021 1.         2.         4.         3.
 5.        ]
[0.         0.03436194 1.         2.         4.         3.
 5.         6.         8.        ]
[ 0.          0.26739526  1.          3.          5.          9.
  2.          6.          8.          4.         11.         12.
  7.         13.         10.         17.         15.         14.
 18.         23.         16.        ]
[ 0.          0.26547415  2.          3.          1.          4.
  5.          6.         19.          7.          8.        ]
[ 3.          0.          1.89997444  1.          5.          4.
  2.          6.          7.          8.          9.         10.
 14.         13.         12.         11.         22.         16.
 25.        ]
```

In [44]:
```
normalised_home_loan.dropna(axis=0)
```

Out[44]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR
207339	340318	1	0	0	(
8756	110186	1	0	1	'
230344	366811	1	0	0	(
178329	306645	1	0	1	'
55586	164407	1	0	1	(
...	...	...	...	...	.
303856	452050	0	0	0	(
140173	262532	0	0	0	(
44575	151640	0	1	0	(
106175	223189	0	0	0	(
139806	262117	0	0	0	(

49650 rows × 122 columns

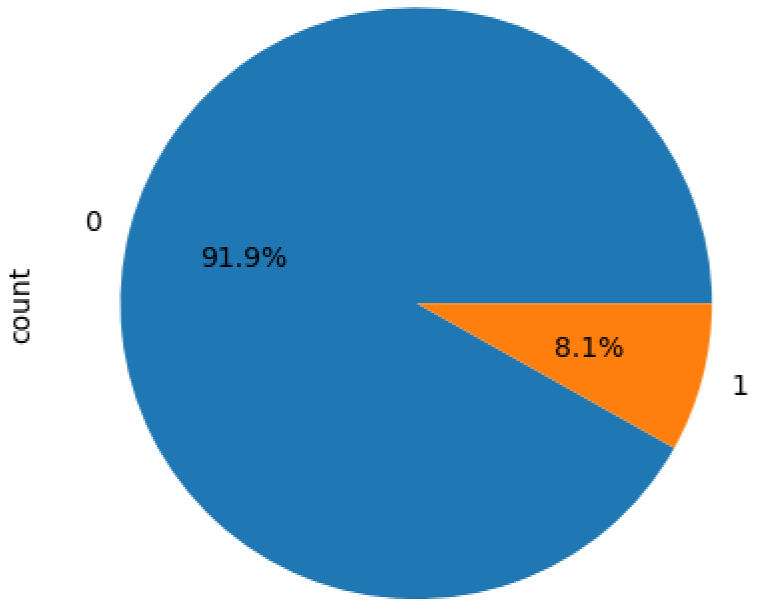
Column - 'SK_ID_CURR' - to remove, 'TARGET' - Tells if person has defaulted. We have balanced it. Adding the parameters we thik is important. 'NAME_CONTRACT_TYPE' - It is Type of loan 'CODE_GENDER' - Gender 'FLAG_OWN_CAR' - Needed 'CNT_CHILDREN' - Count of children 'AMT_INCOME_TOTAL' - Better to group it

Now adding the important ones that we got earlier 21 FLAG_MOBIL 0.079671 24 FLAG_CONT_MOBILE 0.058517 4 FLAG_OWN_REALTY 0.056045 22 FLAG_EMP_PHONE 0.055531 96 FLAG_DOCUMENT_3 0.055391 85 FONDKAPREMONT_MODE 0.054326 14 NAME_HOUSING_TYPE 0.051551 88 WALLSMATERIAL_MODE 0.044663 61 COMMONAREA_MODE 0.040486 47 COMMONAREA_AVG 0.040430

Visual represntation of the individual componenent

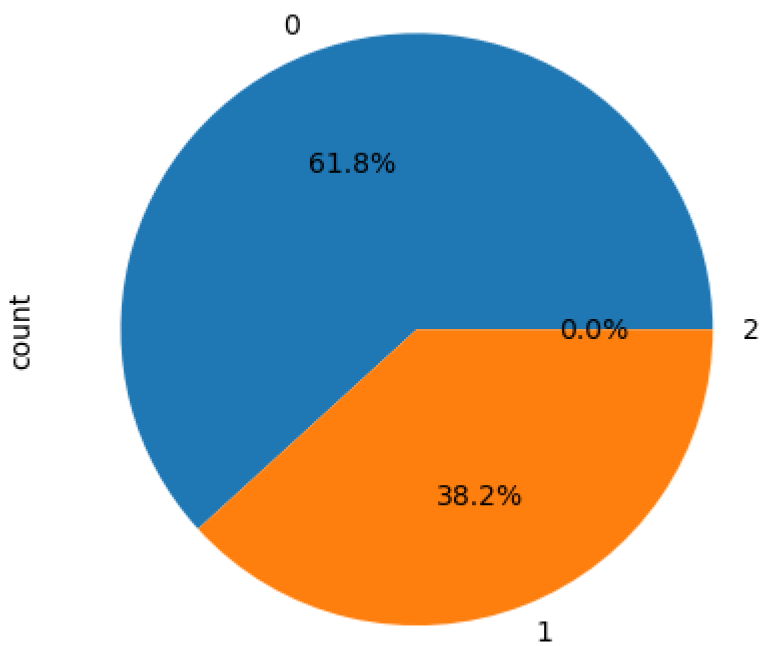
In [45]:
```
normalised_home_loan.NAME_CONTRACT_TYPE.value_counts().plot(kind='pie',autopct="
```

Out[45]: <Axes: ylabel='count'>



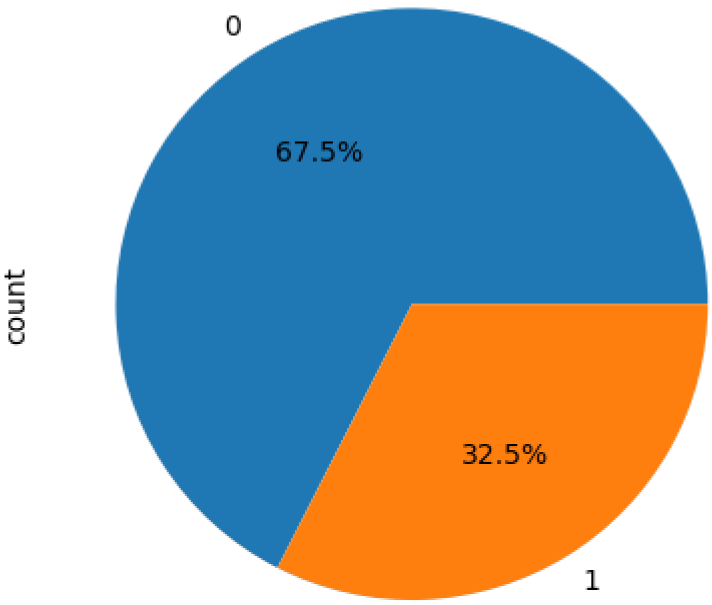
In [46]:
```
normalised_home_loan.CODE_GENDER.value_counts().plot(kind='pie',autopct="%1.1f%%
```

Out[46]: <Axes: ylabel='count'>



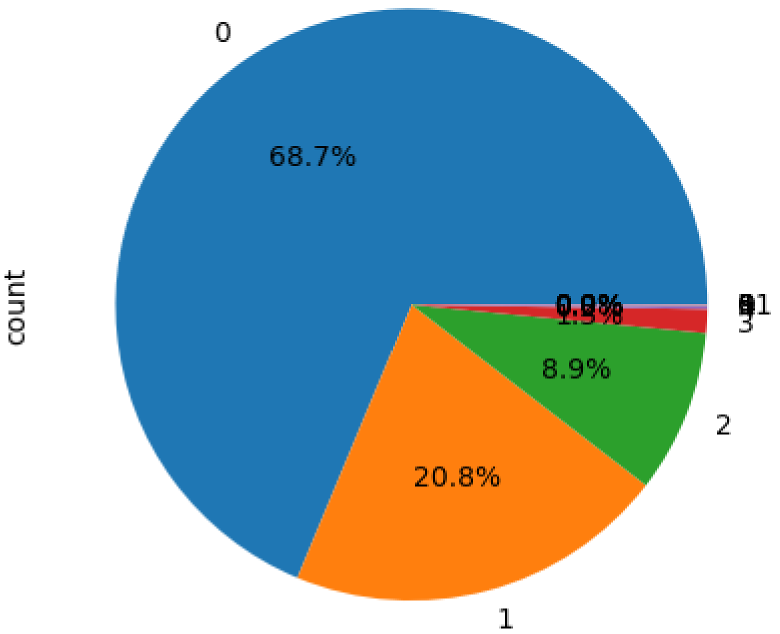
In [47]:
```
normalised_home_loan.FLAG_OWN_CAR.value_counts().plot(kind='pie',autopct="%1.1f%
```

Out[47]:
```
<Axes: ylabel='count'>
```



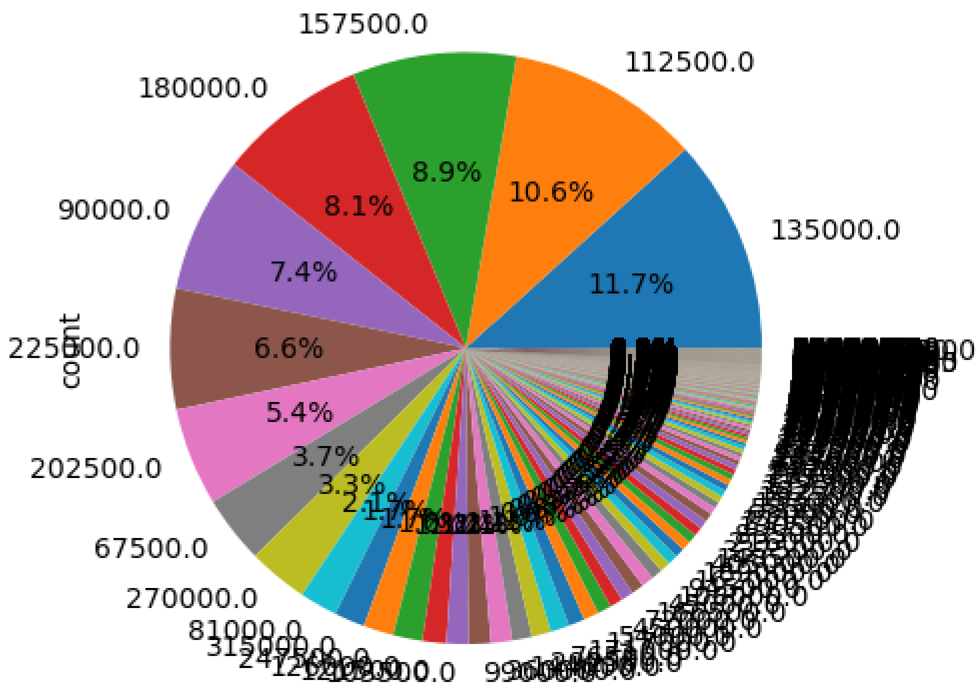
In [48]:
```
normalised_home_loan.CNT_CHILDREN.value_counts().plot(kind='pie',autopct="%1.1f%
```

Out[48]:
```
<Axes: ylabel='count'>
```



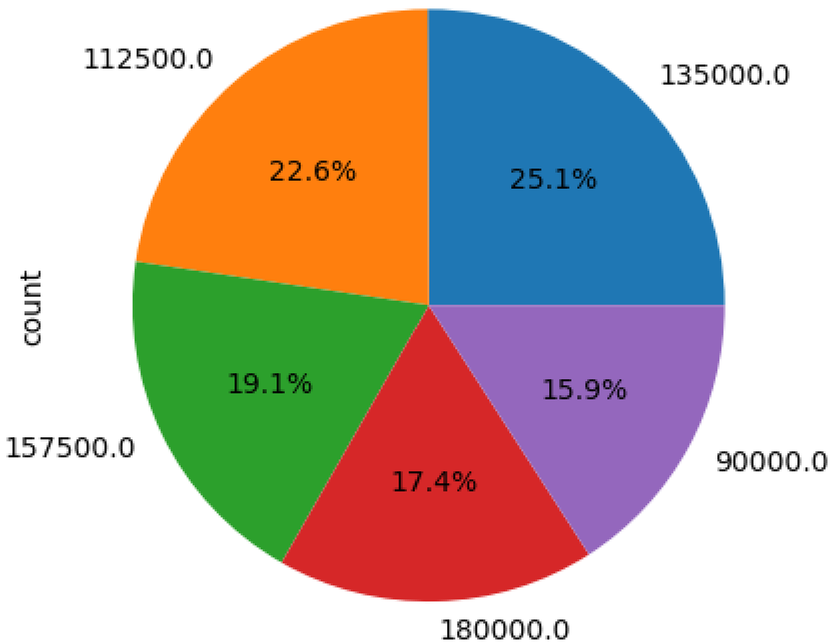
In [49]:
```
normalised_home_loan.AMT_INCOME_TOTAL.value_counts().plot(kind='pie',autopct="%1
```

Out[49]:
```
<Axes: ylabel='count'>
```



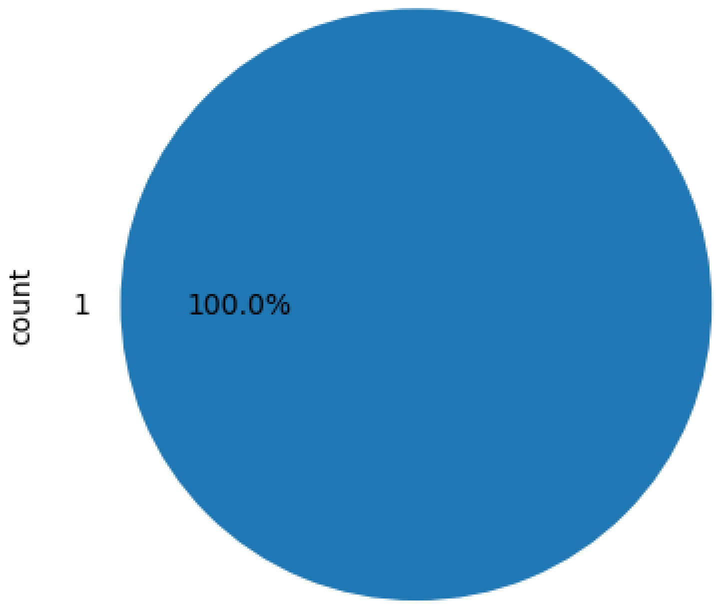
In [50]:
```
normalised_home_loan.AMT_INCOME_TOTAL.value_counts().nlargest(5).plot(kind='pie'
```

Out[50]: <Axes: ylabel='count'>



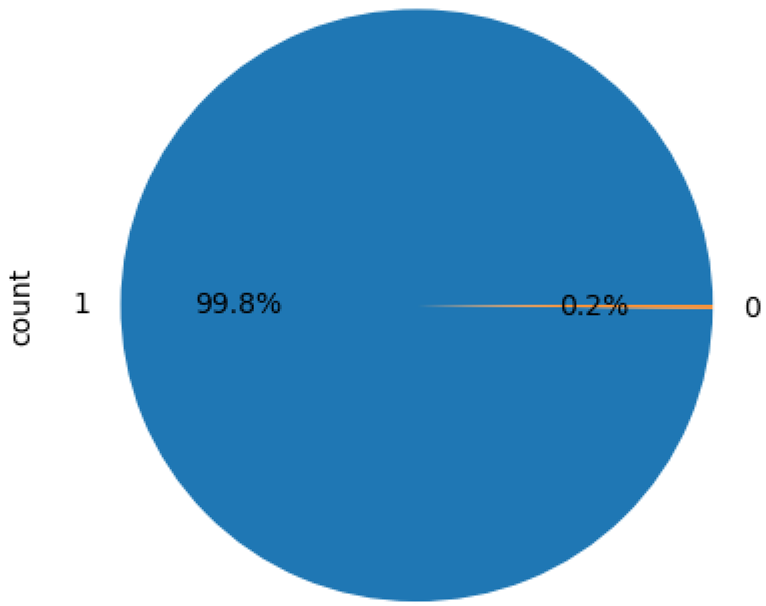
In [51]:
```
normalised_home_loan.FLAG_MOBIL.value_counts().plot(kind='pie', autopct="%1.1f%%
```

Out[51]: <Axes: ylabel='count'>



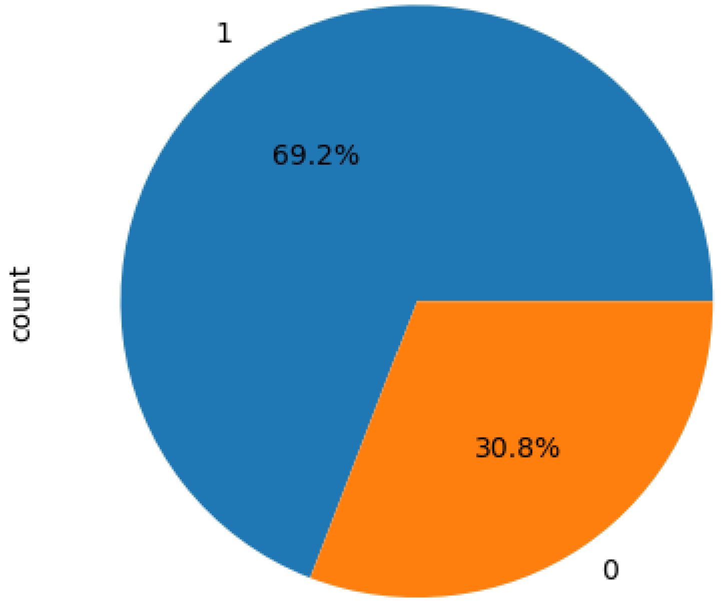
In [52]:
```
normalised_home_loan.FLAG_CONT_MOBILE.value_counts().plot(kind='pie', autopct="%
```

Out[52]: <Axes: ylabel='count'>



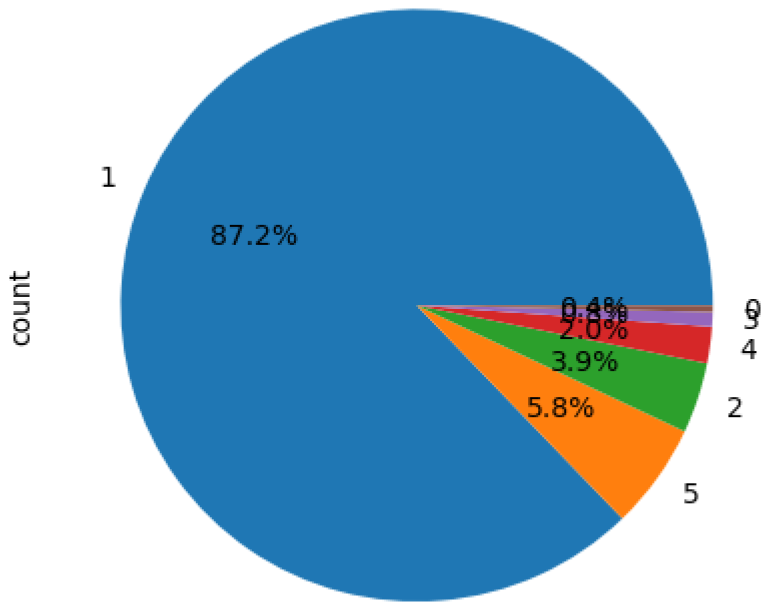
In [53]:
```
normalised_home_loan.FLAG_OWN_REALTY.value_counts().plot(kind='pie', autopct="%1
```

Out[53]: <Axes: ylabel='count'>



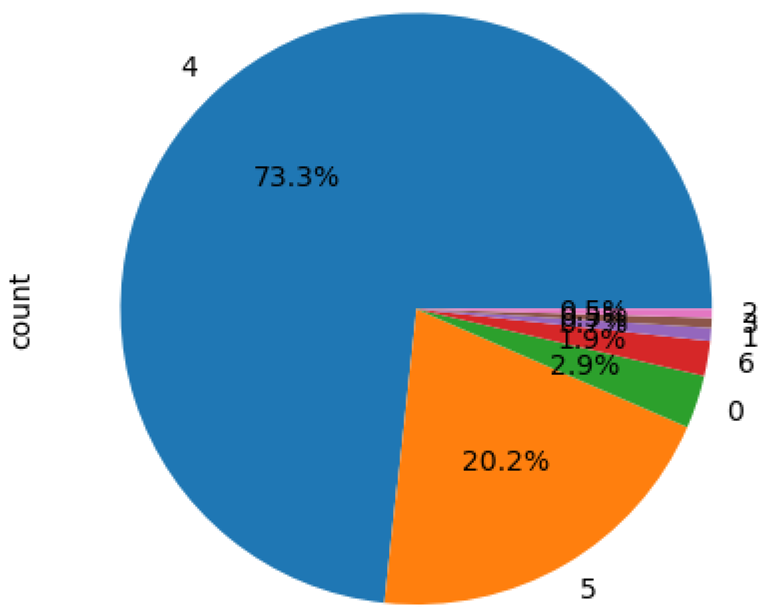
In [54]:
```
normalised_home_loan.NAME_HOUSING_TYPE.value_counts().plot(kind='pie', autopct="
```

Out[54]: <Axes: ylabel='count'>



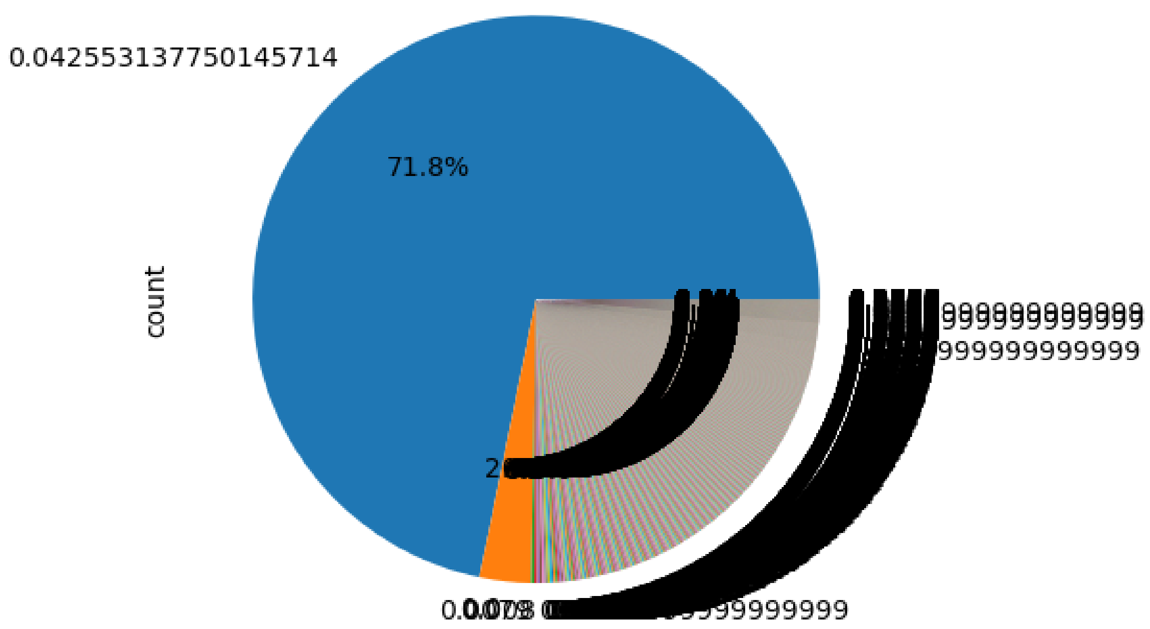
In [55]:
```
normalised_home_loan.WALLSMATERIAL_MODE.value_counts().plot(kind='pie', autopct=
```

Out[55]: <Axes: ylabel='count'>



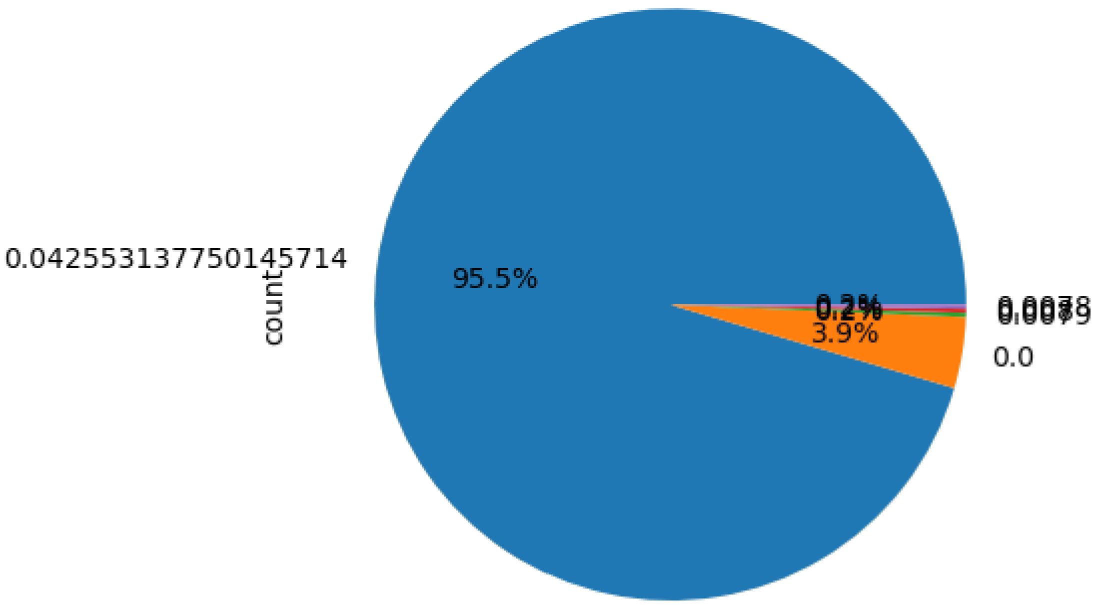
In [56]:
```
normalised_home_loan.COMMONAREA_MODE.value_counts().plot(kind='pie', autopct="%1
```

Out[56]: <Axes: ylabel='count'>



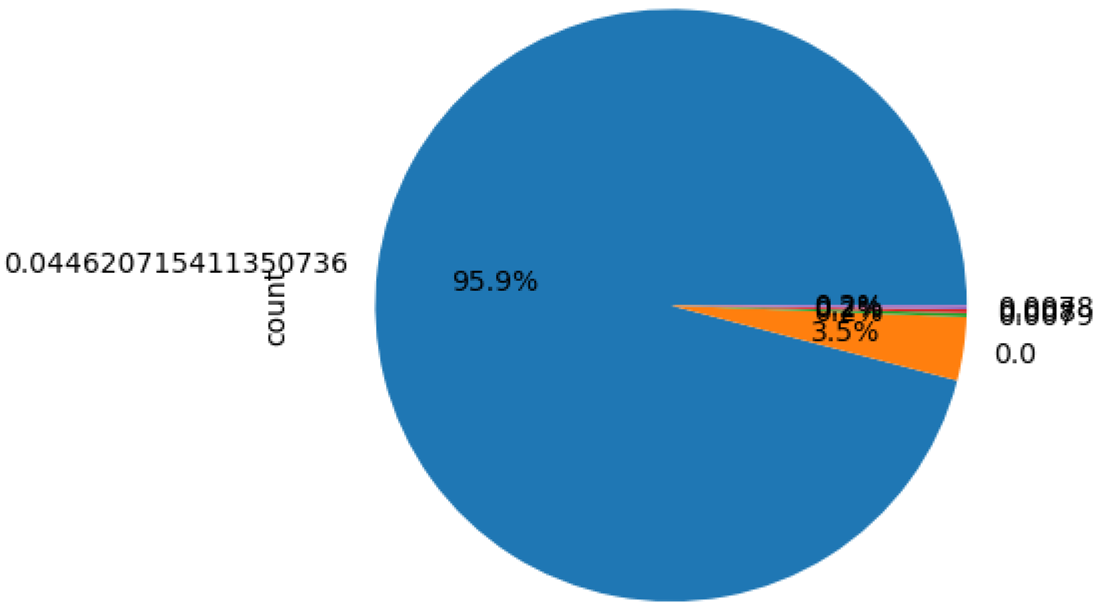
In [57]:
```
normalised_home_loan.COMMONAREA_MODE.value_counts().nlargest(5).plot(kind='pie',
```

Out[57]: <Axes: ylabel='count'>



In [58]:
```
normalised_home_loan.COMMONAREA_AVG.value_counts().nlargest(5).plot(kind='pie',
```

Out[58]: `<Axes: ylabel='count'>`



The columns we have selected 'NAME_CONTRACT_TYPE' - It is Type of loan 'CODE_GENDER' - Gender 'FLAG_OWN_CAR' - 'CNT_CHILDREN' - Count of children 'AMT_INCOME_TOTAL' - top categories

Now adding the important ones that we got earlier FLAG_CONT_MOBILE If they have mobile FLAG_OWN_REALTY - If they have real estate NAME_HOUSING_TYPE - type of house WALLSMATERIAL_MODE - walls type COMMONAREA_MODE - common area type COMMONAREA_AVG - avg common area

In [59]:
```
normalised_home_loan_features=['SK_ID_CURR','NAME_CONTRACT_TYPE','CNT_CHILDREN',
```

In [60]:
```
normalised_home_loan_features
```

Out[60]:
```
['SK_ID_CURR',
 'NAME_CONTRACT_TYPE',
 'CNT_CHILDREN',
 'AMT_INCOME_TOTAL',
 'FLAG_CONT_MOBILE',
 'FLAG_OWN_REALTY',
 'NAME_HOUSING_TYPE',
 'WALLSMATERIAL_MODE',
 'COMMONAREA_MODE',
 'COMMONAREA_AVG']
```

To start calculating sensitivity Sensitivity is a measure of the proportion of actual positive cases that got predicted as positive (or, how many of the true positives were recalled). So, high Sensitivity means that the model predicted the positive cases very well

In [163…
```
from sklearn.model_selection import train_test_split
X=normalised_home_loan[normalised_home_loan_features]
```

In [164…
```
X
```

Out[164…

	SK_ID_CURR	NAME_CONTRACT_TYPE	CNT_CHILDREN	AMT_INCOME_TOTAL	FI
207339	340318	0	0	112500.0	
8756	110186	0	0	135000.0	
230344	366811	0	0	112500.0	
178329	306645	0	0	157500.0	
55586	164407	0	0	157500.0	
...	...	...	...	...	
303856	452050	0	0	180000.0	
140173	262532	0	0	202500.0	
44575	151640	1	0	180000.0	
106175	223189	0	0	180000.0	
139806	262117	0	0	243000.0	

49650 rows × 10 columns

setting up parameters blobs_random_seed = 42: This sets the seed for the random number generator to 42. centers = [(0,0), (5,5)] - defines centers. In this case, there will be two clusters: one centered at (0,0) and the other at (5,5). cluster_std = 1: This sets the standard deviation of the clusters. A higher value will make the clusters more spread out.

frac_test_split = 0.33: This is likely the fraction of the data that will be used for the test set in a train/test split. num_features_for_samples = 2: This is the number of features for each sample in the synthetic dataset. In this case, each sample will have two features.num_samples_total = 49650: This is the total number of samples in the synthetic dataset. See from above.

In [165…

```
X_train, X_test, y_train, y_test = train_test_split(inputs, targets, test_size=0
```

In [166…

```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(33265, 2) (16385, 2) (33265,) (16385,)
```

In [ ]:

```
#Since the target variable is of categorical data (either default or not), using
```

In [71]:

```
trainX = tf.constant(X_train, dtype='float32')
trainY = tf.constant(y_train, dtype='float32')
testX = tf.constant(X_test, dtype='float32')
testY = tf.constant(y_test, dtype='float32')
```

In [167…

```
# Assuming your data has 'n' features
n = trainX.shape[1]

# Create a variable for weights
weights = tf.Variable(tf.random.normal(shape=(n, 1), dtype='float32'))

# Create a variable for biases
bias = tf.Variable(tf.zeros(shape=(1,), dtype='float32'))
```

In [168…

```
print(n, weights, bias)
```

```
2 <tf.Variable 'Variable:0' shape=(2, 1) dtype=float32, numpy=
array([[-0.21015579],
       [-1.1603422 ]], dtype=float32)> <tf.Variable 'Variable:0' shape=(1,) dtype
=float32, numpy=array([0.], dtype=float32)>
```

In [169…

```
import tensorflow as tf

# Define the logistic regression model
class LogisticRegression(tf.keras.Model):
    def __init__(self):
        super(LogisticRegression, self).__init__()
        self.dense = tf.keras.layers.Dense(1, activation='sigmoid')

    def call(self, inputs, training=None, mask=None):
        output = self.dense(inputs)
        return output

# Instantiate the model
model = LogisticRegression()

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']

# Train the model
model.fit(trainX, trainY, epochs=10, batch_size=32, validation_data=(testX, test

# Evaluate the model
```

```
loss, accuracy = model.evaluate(testX, testY)
print(f"Loss: {loss}, Accuracy: {accuracy}")
```

```
Epoch 1/10
1040/1040 [==============================] - 8s 5ms/step - loss: 0.7824 - accurac
y: 0.5809 - val_loss: 0.3779 - val_accuracy: 0.8236
Epoch 2/10
1040/1040 [==============================] - 4s 4ms/step - loss: 0.2714 - accurac
y: 0.8956 - val_loss: 0.1916 - val_accuracy: 0.9467
Epoch 3/10
1040/1040 [==============================] - 4s 4ms/step - loss: 0.1478 - accurac
y: 0.9698 - val_loss: 0.1110 - val_accuracy: 0.9857
Epoch 4/10
1040/1040 [==============================] - 5s 4ms/step - loss: 0.0892 - accurac
y: 0.9911 - val_loss: 0.0695 - val_accuracy: 0.9957
Epoch 5/10
1040/1040 [==============================] - 4s 4ms/step - loss: 0.0577 - accurac
y: 0.9970 - val_loss: 0.0462 - val_accuracy: 0.9982
Epoch 6/10
1040/1040 [==============================] - 3s 3ms/step - loss: 0.0392 - accurac
y: 0.9985 - val_loss: 0.0320 - val_accuracy: 0.9991
Epoch 7/10
1040/1040 [==============================] - 3s 3ms/step - loss: 0.0277 - accurac
y: 0.9990 - val_loss: 0.0229 - val_accuracy: 0.9996
Epoch 8/10
1040/1040 [==============================] - 4s 4ms/step - loss: 0.0202 - accurac
y: 0.9992 - val_loss: 0.0169 - val_accuracy: 0.9996
Epoch 9/10
1040/1040 [==============================] - 4s 4ms/step - loss: 0.0151 - accurac
y: 0.9993 - val_loss: 0.0127 - val_accuracy: 0.9996
Epoch 10/10
1040/1040 [==============================] - 3s 3ms/step - loss: 0.0115 - accurac
y: 0.9995 - val_loss: 0.0098 - val_accuracy: 0.9997
513/513 [==============================] - 1s 2ms/step - loss: 0.0098 - accuracy:
0.9997
Loss: 0.009800774045288563, Accuracy: 0.99969482421875
```

In [170…

```
# Predict the values
predicted_values = model.predict(testX)

# Convert the predicted values to a suitable format
predicted_values = tf.squeeze(predicted_values)

# Calculate the difference
difference = tf.abs(predicted_values - testY)

# Create a DataFrame
df = pd.DataFrame({
    'Predicted Values': predicted_values.numpy(),
    'Actual Values': testY.numpy(),
    'Difference': difference.numpy()
})

# Print the DataFrame
print(df)
```

```
513/513 [==============================] - 2s 3ms/step
       Predicted Values  Actual Values  Difference
0              0.003062            0.0    0.003062
1              0.996138            1.0    0.003862
2              0.991433            1.0    0.008567
3              0.021649            0.0    0.021649
4              0.000256            0.0    0.000256
...                 ...            ...         ...
16380          0.999531            1.0    0.000469
16381          0.999976            1.0    0.000024
16382          0.015913            0.0    0.015913
16383          0.998002            1.0    0.001998
16384          0.000675            0.0    0.000675

[16385 rows x 3 columns]
```

In [172…

```
import numpy as np
from sklearn.metrics import confusion_matrix, recall_score
# Convert the predicted values to binary
predicted_values_binary = np.round(predicted_values)
# Calculate the confusion matrix
cm = confusion_matrix(testY, predicted_values_binary)
print('Confusion Matrix: \n', cm)
# Calculate sensitivity
sensitivity = recall_score(testY, predicted_values_binary)
print('Sensitivity: \n', sensitivity)
```

```
Confusion Matrix:
 [[8198    5]
 [   0 8182]]
Sensitivity:
 1.0
```

TO Calculate Sensitivity, using confusion matrix. Formula of sensitivity Sensitivity = True Positives / (True Positives + False Negatives)

In [173…

```
# Calculate sensitivity
sensitivity = TP / (TP + FN)
print('Sensitivity: ', sensitivity)
print(predicted_labels_np)
print(y_test_np)
```

```
Sensitivity:  nan
[[1. 0. 1. ... 1. 0. 1.]
 [1. 1. 1. ... 0. 1. 0.]
 [1. 1. 1. ... 0. 1. 0.]
 ...
 [1. 0. 0. ... 1. 0. 0.]
 [1. 1. 1. ... 0. 1. 0.]
 [1. 0. 0. ... 1. 0. 1.]]
[[0.4951737  0.49990004 0.5026408  ... 0.49776515 0.49933618 0.4999025 ]
 [0.49399248 0.518196   0.5243953  ... 0.5165168  0.5071083  0.52073383]
 [0.49431065 0.5169351  0.52248305 ... 0.5153087  0.5064719  0.5190457 ]
 ...
 [0.49845693 0.5030438  0.50027335 ... 0.5022285  0.49919215 0.4997525 ]
 [0.4970211  0.51967525 0.52069163 ... 0.51914436 0.5064119  0.5190805 ]
 [0.4984699  0.49787593 0.49468753 ... 0.4968183  0.4971337  0.49421087]]
```

In [174…

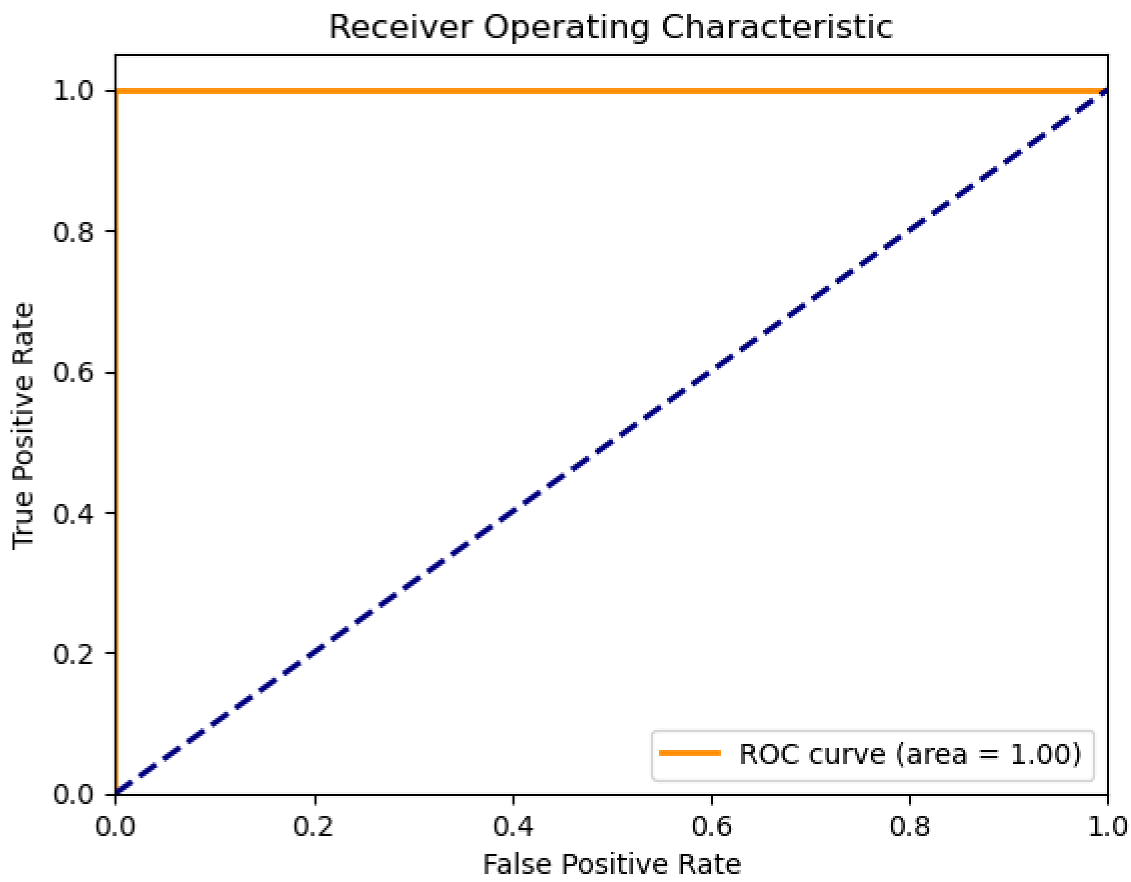
```
from sklearn.metrics import roc_auc_score
# Calculate the AUC-ROC
```

```
auc_roc = roc_auc_score(testY, predicted_values)
# Print the AUC-ROC
print('AUC-ROC: ', auc_roc)
```

```
AUC-ROC:  0.9999999702012663
```

In [175…

```
from sklearn.metrics import roc_curve, auc
# Calculate the ROC curve
fpr, tpr, thresholds = roc_curve(testY, predicted_values)
# Calculate the AUC
roc_auc = auc(fpr, tpr)
# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' %
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```



In [177…

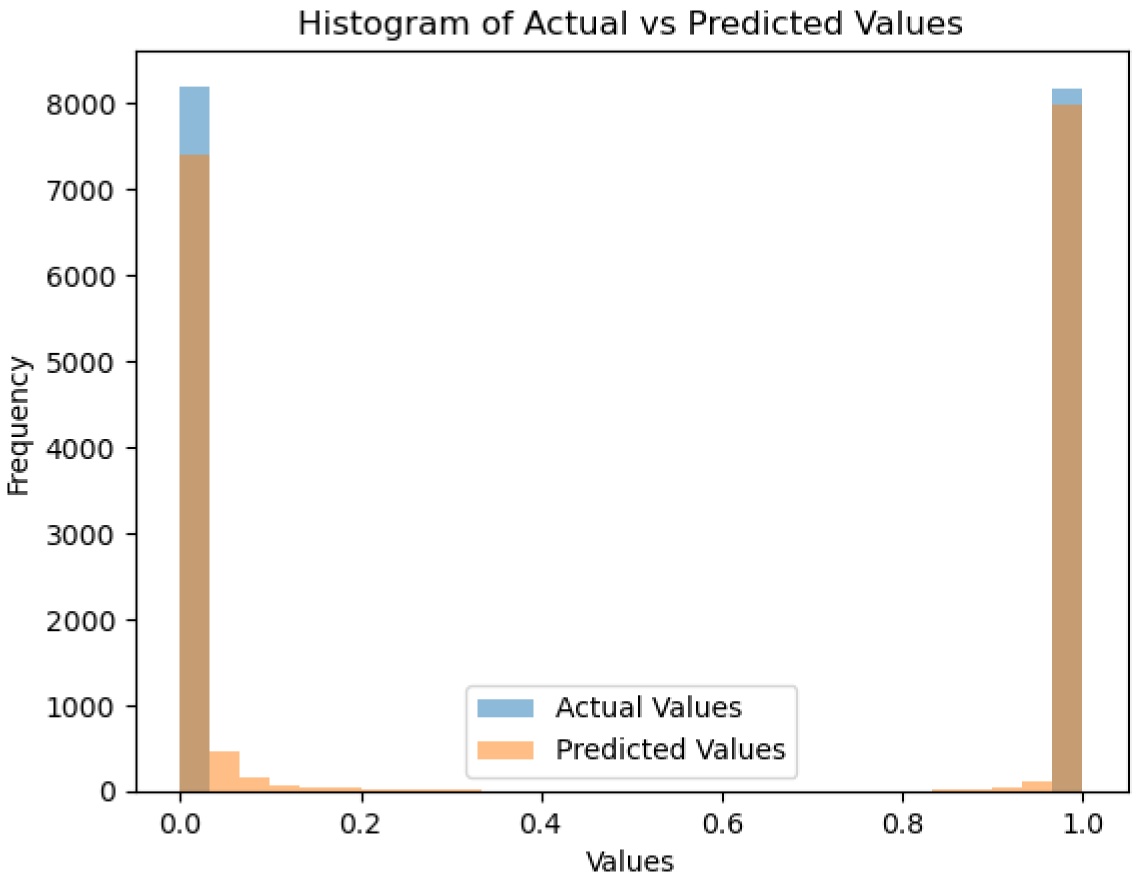
```
# Create a new figure
plt.figure()
# Plot a histogram of the actual values
plt.hist(testY, bins=30, alpha=0.5, label='Actual Values')

# Plot a histogram of the predicted values
plt.hist(predicted_values, bins=30, alpha=0.5, label='Predicted Values')

# Add labels and title
plt.xlabel('Values')
```

```
plt.ylabel('Frequency')
plt.title('Histogram of Actual vs Predicted Values')
plt.legend()


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

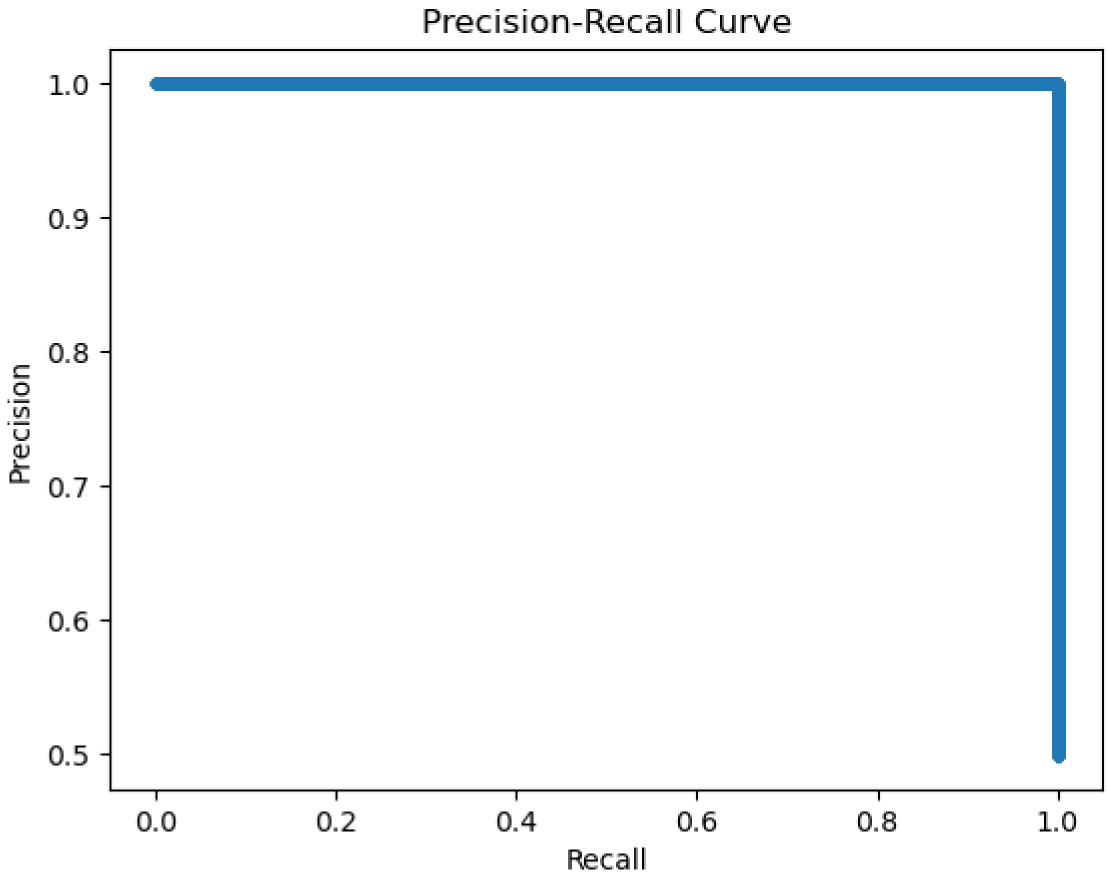


In [178…

```
from sklearn.metrics import precision_recall_curve
import matplotlib.pyplot as plt

# Calculate precision and recall
precision, recall, _ = precision_recall_curve(testY, predicted_values)

# Plot the precision-recall curve
plt.plot(recall, precision, marker='.')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.show()
```


Precision-Recall Curve
1.0
0.9
0.8
0.7
0.6
0.5
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall

In [ ]: