Assignment 03

1. Design a deep learning experiment for a multi class classification dataset https://www.kaggle.com/datasets/abisheksudarshan/customer-segmentation.

```
- It is a multi class classification task where “var_1” is a class label column having 3 categories as Cat_6: 65%, Cat_4: 13%, Other: 22%.
- There is a slight imblance in class distribution.
- This link contains two files ‘train.csv’ and ‘test.csv’. You need to divide the ‘train.csv’ in appropriate percentage to get the validation set. Your
experiment should involve following step in appropriate order.
```

Importing the necessary Lib

In [1]:
```python
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
import pandas as pd
import numpy as np
import time
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style="whitegrid", color_codes=True, palette="dark" )
import plotly.express as px

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
```

In [3]:
```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from keras.callbacks import Callback
from sklearn.metrics import classification_report, confusion_matrix, f1_score, roc_curve, auc
from imblearn.over_sampling import SMOTE
```

Preprocessing the Train data:

* Loading the training dataset :

In [4]:
```python
train_data = pd.read_csv('train.csv')
display(train_data)
```

	ID	Gender	Ever_Married	Age	Graduated	Profession	Work_Experience	Spending_Score	Family_Size	Var_1	Segmentation
0	462809	Male	No	22	No	Healthcare	1.0	Low	4.0	Cat_4	D
1	462643	Female	Yes	38	Yes	Engineer	NaN	Average	3.0	Cat_4	A
2	466315	Female	Yes	67	Yes	Engineer	1.0	Low	1.0	Cat_6	B
3	461735	Male	Yes	67	Yes	Lawyer	0.0	High	2.0	Cat_6	B
4	462669	Female	Yes	40	Yes	Entertainment	NaN	High	6.0	Cat_6	A
...	...	...	...	...	...	...	...	...	...	...	...
8063	464018	Male	No	22	No	NaN	0.0	Low	7.0	Cat_1	D
8064	464685	Male	No	35	No	Executive	3.0	Low	4.0	Cat_4	D
8065	465406	Female	No	33	Yes	Healthcare	1.0	Low	1.0	Cat_6	D
8066	467299	Female	No	27	Yes	Healthcare	1.0	Low	4.0	Cat_6	B
8067	461879	Male	Yes	37	Yes	Executive	0.0	Average	3.0	Cat_4	B

8068 rows × 11 columns

Dropping the "Segmentation" column

In [5]:
```python
train_data.drop(columns=['Segmentation'], inplace=True)
display(train_data)
```

	ID	Gender	Ever_Married	Age	Graduated	Profession	Work_Experience	Spending_Score	Family_Size	Var_1
0	462809	Male	No	22	No	Healthcare	1.0	Low	4.0	Cat_4
1	462643	Female	Yes	38	Yes	Engineer	NaN	Average	3.0	Cat_4
2	466315	Female	Yes	67	Yes	Engineer	1.0	Low	1.0	Cat_6
3	461735	Male	Yes	67	Yes	Lawyer	0.0	High	2.0	Cat_6
4	462669	Female	Yes	40	Yes	Entertainment	NaN	High	6.0	Cat_6
...	...	...	...	...	...	...	...	...	...	...
8063	464018	Male	No	22	No	NaN	0.0	Low	7.0	Cat_1
8064	464685	Male	No	35	No	Executive	3.0	Low	4.0	Cat_4
8065	465406	Female	No	33	Yes	Healthcare	1.0	Low	1.0	Cat_6
8066	467299	Female	No	27	Yes	Healthcare	1.0	Low	4.0	Cat_6
8067	461879	Male	Yes	37	Yes	Executive	0.0	Average	3.0	Cat_4

8068 rows × 10 columns

Exploratory Data Analysis (EDA) :

* Checking the shape of the data :

In [6]:
```python
print("Shape of the dataset : ", train_data.shape)
```

```
Shape of the dataset :  (8068, 10)
```

train_data has 8068 rows and 10 columns

* Checking the Duplicate rows in the dataset :

In [7]:
```python
duplicate_rows = train_data[train_data.duplicated()]

if not duplicate_rows.empty:
    print("Duplicate rows found. Details:")
    print(duplicate_rows)
else:
    print("No duplicate rows found.")
```

```
No duplicate rows found.
```

* Information related to dataset :

In [8]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8068 entries, 0 to 8067
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ID               8068 non-null   int64  
 1   Gender           8068 non-null   object 
 2   Ever_Married     7928 non-null   object 
 3   Age              8068 non-null   int64  
 4   Graduated        7990 non-null   object 
 5   Profession       7944 non-null   object 
 6   Work_Experience  7239 non-null   float64
 7   Spending_Score   8068 non-null   object 
 8   Family_Size      7733 non-null   float64
 9   Var_1            7992 non-null   object 
dtypes: float64(2), int64(2), object(6)
memory usage: 630.4+ KB
```

* Defining the columns as per the Data type :

In [9]:
```
numeric_columns = list(train_data.select_dtypes(include=['int']).columns)
categorical_columns = list(train_data.select_dtypes(include=['object']).columns)
float_columns = train_data.select_dtypes(include=['float']).columns.tolist()

print("Numeric columns :",numeric_columns)
print("Float columns :",float_columns)
print("Categorical columns :",categorical_columns)
```

```
Numeric columns : ['ID', 'Age']
Float columns : ['Work_Experience', 'Family_Size']
Categorical columns : ['Gender', 'Ever_Married', 'Graduated', 'Profession', 'Spending_Score', 'Var_1']
```

* Statistical information with respect to data types in dataset :

In [10]:
```
display(train_data[numeric_columns].describe().T)
display(train_data[categorical_columns].describe().T)
display(train_data[float_columns].describe().T)
```

	count	mean	std	min	25%	50%	75%	max
ID	8068.0	463479.214551	2595.381232	458982.0	461240.75	463472.5	465744.25	467974.0
Age	8068.0	43.466906	16.711696	18.0	30.00	40.0	53.00	89.0

	count	unique	top	freq
Gender	8068	2	Male	4417
Ever_Married	7928	2	Yes	4643
Graduated	7990	2	Yes	4968
Profession	7944	9	Artist	2516
Spending_Score	8068	3	Low	4878
Var_1	7992	7	Cat_6	5238

	count	mean	std	min	25%	50%	75%	max
Work_Experience	7239.0	2.641663	3.406763	0.0	0.0	1.0	4.0	14.0
Family_Size	7733.0	2.850123	1.531413	1.0	2.0	3.0	4.0	9.0

Cheking and handelling the null values if any in dataset :

In [11]:
```
null_counts = train_data.isnull().sum()

if null_counts.any():
    print("Null values present. Details:")
    print(null_counts)
    null_rows = train_data[train_data.isnull().any(axis=1)]
    #print("\nRows with null values:")
    #display(null_rows)
    total_nulls = train_data.isnull().sum().sum()
    print("Total Null Values in the data :", total_nulls)
else:
    print("No null values present.")
```

```
Null values present. Details:
ID                   0
Gender               0
Ever_Married       140
Age                  0
Graduated           78
Profession         124
Work_Experience    829
Spending_Score       0
Family_Size        335
Var_1               76
dtype: int64
Total Null Values in the data : 1582
```

* Frequency of Unique Values in Columns with null values :

In [12]:
```
total_null_values = 0

for column_list, column_type in [(float_columns, "Float"), (categorical_columns, "Categorical")]:
    for column in column_list:
        unique_values = train_data[column].value_counts()
        null_values = train_data[column].isnull().sum()
        total_null_values += null_values
        if null_values > 0:
            print(f"\n{column} ({column_type}):")
            print(f"\tValue".ljust(10), "Count")
            print(''.ljust(5), '-' * 18)
            for value, count in unique_values.items():
                print(f"\t{str(value).ljust(10)} {count}") if column_type == "Float" else print(f"\t{value.ljust(10)} {count}")
            print(f"\t{'Null'.ljust(10)} {null_values}")

print("\nTotal Null Values:", total_null_values)
```

```
Work_Experience (Float):
        Value     Count
      ------------------
        1.0        2354
        0.0        2318
        9.0        474
        8.0        463
        2.0        286
        3.0        255
        4.0        253
        6.0        204
        7.0        196
        5.0        194
        10.0       53
        11.0       50
        12.0       48
        13.0       46
        14.0       45
        Null       829

Family_Size (Float):
        Value     Count
      ------------------
        2.0        2390
        3.0        1497
        1.0        1453
        4.0        1379
        5.0        612
        6.0        212
        7.0        96
        8.0        50
        9.0        44
        Null       335

Ever_Married (Categorical):
        Value     Count
      ------------------
        Yes        4643
        No         3285
        Null       140

Graduated (Categorical):
        Value     Count
      ------------------
        Yes        4968
        No         3022
        Null       78

Profession (Categorical):
        Value     Count
      ------------------
        Artist     2516
        Healthcare 1332
        Entertainment 949
        Engineer   699
        Doctor     688
        Lawyer     623
        Executive  599
        Marketing  292
        Homemaker  246
        Null       124

Var_1 (Categorical):
        Value     Count
      ------------------
        Cat_6      5238
        Cat_4      1089
        Cat_3      822
        Cat_2      422
        Cat_7      203
        Cat_1      133
        Cat_5      85
        Null       76

Total Null Values: 1582
```

For Float_columns :

1. Work_Experience:
   - The null values in the Work_Experience field will be imputed using the median. The median is chosen because it is resilient to outliers and represents the data's core tendency.
2. Family_Size:
   - Similar to Work_Experience, null values in the Family_Size field will be imputed using the median. Again, the median is chosen above the mean for dealing with outliers effectively.

By replacing null values with the median, we ensure that the distribution of work experience and family size remains relatively constant, preserving the dataset's integrity.

For categorical_columns :

1. Ever_Married:
   - Replace null values with the column's mode (most frequent value), "Yes". This preserves the distribution of the data.
2. Graduated:
   - To maintain the distribution, replace null values with the column's mode, "Yes".
3. Profession:
   - Given the tiny number of null values (124 out of 11184), it may be appropriate to impute them with the "Artist" mode.

There are no null values in the Gender, Spending_Score, and Segmentation column, so no action is needed.

For "Var_1" column which is target column so i am going to remove all the rows with null values.

Code for imputing the null values :

* Imputing null values in (Ever_Married, Graduated, Profession, column with mode

In [13]:
```
train_data['Ever_Married'].fillna(train_data['Ever_Married'].mode()[0], inplace=True)

train_data['Graduated'].fillna(train_data['Graduated'].mode()[0], inplace=True)

train_data['Profession'].fillna(train_data['Profession'].mode()[0], inplace=True)
```

* Imputing null values in (Work_Experience, Family_Size) column with median

In [14]:
```
train_data['Work_Experience'].fillna(train_data['Work_Experience'].median(), inplace=True)

train_data['Family_Size'].fillna(train_data['Family_Size'].median(), inplace=True)
```

* Removing the rows where null values which are present in the target column

In [15]:
```
train_data.dropna(subset=['Var_1'], inplace=True)
```

Checking the null value count after imputing the null values:

In [16]:
```
print("Total Null Values Remaining after handelling the null values :", train_data.isnull().sum().sum())
print("Shape of the data after Removing rows with null values in the 'Var_1' column :", train_data.shape)
```

```
Total Null Values Remaining after handelling the null values : 0
Shape of the data after Removing rows with null values in the 'Var_1' column : (7992, 10)
```

In [17]:
```
train_data.isnull().sum()
```

Out[17]:
```
ID                 0
Gender             0
Ever_Married       0
Age                0
Graduated          0
Profession         0
Work_Experience    0
Spending_Score     0
Family_Size        0
Var_1              0
dtype: int64
```

Visualization

* Analysing the target variable distrubution :

In [18]:
```
Var_1_groupby = train_data.groupby('Var_1').size()
print(Var_1_groupby)
```

```
Var_1
Cat_1     133
Cat_2     422
Cat_3     822
Cat_4    1089
Cat_5      85
Cat_6    5238
Cat_7     203
dtype: int64
```

In [19]:
```
train_data.loc[~train_data['Var_1'].isin(['Cat_6', 'Cat_4']), 'Var_1'] = 'others'
```

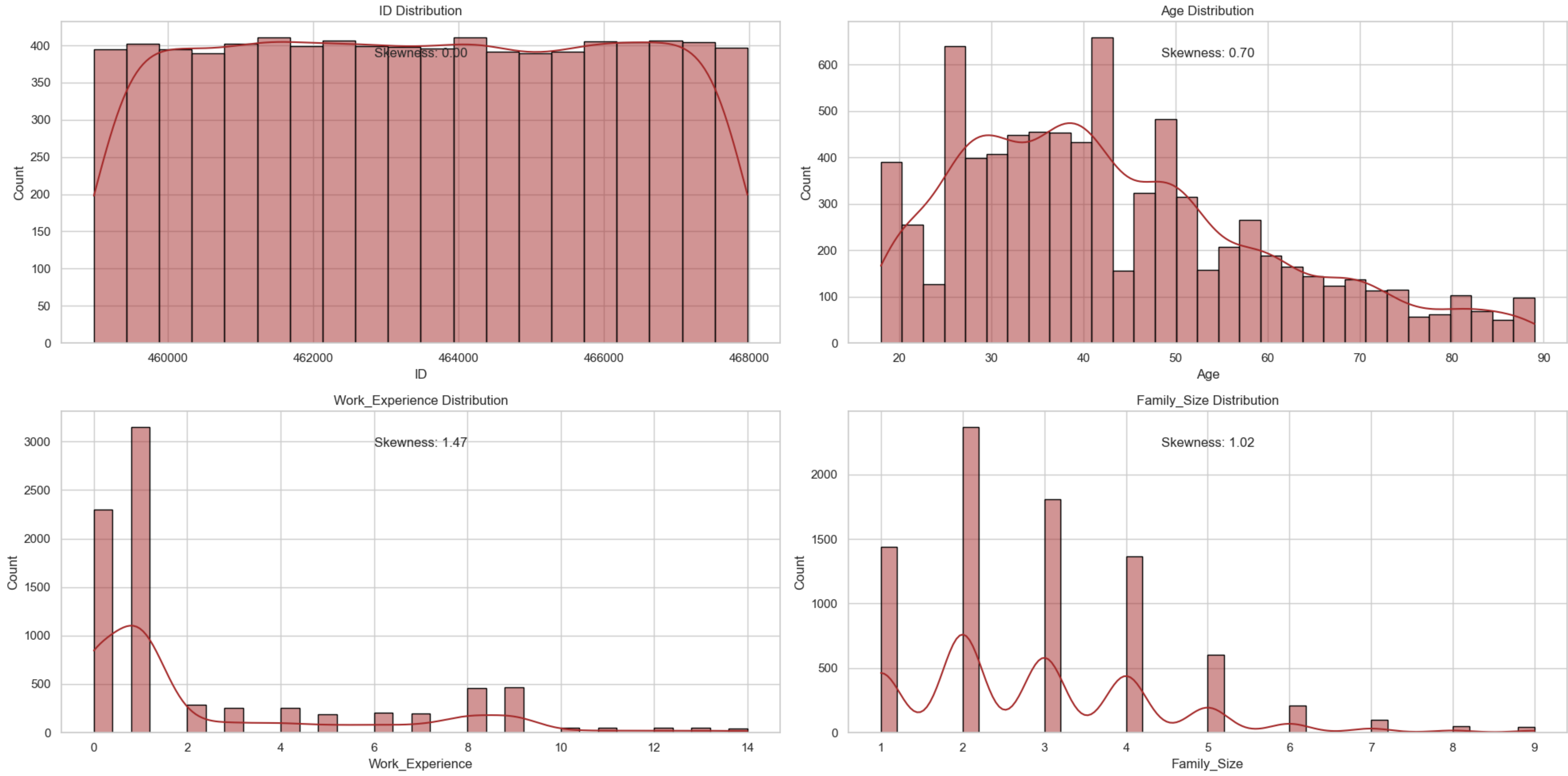
In [20]:
```
Var_1_groupby = train_data.groupby('Var_1').size()
print(Var_1_groupby)
```

```
Var_1
Cat_4     1089
Cat_6     5238
others    1665
dtype: int64
```

In [21]:
```
custom_colors = px.colors.qualitative.Pastel

fig_pie = px.pie(Var_1_groupby, values=Var_1_groupby.values, names=Var_1_groupby.index,
                 title='Distribution of Var_1',
                 hole=0.4, color_discrete_sequence=custom_colors,
                 width=700, height=600)
fig_pie.show()
```

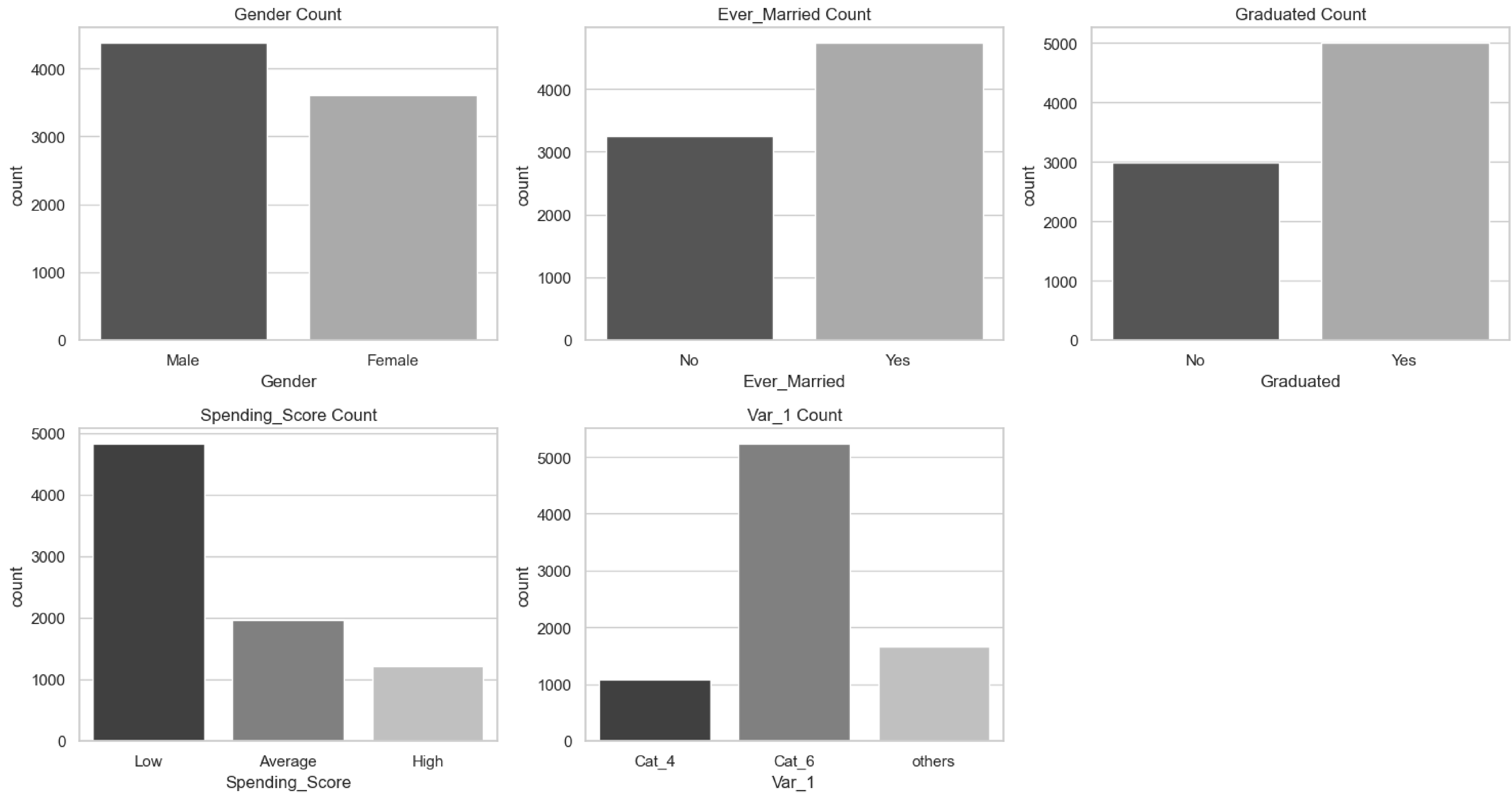
* Distribution and skewness of numerical, Float columns:

In [22]:
```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(20, 10))

for i, col in enumerate(numeric_columns[:2]):
    sns.histplot(data=train_data, x=col, ax=axes[0, i], kde=True, color="brown", edgecolor='black')
    skewness_value = train_data[col].skew()
    axes[0, i].text(0.5, 0.9, f'Skewness: {skewness_value:.2f}', horizontalalignment='center', verticalalignment='center', transform=axes[0, i].transAxes, fontsize=12)
    axes[0, i].set_title(f'{col} Distribution')

for i, col in enumerate(float_columns[:2]):
    sns.histplot(data=train_data, x=col, ax=axes[1, i], kde=True, color="brown", edgecolor='black')
    skewness_value = train_data[col].skew()
    axes[1, i].text(0.5, 0.9, f'Skewness: {skewness_value:.2f}', horizontalalignment='center', verticalalignment='center', transform=axes[1, i].transAxes, fontsize=12)
    axes[1, i].set_title(f'{col} Distribution')

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

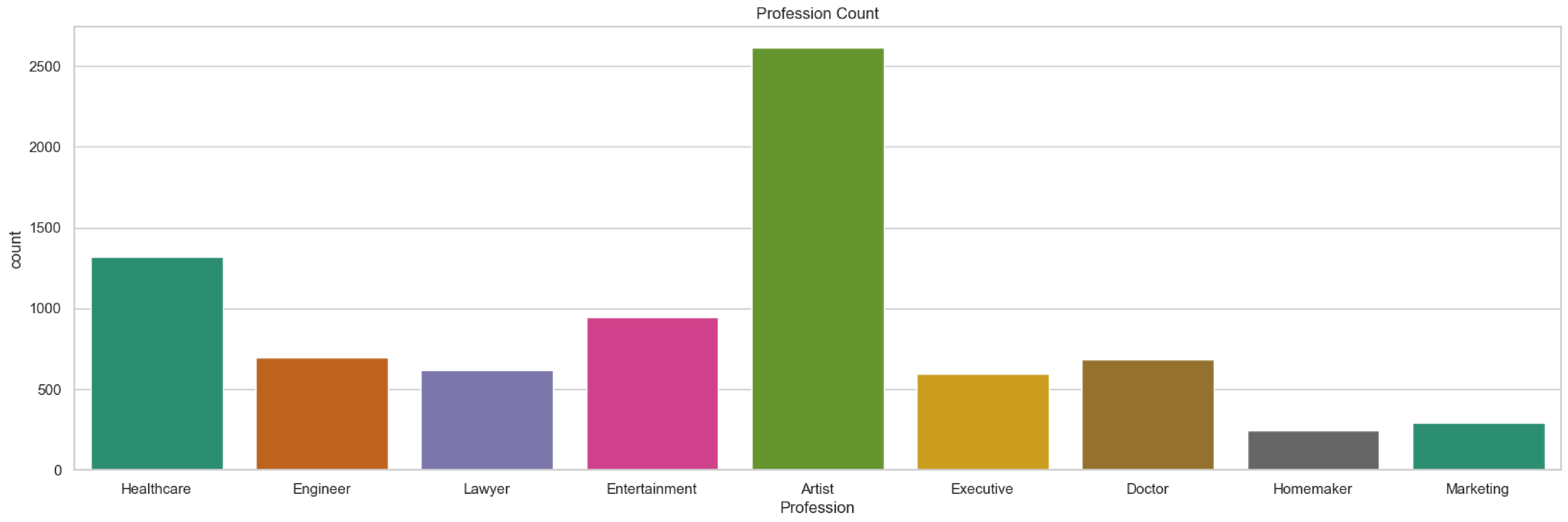


* Histogram for distribution of Categorical columns :

In [23]:
```
hist_graph_cc = ['Gender', 'Ever_Married', 'Graduated', 'Spending_Score', 'Var_1']
fig, axes = plt.subplots(2, 3, figsize=(15, 8))

axes = axes.flatten()

for i, cat_col in enumerate(hist_graph_cc):
    sns.countplot(data=train_data, x=cat_col, ax=axes[i], palette = 'gray')
    axes[i].set_title(f'{cat_col} Count')
fig.delaxes(axes[-1])
plt.tight_layout()
plt.show()
```



In [24]:
```
plt.figure(figsize=(20, 6))
sns.countplot(x='Profession', data=train_data, palette = 'Dark2')
plt.title("Profession Count")
plt.show()
```



Encoding :

* Encoding the categorical columns in dataframe except "Var_1"(target variable column):

In [25]:
```
numeric = ['ID', 'Age']
float_cols = ['Work_Experience', 'Family_Size']
categorical = ['Gender', 'Ever_Married', 'Graduated', 'Profession', 'Spending_Score']
target_variable = ['Var_1']
```

In [26]:
```
encoded_df = pd.get_dummies(train_data, columns = categorical)
encoded_df.drop(columns=numeric + float_cols, inplace=True)
pd.set_option('display.max_columns', None)
encoded_df.sample(7)
```

Out[26]:

	Var_1	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_Engineer	Profession_Entertainment	Profession_Execu
2648	Cat_6	False	True	True	False	True	False	False	True	False	False	F
1544	Cat_6	True	False	True	False	False	True	True	False	False	False	F
5995	others	False	True	False	True	False	True	False	False	False	False	
2880	Cat_4	True	False	True	False	False	True	False	False	False	False	F
6563	Cat_6	True	False	True	False	True	False	False	True	False	False	F
4046	Cat_6	True	False	False	True	False	True	False	False	True	False	F
6381	Cat_6	True	False	True	False	True	False	False	False	False	False	F

In [27]:
```
print("Original dataframe shape:", train_data.shape)
print("Encoded dataframe shape:", encoded_df.shape)
```

```
Original dataframe shape: (7992, 10)
Encoded dataframe shape: (7992, 19)
```

Scaling using Standard Scaler :

* Normalize the numeric and float columns using Standard Scaler :

In [28]:
```
scaler = StandardScaler()

train_data[numeric_columns] = scaler.fit_transform(train_data[numeric])

scaled_numeric_float = scaler.fit_transform(train_data[numeric + float_cols])
scaled_numeric_float_df = pd.DataFrame(scaled_numeric_float, columns=numeric + float_cols)

scaled_numeric_float_df.sample(6)
```

Out[28]:

	ID	Age	Work_Experience	Family_Size
4872	-0.063922	1.708718	-0.757372	-1.236169
1328	1.582030	1.169852	-0.757372	0.761296
2859	-1.660932	0.690859	-0.451252	-0.570347
6148	-1.492136	-1.404733	-0.451252	1.427118
3740	0.457110	-0.087504	-0.757372	0.761296
886	0.374639	1.828467	-0.451252	-0.570347

In [29]:
```
scaled_numeric_float_df.shape
```

Out[29]:
```
(7992, 4)
```

Creating the main dataframe :

* Concatenating the encoded and scaled data and creating one dataframe for further analysis:

In [30]:
```
scaled_numeric_float_df.reset_index(drop=True, inplace=True)
encoded_df.reset_index(drop=True, inplace=True)

main_train_df = pd.concat([scaled_numeric_float_df, encoded_df], axis=1)
main_train_df
```

Out[30]:

	ID	Age	Work_Experience	Family_Size	Var_1	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_
0	-0.259695	-1.284985	-0.451252	0.761296	Cat_4	False	True	True	False	True	False	False	False	
1	-0.323668	-0.327000	-0.451252	0.095474	Cat_4	True	False	False	True	False	True	False	False	
2	1.091443	1.409348	-0.451252	-1.236169	Cat_6	True	False	False	True	False	True	False	False	
3	-0.673591	1.409348	-0.757372	-0.570347	Cat_6	False	True	False	True	False	True	False	False	
4	-0.313648	-0.207252	-0.451252	2.092939	Cat_6	True	False	False	True	False	True	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7987	0.206228	-1.284985	-0.757372	2.758761	others	False	True	True	False	True	False	True	False	
7988	0.463276	-0.506622	0.160989	0.761296	Cat_4	False	True	True	False	True	False	False	False	
7989	0.741134	-0.626370	-0.451252	-1.236169	Cat_6	True	False	True	False	False	True	False	False	
7990	1.470656	-0.985615	-0.451252	0.761296	Cat_6	True	False	True	False	False	True	False	False	
7991	-0.618097	-0.386874	-0.757372	0.095474	Cat_4	False	True	False	True	False	True	False	False	

7992 rows × 23 columns

In [31]:

```
main_df_nullcount = main_train_df.isnull().sum()

if main_df_nullcount.any():
    print("Null values present. Details:")
    print(main_df_nullcount)
    total_nulls = train_data.isnull().sum().sum()
    print("Total Null Values in the data :", total_nulls)
else:
    print("No null values present.")
    print("Shape of the data :" , main_train_df.shape)
```

```
No null values present.
Shape of the data : (7992, 23)
```

* Mapping the target column :

In [32]:

```
name_mapping = { 'Cat_4':0,'Cat_6':1, 'others':2}
main_train_df["Var_1"] = main_train_df['Var_1'].map(name_mapping)
main_train_df
```

Out[32]:

	ID	Age	Work_Experience	Family_Size	Var_1	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_
0	-0.259695	-1.284985	-0.451252	0.761296	0	False	True	True	False	True	False	False	False	
1	-0.323668	-0.327000	-0.451252	0.095474	0	True	False	False	True	False	True	False	False	
2	1.091443	1.409348	-0.451252	-1.236169	1	True	False	False	True	False	True	False	False	
3	-0.673591	1.409348	-0.757372	-0.570347	1	False	True	False	True	False	True	False	False	
4	-0.313648	-0.207252	-0.451252	2.092939	1	True	False	False	True	False	True	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7987	0.206228	-1.284985	-0.757372	2.758761	2	False	True	True	False	True	False	True	False	
7988	0.463276	-0.506622	0.160989	0.761296	0	False	True	True	False	True	False	False	False	
7989	0.741134	-0.626370	-0.451252	-1.236169	1	True	False	True	False	False	True	False	False	
7990	1.470656	-0.985615	-0.451252	0.761296	1	True	False	True	False	False	True	False	False	
7991	-0.618097	-0.386874	-0.757372	0.095474	0	False	True	False	True	False	True	False	False	

7992 rows × 23 columns

1.1 Shuffling of the data before training (2 points)

* Shuffling the data

In [33]:

```
main_train_df = main_train_df.sample(frac=1).reset_index(drop=True)
print("Data after shuffling : ", '\n')
display(main_train_df)
```

```
Data after shuffling :
```

	ID	Age	Work_Experience	Family_Size	Var_1	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_
0	1.533472	-0.027630	-0.451252	1.427118	1	True	False	False	True	False	True	True	False	
1	1.315734	0.511237	-0.757372	0.095474	1	False	True	False	True	True	False	False	True	
2	-1.539923	1.409348	-0.451252	0.095474	1	False	True	False	True	True	False	False	False	
3	-0.028467	-0.027630	1.385471	1.427118	2	True	False	False	True	True	False	False	False	
4	-1.007715	-0.506622	-0.451252	-0.570347	1	False	True	False	True	False	True	True	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7987	-1.637424	2.367333	-0.451252	-1.236169	1	True	False	False	True	True	False	False	False	
7988	0.241298	0.211867	-0.757372	0.095474	1	False	True	False	True	True	False	False	False	
7989	1.236731	-0.985615	-0.451252	-1.236169	2	True	False	False	True	True	False	False	False	
7990	-0.370298	-0.147378	-0.451252	1.427118	0	False	True	False	True	True	False	False	False	
7991	-1.238942	-0.686244	1.997712	-0.570347	1	False	True	False	True	False	True	True	False	

7992 rows × 23 columns

Defining X as features and y as target column :

In [34]:

```
X = main_train_df.drop(columns=['Var_1'])
y = main_train_df['Var_1']
#display(X, y)
```

* Splitting the data into training and validation sets

In [35]:

```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, stratify = y, random_state=65)

print('Train Test split ratio is : [80, 20]','\n')
print("Training set:")
print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)


print("\nTesting set:")
print("X_val shape:", X_val.shape)
print("y_val shape:", y_val.shape)
```

```
Train Test split ratio is : [80, 20]

Training set:
X_train shape: (6393, 22)
y_train shape: (6393,)

Testing set:
X_val shape: (1599, 22)
y_val shape: (1599,)
```

1.2 Design and train a neural network model (e.g. you can use DNN network or if you want to use any other models it is also acceptable) (10 points)

* Defining the model :

In [36]:
```
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.14),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(32, activation='relu'),
    Dropout(0.10),
    Dense(7, activation='softmax')
])
```

* Compile the model

In [37]:
```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

In [38]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	2,944
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 32)	2,080
dropout_2 (Dropout)	(None, 32)	0
dense_3 (Dense)	(None, 7)	231

Total params: 13,511 (52.78 KB)
Trainable params: 13,511 (52.78 KB)
Non-trainable params: 0 (0.00 B)

1.3 Use validation data for model tuning and monitor the f1-score while applying the early stopping logic from keras library (10 points)

* Creating the "F1ScoreCallback" :

In [39]:
```
class F1scoreCallback(tf.keras.callbacks.Callback):
    def __init__(self, X, y, type):
        super(F1scoreCallback, self).__init__()
        self.X = X
        self.y = y
        self.f1_scores = []
        self.type = type

    def on_epoch_end(self, epoch, logs=None):
        y_pred_probs = self.model.predict(self.X)
        y_pred = np.argmax(y_pred_probs, axis=-1)
        if self.y.ndim > 1:
            y_true = np.argmax(self.y, axis=1)
        else:
            y_true = self.y
        f1 = f1_score(y_true, y_pred, average='macro')
        self.f1_scores.append(f1)
        #print(f'Epoch {epoch+1} - {self.type}_f1_score: {f1:.4f}')
        if logs is not None:
            logs[f'{self.type}_f1_score'] = f1
```

* Define early stopping criteria with the F1-score callback

In [88]:
```
train_f1score_callback = F1scoreCallback(X_train, y_train, type='train')
val_f1score_callback = F1scoreCallback(X_val, y_val, type='val')

early_stopping = EarlyStopping(monitor='val_accuracy', mode='max', patience=10, restore_best_weights=True)
```

* Train the model

In [89]:
```
history = model.fit(X_train, y_train,
                    validation_data=(X_val, y_val),
                    epochs=150,
                    batch_size=64,
                    callbacks=[early_stopping, train_f1score_callback, val_f1score_callback])
```

```
Epoch 1/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/stepy: 0.6562 - loss: 0.89
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 225us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6450 - loss: 0.8956 - val_accuracy: 0.6592 - val_loss: 0.8251 - train_f1_score: 0.2915 - val_f1_score: 0.2878
Epoch 2/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 206us/step: 0.7188 - loss: 0.82
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 223us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6451 - loss: 0.8524 - val_accuracy: 0.6629 - val_loss: 0.8213 - train_f1_score: 0.3356 - val_f1_score: 0.3288
Epoch 3/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/step: 0.6562 - loss: 0.87
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 225us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6611 - loss: 0.8318 - val_accuracy: 0.6623 - val_loss: 0.8189 - train_f1_score: 0.3527 - val_f1_score: 0.3430
Epoch 4/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 208us/step: 0.7188 - loss: 0.73
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 216us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6640 - loss: 0.8262 - val_accuracy: 0.6648 - val_loss: 0.8175 - train_f1_score: 0.3330 - val_f1_score: 0.3259
Epoch 5/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/step: 0.6094 - loss: 0.86
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 217us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6550 - loss: 0.8249 - val_accuracy: 0.6617 - val_loss: 0.8130 - train_f1_score: 0.3516 - val_f1_score: 0.3336
Epoch 6/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 372us/step: 0.5781 - loss: 0.
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 221us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6600 - loss: 0.8193 - val_accuracy: 0.6654 - val_loss: 0.8121 - train_f1_score: 0.3607 - val_f1_score: 0.3517
Epoch 7/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 206us/step: 0.6719 - loss: 0.85
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 221us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6566 - loss: 0.8254 - val_accuracy: 0.6648 - val_loss: 0.8112 - train_f1_score: 0.3571 - val_f1_score: 0.3463
Epoch 8/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 208us/step: 0.7656 - loss: 0.67
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 215us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6720 - loss: 0.8006 - val_accuracy: 0.6642 - val_loss: 0.8092 - train_f1_score: 0.3643 - val_f1_score: 0.3506
Epoch 9/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/step: 0.6094 - loss: 0.89
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 218us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6615 - loss: 0.8224 - val_accuracy: 0.6679 - val_loss: 0.8103 - train_f1_score: 0.3647 - val_f1_score: 0.3599
Epoch 10/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 209us/step: 0.7344 - loss: 0.76
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 221us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6731 - loss: 0.7903 - val_accuracy: 0.6667 - val_loss: 0.8117 - train_f1_score: 0.3552 - val_f1_score: 0.3443
Epoch 11/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 208us/step: 0.6562 - loss: 0.78
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 226us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6598 - loss: 0.8088 - val_accuracy: 0.6648 - val_loss: 0.8066 - train_f1_score: 0.3702 - val_f1_score: 0.3529
Epoch 12/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 214us/stepy: 0.7656 - loss: 0.74
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 227us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6634 - loss: 0.7999 - val_accuracy: 0.6654 - val_loss: 0.8064 - train_f1_score: 0.3585 - val_f1_score: 0.3401
Epoch 13/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 213us/step: 0.6719 - loss: 0.74
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 228us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6621 - loss: 0.8033 - val_accuracy: 0.6660 - val_loss: 0.8068 - train_f1_score: 0.3586 - val_f1_score: 0.3403
Epoch 14/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 211us/step: 0.7656 - loss: 0.62
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 222us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6740 - loss: 0.7808 - val_accuracy: 0.6710 - val_loss: 0.8095 - train_f1_score: 0.3808 - val_f1_score: 0.3790
Epoch 15/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 209us/step accuracy: 0.6481 - loss: 0.82
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 225us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6650 - loss: 0.7973 - val_accuracy: 0.6692 - val_loss: 0.8065 - train_f1_score: 0.3772 - val_f1_score: 0.3685
Epoch 16/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 212us/step: 0.6719 - loss: 0.78
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 216us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6661 - loss: 0.7910 - val_accuracy: 0.6685 - val_loss: 0.8121 - train_f1_score: 0.3808 - val_f1_score: 0.3668
Epoch 17/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 210us/step: 0.7031 - loss: 0.73
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 229us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6699 - loss: 0.7827 - val_accuracy: 0.6679 - val_loss: 0.8106 - train_f1_score: 0.3784 - val_f1_score: 0.3655
Epoch 18/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 212us/step: 0.6875 - loss: 0.78
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 228us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6711 - loss: 0.7816 - val_accuracy: 0.6648 - val_loss: 0.8061 - train_f1_score: 0.3678 - val_f1_score: 0.3517
Epoch 19/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/step: 0.7188 - loss: 0.76
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 224us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6725 - loss: 0.7758 - val_accuracy: 0.6654 - val_loss: 0.8076 - train_f1_score: 0.3815 - val_f1_score: 0.3577
Epoch 20/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 209us/step: 0.7500 - loss: 0.65
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 217us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6710 - loss: 0.7788 - val_accuracy: 0.6685 - val_loss: 0.8061 - train_f1_score: 0.3811 - val_f1_score: 0.3657
Epoch 21/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 211us/step: 0.7031 - loss: 0.75
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 227us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6750 - loss: 0.7735 - val_accuracy: 0.6742 - val_loss: 0.8067 - train_f1_score: 0.4003 - val_f1_score: 0.3869
Epoch 22/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 213us/step: 0.7500 - loss: 0.65
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 220us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6791 - loss: 0.7617 - val_accuracy: 0.6667 - val_loss: 0.8121 - train_f1_score: 0.4134 - val_f1_score: 0.3784
Epoch 23/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 208us/step: 0.7344 - loss: 0.69
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 216us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6705 - loss: 0.7773 - val_accuracy: 0.6654 - val_loss: 0.8113 - train_f1_score: 0.3761 - val_f1_score: 0.3500
Epoch 24/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 213us/step: 0.7656 - loss: 0.64
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 222us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6811 - loss: 0.7615 - val_accuracy: 0.6698 - val_loss: 0.8103 - train_f1_score: 0.4111 - val_f1_score: 0.3825
Epoch 25/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 212us/step accuracy: 0.6819 - loss: 0.771
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 231us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6788 - loss: 0.7698 - val_accuracy: 0.6704 - val_loss: 0.8092 - train_f1_score: 0.4195 - val_f1_score: 0.3909
Epoch 26/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 209us/step: 0.6562 - loss: 0.89
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 215us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6743 - loss: 0.7733 - val_accuracy: 0.6673 - val_loss: 0.8097 - train_f1_score: 0.4008 - val_f1_score: 0.3701
Epoch 27/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 213us/step: 0.6562 - loss: 0.68
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 226us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6779 - loss: 0.7578 - val_accuracy: 0.6673 - val_loss: 0.8141 - train_f1_score: 0.4529 - val_f1_score: 0.4117
Epoch 28/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/step: 0.7344 - loss: 0.60
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 218us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6810 - loss: 0.7612 - val_accuracy: 0.6617 - val_loss: 0.8102 - train_f1_score: 0.3910 - val_f1_score: 0.3507
Epoch 29/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 209us/step: 0.6094 - loss: 0.90
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 225us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6783 - loss: 0.7676 - val_accuracy: 0.6635 - val_loss: 0.8134 - train_f1_score: 0.4269 - val_f1_score: 0.3811
Epoch 30/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 208us/step: 0.6719 - loss: 0.71
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 221us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6820 - loss: 0.7499 - val_accuracy: 0.6598 - val_loss: 0.8163 - train_f1_score: 0.4415 - val_f1_score: 0.3794
Epoch 31/150
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 206us/step: 0.7031 - loss: 0.74
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 225us/step
100/100 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.6748 - loss: 0.7730 - val_accuracy: 0.6629 - val_loss: 0.8163 - train_f1_score: 0.4326 - val_f1_score: 0.3881
```

Classification report for the Validation dataset.

In [90]:
```
test_loss, test_accuracy = model.evaluate(X_val, y_val)
print(f'Test Loss: {test_loss}, Test Accuracy: {test_accuracy:.4f}')

val_prediction = model.predict(X_val)
y_val_predected = np.argmax(val_prediction, axis=1)
```

```
f1 = f1_score(y_val, y_val_predected, average='macro')
print(f'F1-score: {f1}')
```

```
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 304us/step - accuracy: 0.6838 - loss: 0.7898
Test Loss: 0.8067430853843689, Test Accuracy: 0.6742
50/50 ━━━━━━━━━━━━━━━━━━━━ 0s 221us/step
F1-score: 0.3869070458239922
```

In [91]:
```
train_f1_scores = train_f1score_callback.f1_scores
val_f1_scores = val_f1score_callback.f1_scores
print("Training set f1-score :", train_f1_scores)
print("Validation set f1-score :", val_f1_scores)
```

```
Training set f1-score : [0.29150019561672197, 0.33560924601314185, 0.35270784116741466, 0.3329673811659593, 0.3516467537745867, 0.36068428823036003, 0.3570694689115049, 0.364286
3980025453, 0.36467973467918346, 0.35517471309373744, 0.3701698557423361, 0.35849984125241807, 0.35858736210335085, 0.3808111982884961, 0.377155686577282, 0.38082776798581747,
0.3783880663476577, 0.3677579872851629, 0.3814640654942545, 0.3811083976409004, 0.40033971350937897, 0.41341195630941147, 0.3761140198213866, 0.4111471008103467, 0.4195322886181
9597, 0.40082405083725914, 0.4528668437723984, 0.39101444884136033, 0.4268664561546755, 0.4414760812961993, 0.4325808724623273]
Validation set f1-score : [0.2878310370431483, 0.3288339189340302, 0.34299769729956037, 0.3259106686731183, 0.3335941300816247, 0.3517246615346654, 0.34632955696785483, 0.350620
9389126495, 0.3599272462456566, 0.3442753113586352, 0.3529133072708965, 0.3400613413487051, 0.3402666267943371, 0.3790316371355795, 0.3684728722482233, 0.3667667762901894, 0.365
4877181048494, 0.3516659866721066, 0.35767266306954065, 0.3657169590884372, 0.3869070458239922, 0.37840806438713215, 0.34997610536139634, 0.38253070133918204, 0.3909421653248588
7, 0.3701275407505731, 0.4116652053295386, 0.3506955125452506, 0.38111972978698255, 0.3794404001276372, 0.3880828509262955]
```

1.4 Use test data to calculate the appropriate classification metrics. (5 points)

Processing the test_data file for testing the model.

* Load the test data

In [92]:
```
test_data = pd.read_csv('test.csv')
#display(test_data)
test_data.shape
```

Out[92]:
```
(2627, 10)
```

* Check the null values in the test data :

In [93]:
```
print(test_data.isnull().sum())
print("Total null vales : ", test_data.isnull().sum().sum())
```

```
ID                   0
Gender               0
Ever_Married        50
Age                  0
Graduated           24
Profession          38
Work_Experience    269
Spending_Score       0
Family_Size        113
Var_1               32
dtype: int64
Total null vales :  526
```

Going to delete the rows with null values : As there are only 526 null values.

Handelling the null values

In [94]:
```
columns_with_null = ['Ever_Married', 'Graduated', 'Profession', 'Work_Experience', 'Family_Size', 'Var_1']

test_data = test_data.dropna(subset=columns_with_null)
```

In [95]:
```
test_data_null = test_data.isnull().sum().sum()
print("Total Null Values Remaining after handelling the null values in Test data:", test_data_null)
```

```
Total Null Values Remaining after handelling the null values in Test data: 0
```

In [96]:
```
print("Shape of the data after Removing rows with null values in the 'Var_1' column :", test_data.shape)
```

```
Shape of the data after Removing rows with null values in the 'Var_1' column : (2154, 10)
```

In [97]:
```
test_data.isnull().sum()
```

Out[97]:
```
ID                 0
Gender             0
Ever_Married       0
Age                0
Graduated          0
Profession         0
Work_Experience    0
Spending_Score     0
Family_Size        0
Var_1              0
dtype: int64
```

In [98]:
```
test_data.loc[~test_data['Var_1'].isin(['Cat_6', 'Cat_4']), 'Var_1'] = 'others'
```

Encoding the test data :

In [99]:
```
test_encoded = pd.get_dummies(test_data, columns = categorical)
test_encoded.drop(columns=numeric + float_cols, inplace=True)
pd.set_option('display.max_columns', None)
test_encoded
```

Out[99]:

	Var_1	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_Engineer	Profession_Entertainment	Profession_Execu
0	Cat_6	True	False	False	True	False	True	False	False	True	False	F
1	Cat_6	False	True	False	True	False	True	False	False	False	False	F
3	Cat_6	False	True	False	True	True	False	False	False	False	False	
5	Cat_4	False	True	False	True	False	True	False	True	False	False	F
6	Cat_6	False	True	False	True	False	True	False	True	False	False	F
...	...	...	...	...	...	...	...	...	...	...	...	
2621	Cat_6	True	False	True	False	False	True	False	False	False	True	F
2622	Cat_6	False	True	True	False	True	False	False	False	False	False	F
2623	Cat_6	True	False	True	False	False	True	False	True	False	False	F
2625	Cat_4	False	True	False	True	False	True	False	False	False	False	
2626	others	True	False	True	False	False	True	False	False	False	False	F

2154 rows × 19 columns

In [100…
```
print("Original test dataframe shape:", test_data.shape)
print("Test_Encoded dataframe shape:", test_encoded.shape)
```

```
Original test dataframe shape: (2154, 10)
Test_Encoded dataframe shape: (2154, 19)
```

Scaling using Standard Scaler :

* Normalize the numeric and float columns using Standard Scaler :

In [101…
```
test_data[numeric_columns] = scaler.fit_transform(test_data[numeric])

test_scaled_numeric_float = scaler.fit_transform(test_data[numeric + float_cols])
test_scaled_numeric_float_df = pd.DataFrame(test_scaled_numeric_float, columns=numeric + float_cols)

test_scaled_numeric_float_df
```

Out[101]:

	ID	Age	Work_Experience	Family_Size
0	-1.739862	-0.445248	-0.762986	-1.172702
1	-1.737932	-0.385575	1.629258	0.742385
2	-1.735616	0.927231	2.526349	-0.534340
3	-1.734458	0.211155	-0.762986	1.380748
4	-1.733686	1.046577	0.732167	0.104023
...	...	...	...	...
2149	1.718831	-0.504921	-0.463955	-0.534340
2150	1.720374	-0.862959	1.928288	0.742385
2151	1.721918	-0.504921	-0.463955	-1.172702
2152	1.723076	0.211155	-0.463955	1.380748
2153	1.725778	-0.027537	1.928288	0.104023

2154 rows × 4 columns

Creating the main testing dataframe

* Concatenating the encoded and scaled data and creating one dataframe for further analysis:

In [102…
```
test_scaled_numeric_float_df.reset_index(drop=True, inplace=True)
test_encoded.reset_index(drop=True, inplace=True)

test_data_main = pd.concat([test_scaled_numeric_float_df, test_encoded], axis=1)
test_data_main
```

Out[102]:

	ID	Age	Work_Experience	Family_Size	Var_1	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession
0	-1.739862	-0.445248	-0.762986	-1.172702	Cat_6	True	False	False	True	False	True	False	False	
1	-1.737932	-0.385575	1.629258	0.742385	Cat_6	False	True	False	True	False	True	False	False	
2	-1.735616	0.927231	2.526349	-0.534340	Cat_6	False	True	False	True	True	False	False	False	
3	-1.734458	0.211155	-0.762986	1.380748	Cat_4	False	True	False	True	False	True	False	True	
4	-1.733686	1.046577	0.732167	0.104023	Cat_6	False	True	False	True	False	True	False	True	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2149	1.718831	-0.504921	-0.463955	-0.534340	Cat_6	True	False	True	False	False	True	False	False	
2150	1.720374	-0.862959	1.928288	0.742385	Cat_6	False	True	True	False	True	False	False	False	
2151	1.721918	-0.504921	-0.463955	-1.172702	Cat_6	True	False	True	False	False	True	False	True	
2152	1.723076	0.211155	-0.463955	1.380748	Cat_4	False	True	False	True	False	True	False	False	
2153	1.725778	-0.027537	1.928288	0.104023	others	True	False	True	False	False	True	False	False	

2154 rows × 23 columns

* Mapping Target column :

In [103…
```
test_data_main["Var_1"] = test_data_main['Var_1'].map(name_mapping)
test_data_main
```

Out[103]:

	ID	Age	Work_Experience	Family_Size	Var_1	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_
0	-1.739862	-0.445248	-0.762986	-1.172702	1	True	False	False	True	False	True	False	False	
1	-1.737932	-0.385575	1.629258	0.742385	1	False	True	False	True	False	True	False	False	
2	-1.735616	0.927231	2.526349	-0.534340	1	False	True	False	True	True	False	False	False	
3	-1.734458	0.211155	-0.762986	1.380748	0	False	True	False	True	False	True	False	True	
4	-1.733686	1.046577	0.732167	0.104023	1	False	True	False	True	False	True	False	True	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2149	1.718831	-0.504921	-0.463955	-0.534340	1	True	False	True	False	False	True	False	False	
2150	1.720374	-0.862959	1.928288	0.742385	1	False	True	True	False	True	False	False	False	
2151	1.721918	-0.504921	-0.463955	-1.172702	1	True	False	True	False	False	True	False	True	
2152	1.723076	0.211155	-0.463955	1.380748	0	False	True	False	True	False	True	False	False	
2153	1.725778	-0.027537	1.928288	0.104023	2	True	False	True	False	False	True	False	False	

2154 rows × 23 columns

* Defining the X, Y as featues and target respectively :

In [104…
```
test_X = test_data_main.drop(columns=['Var_1'])
test_Y = test_data_main['Var_1']
```

* Testing model using test data and calculating the appropriate classification metrics

In [105…
```
test_data_prediction = model.predict(test_X)
test_data_prediction_np = np.argmax(test_data_prediction, axis=1)

print(classification_report(test_Y, test_data_prediction_np))
```

```
68/68 ━━━━━━━━━━━━━━━━━━━━ 0s 279us/step
              precision    recall  f1-score   support

           0       0.59      0.26      0.36       320
           1       0.69      0.97      0.81      1421
           2       1.00      0.02      0.04       413

    accuracy                           0.69      2154
   macro avg       0.76      0.42      0.40      2154
weighted avg       0.74      0.69      0.59      2154
```

1. Precision, Recall, and F1-score:

- For Class 0, the precision is 0.59, recall is 0.26, and F1-score is 0.36. This indicates that the model has moderate precision but struggles with recall in detecting instances of Class 0. The F1-score, being the harmonic mean of precision and recall, suggests a fair balance between precision and recall for this class.
- For Class 1, the precision is 0.69, recall is 0.97, and the F1-score is 0.81. The model performs well in identifying Class 1 cases, with high precision and recall. The F1-score also signifies a good balance between precision and recall in this class.
- For Class 2, the precision is 1.00, recall is 0.02, and the F1-score is 0.04. The model achieves perfect precision for Class 2 but struggles severely with recall, missing the majority of instances. Consequently, the F1-score is quite low for this class.

2. Overall Accuracy:

- The model's overall accuracy is 69%, indicating that it correctly classifies approximately 69% of the examples in the dataset.

3. Macro and Weighted Averages:

- Macro average: Precision, recall, and F1-score are calculated by averaging the metrics for each class without considering class imbalance. The macro average precision is 0.76, recall is 0.42, and the F1-score is 0.40.

4. Weighted average:

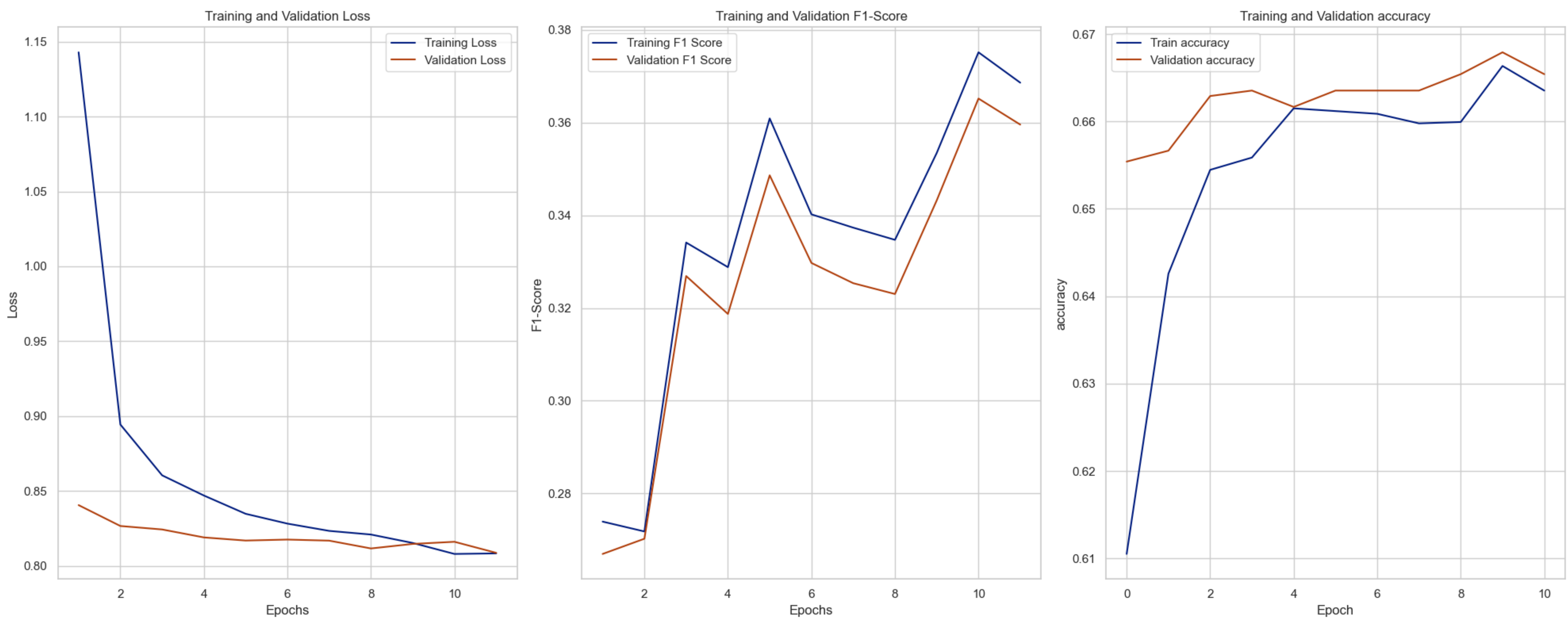
- Precision, recall, and F1-score are computed by considering the support (number of instances) for each class, providing a more balanced representation of total performance. The weighted average precision is 0.74, recall is 0.69, and the F1-score is 0.59.

- Overall, the model demonstrates strong performance in recognizing instances of Class 1, exhibiting high precision and recall. However, it struggles notably with Classes 0 and 2, particularly in terms of recall. The macro and weighted averages offer additional insights into the overall performance, considering both class-specific metrics and class distribution across the dataset.

1. Precision :
   - Precision is defined as the ratio of true positive predictions to total positive predictions made by the model. It measures the model's ability to properly identify instances belonging to a certain class from among all instances expected to be that class.
   - Precision in multi-class classification reveals the dependability of the model's positive predictions for each class. It answers the question: "How many of the instances predicted as Class X are actually Class X?"
   - High precision suggests that the model's prediction of a specific class is likely to be right. It demonstrates the model's capacity to reduce false positives, which is critical in situations where misclassification might have serious implications.
2. Recall :
   - Recall, also known as sensitivity or true positive rate, is computed as the ratio of true positive predictions to the total number of actual instances in a given class. It evaluates the model's ability to correctly identify all instances of a class.
   - In multi-class classification, recall measures the model's ability to capture all instances of each class, regardless of whether they were correctly categorized. It answers the following question: "How many instances of Class X did the model correctly identify?"
   - High recall implies that the model effectively reduces false negatives, guaranteeing that the majority of occurrences in a class are accurately identified. It is critical in situations when missing instances of a specific class can lead to negative consequences.
3. F1-score:
   - The F1-score is the harmonic mean of precision and recall, yielding a single statistic that balances both aspects of model performance. It is calculated as 2 × (precision * recall) divided by (precision + recall).
   - In multi-class classification, the F1-score provides a full evaluation of the model's performance, taking into account both false positives and false negatives. It strikes a balance between precision and recall, resulting in a single score reflecting the model's overall efficacy across all classes.
   - The F1-score is especially beneficial when there is a class imbalance or when the costs of false positives and false negatives differ. It assists in picking models that achieve the appropriate balance between precision and recall based on the application's specific requirements.

1.6 Generate the loss and f1-score curve for training and validation set. (10 points)

In [58]:
```python
epochs = range(1, len(history.history['loss']) + 1)

plt.figure(figsize=(20, 8))

# Plot training and validation loss
plt.subplot(1, 3, 1)
plt.plot(epochs, history.history['loss'], label='Training Loss')
plt.plot(epochs, history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation F1-Score
plt.subplot(1, 3, 2)
plt.plot(epochs, history.history['train_f1_score'], label='Training F1 Score')
plt.plot(epochs, history.history['val_f1_score'], label='Validation F1 Score')
plt.title('Training and Validation F1-Score')
plt.xlabel('Epochs')
plt.ylabel('F1-Score')
plt.legend()

plt.subplot(1, 3, 3)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Training and Validation accuracy')
plt.ylabel('accuracy')
plt.xlabel('Epoch')
plt.legend(['Train accuracy', 'Validation accuracy'], loc='upper left')

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



1. Training and Validation Loss:

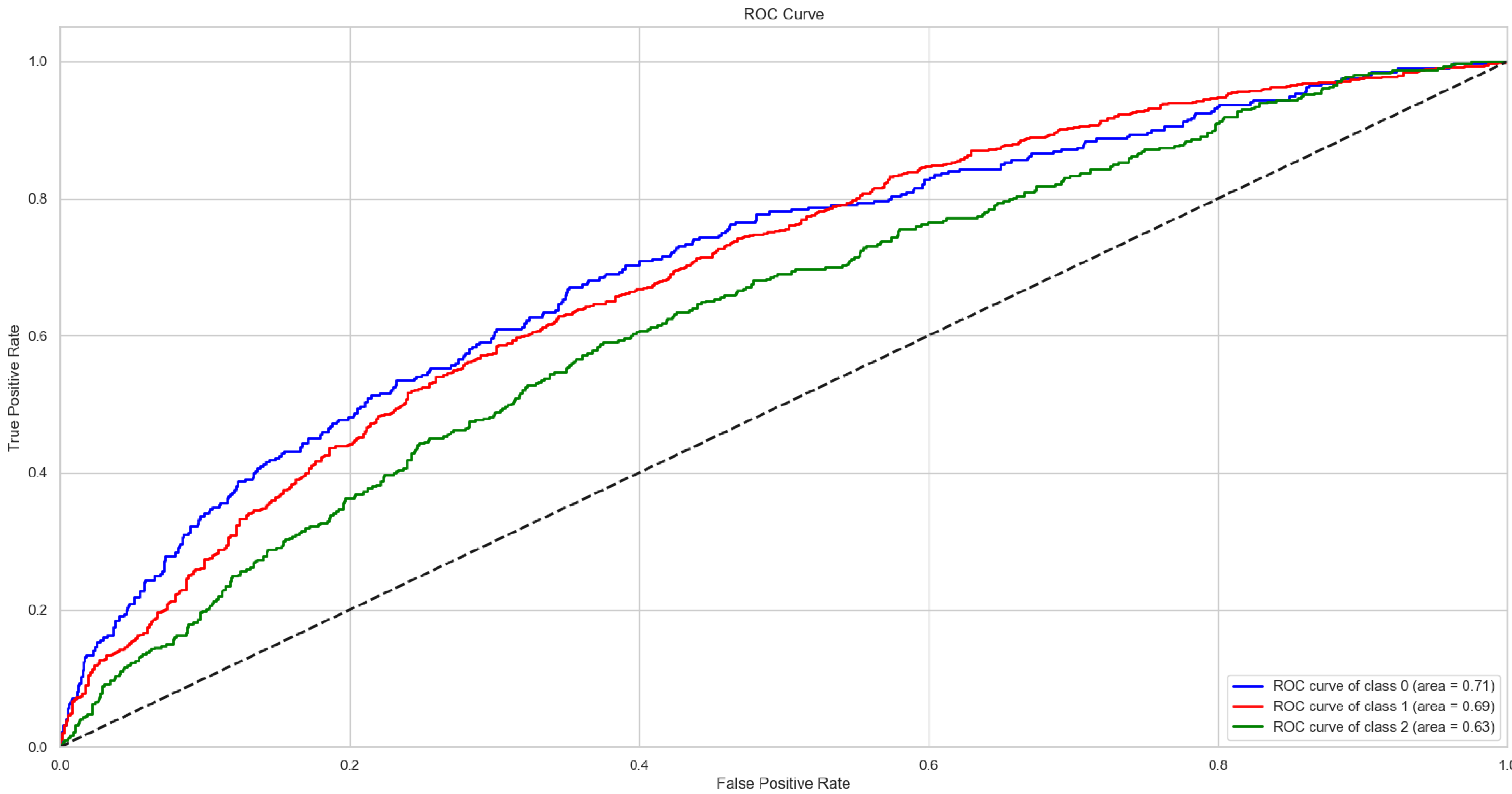
- B The first graph depicts training and validation losses. The training loss (blue line) rapidly declines and then flattens, suggesting that the model is learning from the training data. The validation loss (orange line) rapidly lowers, indicating that the model also generalizes well to new data.

2. Training and Validation:
   - the F1-score for both the training and validation datasets. The training F1 score (blue line) rises with fluctuations, whereas the validation F1 score (orange line) rises as well, but with more noticeable fluctuations. This could imply some degree of overfitting, in which the model performs well on training data but poorly on validation data.
3. Training and Validation Accuracy:
   - The third graph displays the model's accuracy across both the training and validation datasets. The training accuracy (blue line) indicates a consistent improvement, demonstrating that the model is always refining its predictions based on training data. The validation accuracy (orange line) rises but appears to plateau at later epochs, implying that the model may not be improving considerably on validation data in later phases.

1.7 Generate a ROC-AUC curve and comment on your model accuracy and find the optimal threshold from the curve. (10 points)

In [60]:
```
y_prob = model.predict(test_X)

fpr = dict()
tpr = dict()
roc_auc = dict()
num_classes = len(test_Y.unique())
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve((test_Y == i).astype(int), y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(20, 10))
colors = ['blue', 'red', 'green']
for i, color in zip(range(num_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2, label='ROC curve of class {0} (area = {1:0.2f})'''.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc="lower right")
plt.show()
```

```
68/68 ━━━━━━━━━━━━━━━━━━━━ 0s 255us/step
```



1. ROC Curve of Class 0:
   - The blue line depicts the ROC curve for class 0. The area under the curve (AUC) is 0.71, indicating a high level of prediction accuracy in this class.
2. ROC Curve of Class 1:
   - The green line is the ROC curve for class 1. The AUC is 0.69, which is somewhat lower than class 0, but still suggests a reasonable prediction accuracy.
3. ROC Curve for Class 2:
   - The red line depicts the ROC curve for class 2. The AUC is 0.63, the lowest of the three classes, but it still indicates a decent level of prediction accuracy.

- In conclusion, all three classes have good prediction accuracy, with class 0 having the highest AUC and class 2 having the lowest. This implies that the model has the highest prediction performance for class 0 and the lowest for class 2.
- However, all AUC values are relatively high, indicating that the model performs well overall. The ROC curves also show a visual representation of the trade-off between true positive and false positive rates for each class at various threshold levels.

* Finding the optimal threshold for each class :

In [63]:
```
num_samples = test_X.shape[0]
thresholds = np.linspace(0, 1, num_samples)
optimal_thresholds = {}
for i in range(num_classes):
    tpr_minus_fpr = tpr[i] - fpr[i]

    optimal_idx = np.argmax(tpr_minus_fpr)

    optimal_threshold = thresholds[optimal_idx]

    optimal_thresholds[i] = optimal_threshold

print("Optimal Thresholds for each class:", optimal_thresholds)
```

```
Optimal Thresholds for each class: {0: 0.12958662331630283, 1: 0.1709242916860195, 2: 0.1611704598235021}
```

In [64]:
```
distances = np.sqrt((fpr[1] - 0)**2 + (tpr[1] - 1)**2)

optimal_threshold_index = np.argmin(distances)

optimal_threshold = thresholds[optimal_threshold_index]
```

```
print("Optimal Threshold:", optimal_threshold)
```

```
Optimal Threshold: 0.1709242916860195
```

1.8 Repeat the steps from 1.1 to 1.7 with sampling in training set. (you can do over sampling to increase the instances of majority class in training set) Compare and comment on the results you get from sampled data and original data distribution. (50 points) (You are expected to do some research on how to apply sampling over a dataset and which libraries usually employed to do so.)

Sampling the data with respect to target column :

In [65]:
```
smote = SMOTE()

X_resampled, y_resampled = smote.fit_resample(X, y)

train_oversampled_data = pd.concat([pd.DataFrame(X_resampled, columns=X.columns), pd.DataFrame(y_resampled, columns=['Var_1'])], axis=1)
train_oversampled_data
```

Out[65]:

	ID	Age	Work_Experience	Family_Size	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_Engine
0	1.533472	-0.027630	-0.451252	1.427118	True	False	False	True	False	True	True	False	Fa
1	1.315734	0.511237	-0.757372	0.095474	False	True	False	True	True	False	False	True	Fa
2	-1.539923	1.409348	-0.451252	0.095474	False	True	False	True	True	False	False	False	Fa
3	-0.028467	-0.027630	1.385471	1.427118	True	False	False	True	True	False	False	False	Fa
4	-1.007715	-0.506622	-0.451252	-0.570347	False	True	False	True	False	True	True	False	Fa
...	...	...	...	...	...	...	...	...	...	...	...	...	
15709	-1.115205	-1.407858	-0.459239	1.461864	False	True	True	False	True	False	False	False	Fa
15710	0.588106	-0.506622	-0.746141	0.095474	False	True	True	False	False	True	False	False	Fa
15711	-1.041458	-0.125379	-0.451252	0.095474	False	True	False	True	False	True	True	False	Fa
15712	-1.214815	2.107982	-0.655861	-1.236169	True	True	False	True	True	False	False	False	Fa
15713	-1.115723	-0.789465	-0.748922	0.742916	True	False	True	False	False	True	False	False	Ti

15714 rows × 23 columns

Here in this the "train_oversampled_data" is already encoded and scaled above.

In [66]:
```
groupbt_oversampled = train_oversampled_data.groupby('Var_1').size()
print(groupbt_oversampled)
```

```
Var_1
0    5238
1    5238
2    5238
dtype: int64
```

In [67]:
```
custom_colors = px.colors.qualitative.Pastel

fig_pie = px.pie(groupbt_oversampled, values=groupbt_oversampled.values, names=groupbt_oversampled.index,
                 title='Distribution of Var_1',
                 hole=0.4, color_discrete_sequence=custom_colors,
                 width=700, height=600)
fig_pie.show()
```

Here :

```
- 'Cat_4':0,
- 'Cat_6':1,
- 'others':2
```

1.1 Shuffling of the data before training (2 points)

In [68]:
```
train_oversampled_data = train_oversampled_data.sample(frac=1).reset_index(drop=True)
print("Data after shuffling : ", '\n')
display(train_oversampled_data)
```

```
Data after shuffling :
```

	ID	Age	Work_Experience	Family_Size	Gender_Female	Gender_Male	Ever_Married_No	Ever_Married_Yes	Graduated_No	Graduated_Yes	Profession_Artist	Profession_Doctor	Profession_Engine
0	0.807419	-0.626370	0.467109	-1.236169	False	True	True	False	False	True	False	False	Fa
1	1.078194	-0.774191	-0.451252	0.095474	True	False	True	False	True	False	False	True	Fa
2	0.469442	-0.746118	-0.757372	-0.570347	False	True	True	False	True	False	False	True	Fa
3	1.512662	0.211867	-0.757372	0.761296	False	True	False	True	False	True	True	False	Fa
4	0.664409	-0.438299	1.342273	0.381407	True	False	False	True	False	True	True	False	Fa
...	...	...	...	...	...	...	...	...	...	...	...	...	
15709	-1.018821	-0.746118	1.997712	0.095474	True	False	True	False	False	True	False	False	Fa
15710	-0.848191	0.213392	-0.757372	0.905302	False	True	False	True	False	True	True	False	Fa
15711	-1.428934	-0.446748	-0.451252	-0.570347	False	True	True	False	False	True	True	False	Fa
15712	1.585884	1.469222	-0.451252	-1.236169	False	True	False	True	False	True	True	False	Fa
15713	-0.072824	-0.642010	-0.371293	-0.570347	True	True	False	True	True	False	False	False	Fa

15714 rows × 23 columns

* Defining the featues and target columns in X_2 and y_2 :

In [69]:
```
X_2 = train_oversampled_data.drop(columns=['Var_1'])
y_2 = train_oversampled_data['Var_1']
```

* Splitting the data in training and validation :

In [70]:
```
X_train_oversampled, X_val_oversampled, y_train_oversampled, y_val_oversampled = train_test_split(X_2, y_2, test_size=0.2, random_state=65)

print('Train Test split ratio is : [80, 20]','\n')
print("Training set:")
print("X_train shape:", X_train_oversampled.shape)
print("y_train shape:", y_train_oversampled.shape)


print("\nTesting set:")
print("X_val shape:", X_val_oversampled.shape)
print("y_val shape:", y_val_oversampled.shape)
```

```
Train Test split ratio is : [80, 20]

Training set:
X_train shape: (12571, 22)
y_train shape: (12571,)

Testing set:
X_val shape: (3143, 22)
y_val shape: (3143,)
```

1.2 Design and train a neural network model (e.g. you can use DNN network or if you want to use any other models it is also acceptable) (10 points)

In [71]:
```
model_2 = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.14),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(32, activation='relu'),
    Dropout(0.10),
    Dense(7, activation='softmax')
])
```

In [72]:
```
model_2.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

1.3 Use validation data for model tuning and monitor the f1-score while applying the early stopping logic from keras library (10 points)

In [79]:
```
train_f1score_callback_2 = F1scoreCallback(X_train_oversampled, y_train_oversampled, type='train')
val_f1score_callback_2 = F1scoreCallback(X_val_oversampled, y_val_oversampled, type='val')

early_stopping_2 = EarlyStopping(monitor='val_loss', mode='max', patience=10, restore_best_weights=True)
```

In [107…
```
history_2 = model_2.fit(X_train_oversampled, y_train_oversampled,
                    validation_data=(X_val_oversampled, y_val_oversampled),
                    epochs=150,
                    batch_size=128,
                    callbacks=[early_stopping_2, train_f1score_callback_2, val_f1score_callback_2])
```

```
Epoch 1/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/step accuracy: 0.4942 - loss: 1.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 214us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.4945 - loss: 0.9993 - val_accuracy: 0.5266 - val_loss: 0.9701 - train_f1_score: 0.5313 - val_f1_score: 0.5279
Epoch 2/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 204us/step accuracy: 0.5159 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 217us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5153 - loss: 0.9833 - val_accuracy: 0.5317 - val_loss: 0.9522 - train_f1_score: 0.5400 - val_f1_score: 0.5326
Epoch 3/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 203us/step accuracy: 0.5225 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 217us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5215 - loss: 0.9701 - val_accuracy: 0.5374 - val_loss: 0.9467 - train_f1_score: 0.5524 - val_f1_score: 0.5398
Epoch 4/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 205us/step accuracy: 0.5342 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 220us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5339 - loss: 0.9625 - val_accuracy: 0.5520 - val_loss: 0.9309 - train_f1_score: 0.5670 - val_f1_score: 0.5539
Epoch 5/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 206us/step accuracy: 0.5459 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 216us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5450 - loss: 0.9462 - val_accuracy: 0.5539 - val_loss: 0.9259 - train_f1_score: 0.5743 - val_f1_score: 0.5556
Epoch 6/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 207us/step accuracy: 0.5443 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 219us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5463 - loss: 0.9461 - val_accuracy: 0.5686 - val_loss: 0.9136 - train_f1_score: 0.5871 - val_f1_score: 0.5706
Epoch 7/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 205us/step accuracy: 0.5550 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 209us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5550 - loss: 0.9203 - val_accuracy: 0.5698 - val_loss: 0.9105 - train_f1_score: 0.5926 - val_f1_score: 0.5720
Epoch 8/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 206us/step accuracy: 0.5556 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 216us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5572 - loss: 0.9218 - val_accuracy: 0.5749 - val_loss: 0.8942 - train_f1_score: 0.5976 - val_f1_score: 0.5744
Epoch 9/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 205us/step accuracy: 0.5791 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 218us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5782 - loss: 0.8985 - val_accuracy: 0.5892 - val_loss: 0.8842 - train_f1_score: 0.6077 - val_f1_score: 0.5912
Epoch 10/150
393/393 ━━━━━━━━━━━━━━━━━━━━ 0s 205us/step accuracy: 0.5819 - loss: 0.
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 214us/step
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5808 - loss: 0.8992 - val_accuracy: 0.5810 - val_loss: 0.8823 - train_f1_score: 0.6113 - val_f1_score: 0.5829
```

* Classification report for the Validation dataset.

In [108…
```
test_loss_2, test_accuracy_2 = model_2.evaluate(X_val_oversampled, y_val_oversampled)
print(f'Test Loss: {test_loss_2}, Test Accuracy: {test_accuracy_2:.4f}')

val_prediction_2 = model_2.predict(X_val_oversampled)
y_val_predected_2 = np.argmax(val_prediction_2, axis=1)

f1_2 = f1_score(y_val_oversampled, y_val_predected_2, average='macro')
print(f'F1-score: {f1_2}')
```

```
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 278us/step - accuracy: 0.5373 - loss: 0.9690
Test Loss: 0.9700968265533447, Test Accuracy: 0.5266
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 217us/step
F1-score: 0.5278943307522558
```

In [109…
```
train_f1_scores_2 = train_f1score_callback_2.f1_scores
val_f1_scores_2 = val_f1score_callback_2.f1_scores
print("Training set f1-score :", train_f1_scores_2)
print("Validation set f1-score :", val_f1_scores_2)
```

```
Training set f1-score : [0.5211777441914612, 0.5298364079842991, 0.5430120975980318, 0.5561693580297321, 0.5660213901980434, 0.5831342780315294, 0.5820223391416044, 0.5932676645
143968, 0.5961094809009851, 0.60686555273262, 0.5909243753272763, 0.531308479438066, 0.5399622234929096, 0.5523989538015005, 0.5670486304450705, 0.5743079048479326, 0.5870582372
52393, 0.5925731564929122, 0.5976320810476449, 0.6076501855200931, 0.6112888778089679]
Validation set f1-score : [0.5207108502108563, 0.5264930182599356, 0.5295157037232806, 0.543794452367753, 0.5536670266636737, 0.5750701077552806, 0.561912396512764, 0.5751440710
422754, 0.5740015062196709, 0.5796235027705955, 0.574315910369351, 0.5278943307522558, 0.532552991870616, 0.5397956622282681, 0.5538916520380573, 0.5555759106610213, 0.570627585
5263319, 0.5719531405180328, 0.5744486320994703, 0.5912244018940562, 0.5828555396185183]
```

1.4 Use test data to calculate the appropriate classification metrics. (5 points)

In [110…
```
test_data_prediction_2 = model_2.predict(test_X)
test_data_prediction_np_2 = np.argmax(test_data_prediction_2, axis=1)

print(classification_report(test_Y, test_data_prediction_np_2))
```

```
68/68 ━━━━━━━━━━━━━━━━━━━━ 0s 283us/step
              precision    recall  f1-score   support

           0       0.32      0.49      0.38       320
           1       0.81      0.51      0.63      1421
           2       0.26      0.48      0.34       413

    accuracy                           0.50      2154
   macro avg       0.46      0.49      0.45      2154
weighted avg       0.63      0.50      0.54      2154
```

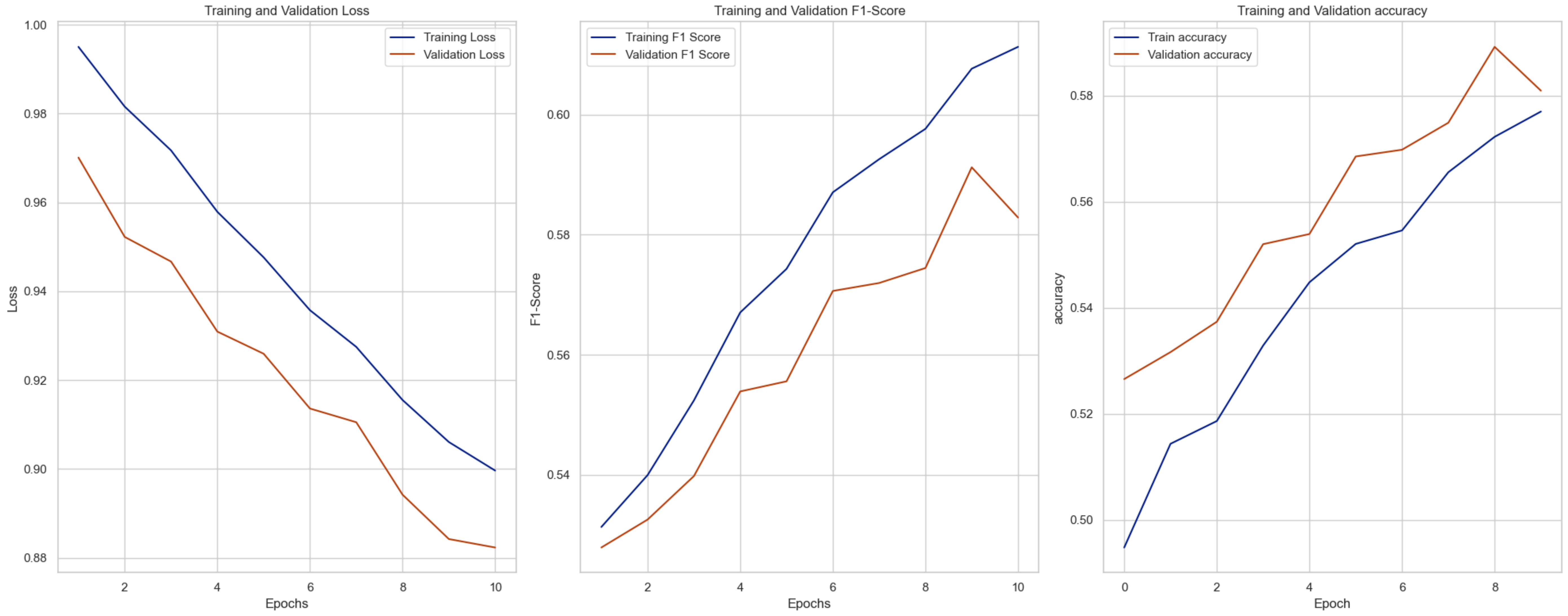
1.5 Explain the significance of each metrics. e.g what recall denotes in terms of multi class classification. (3 points)

1. Precision, Recall, and F1-score:
   - For Class 0, the precision is 0.32, recall is 0.49, and F1-score is 0.38. This indicates that the model has low precision and moderate recall for Class 0, suggesting that it struggles to correctly classify instances of this class.
   - For Class 1, the precision is 0.81, recall is 0.51, and the F1-score is 0.63. The model shows high precision but moderate recall for Class 1, suggesting it performs well in identifying instances of this class but misses some.
   - For Class 2, the precision is 0.26, recall is 0.48, and the F1-score is 0.34. The model has low precision and recall for Class 2, indicating it struggles to detect instances of this class effectively.
2. Overall Accuracy:
   - The model's overall accuracy is 50%, which means it correctly classifies around half of the examples in the dataset.
3. Macro and Weighted Averages:
   - Macro average: Precision, recall, and F1-score are derived by averaging the metrics for each class, without considering class imbalance. The macro average precision is 0.46, recall is 0.49, and the F1-score is 0.45.
4. Weighted average:
   - Precision, recall, and F1-score are calculated using the support (number of instances) for each class, providing a more realistic evaluation of total performance. The weighted average precision is 0.63, recall is 0.50, and the F1 score is 0.54.

- Overall, the model performs relatively better in recognizing instances of Class 1, with high precision but moderate recall. However, it struggles more with Classes 0 and 2, showing low precision and recall. The macro and weighted averages offer additional insights into the overall performance, considering both class-specific metrics and class distribution in the dataset.

1.6 Generate the loss and f1-score curve for training and validation set. (10 points)

In [111…
```
epochs = range(1, len(history_2.history['loss']) + 1)

plt.figure(figsize=(20, 8))

# Plot training and validation loss
plt.subplot(1, 3, 1)
plt.plot(epochs, history_2.history['loss'], label='Training Loss')
plt.plot(epochs, history_2.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation F1-Score
plt.subplot(1, 3, 2)
plt.plot(epochs, history_2.history['train_f1_score'], label='Training F1 Score')
plt.plot(epochs, history_2.history['val_f1_score'], label='Validation F1 Score')
plt.title('Training and Validation F1-Score')
plt.xlabel('Epochs')
plt.ylabel('F1-Score')
plt.legend()

plt.subplot(1, 3, 3)
plt.plot(history_2.history['accuracy'])
plt.plot(history_2.history['val_accuracy'])
plt.title('Training and Validation accuracy')
plt.ylabel('accuracy')
plt.xlabel('Epoch')
plt.legend(['Train accuracy', 'Validation accuracy'], loc='upper left')

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



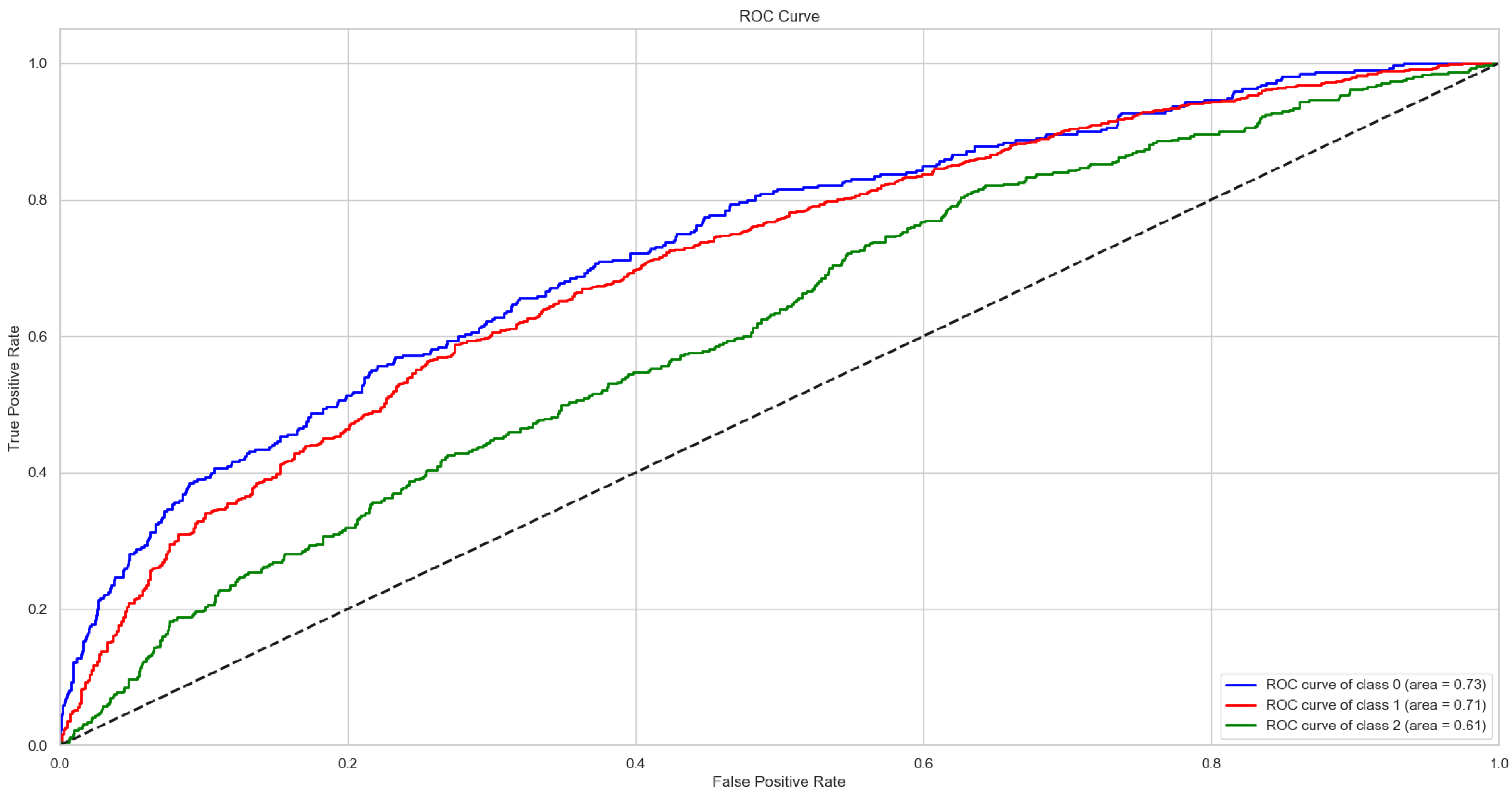
1. Training and Validation Loss:
   - The graph demonstrates that training and validation losses decrease as the number of epochs grows. This implies that the model learns and improves its predictions over time.
2. Training & Validation F1 Score:
   - The F1-Score for both training and validation increases with the number of epochs. This suggests that the F1-Score, which assesses the balance of precision and recall, is improving.
3. Training & Validation Accuracy:
   - Training and validation accuracy improves as the number of epochs grows. This shows that the model's predictions are becoming increasingly accurate with time.

- Overall, these graphs show that the model's performance improves over time, as indicated by lower loss and higher F1-Score and accuracy. However, it is critical to regularly monitor these measures to avoid overfitting, a condition in which the model performs well on training data but badly on unknown data. If validation measures begin to decline while training metrics continue to improve, this could be an indication of overfitting.

1.7 Generate a ROC-AUC curve and comment on your model accuracy and find the optimal threshold from the curve. (10 points)

In [85]:
```
y_prob_2 = model_2.predict(test_X)

fpr_2 = dict()
tpr_2 = dict()
roc_auc_2 = dict()
num_classes_2 = len(test_Y.unique())
for i in range(num_classes_2):
    fpr_2[i], tpr_2[i], _ = roc_curve((test_Y == i).astype(int), y_prob_2[:, i])
    roc_auc_2[i] = auc(fpr_2[i], tpr_2[i])

plt.figure(figsize=(20, 10))
colors = ['blue', 'red', 'green']
for i, color in zip(range(num_classes_2), colors):
    plt.plot(fpr_2[i], tpr_2[i], color=color, lw=2, label='ROC curve of class {0} (area = {1:0.2f})'''.format(i, roc_auc_2[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc="lower right")
plt.show()
```

```
68/68 ━━━━━━━━━━━━━━━━━━━━ 0s 232us/step
```



- The graph is titled "ROC Curve".
- The x-axis is called "False Positive Rate" and runs from 0 to 1.0.
- The y-axis is called "True Positive Rate" and runs from 0.0 to 1.0.
- Three ROC curves are shown in different colors, each indicating a different class:

- Blue: class 0 ROC curve with an AUC of 0.73.
- Green: ROC curve for class 1 with an AUC of 0.71.
- Red: class 2 ROC curve with an AUC of 0.61.

- A dashed line extends diagonally across the plot from the origin (bottom left corner) to the top right. This line represents the random classifier.
- The Area Under the Curve (AUC) measures the classifier's performance. A higher AUC indicates improved classifier performance. In this scenario, the classifier is most effective for class 0 (AUC = 0.73), followed by class 1 (AUC = 0.71), and finally class 2 (AUC = 0.61).

In [115…

```
num_samples_2 = test_X.shape[0]
thresholds_2 = np.linspace(0, 1, num_samples_2)
optimal_thresholds_2 = {}
for i in range(num_classes_2):
    tpr_minus_fpr = tpr_2[i] - fpr_2[i]

    optimal_idx = np.argmax(tpr_minus_fpr)

    optimal_threshold = thresholds_2[optimal_idx]

    optimal_thresholds_2[i] = optimal_threshold

print("Optimal Thresholds for each class:", optimal_thresholds_2)
```

```
Optimal Thresholds for each class: {0: 0.13283790060380865, 1: 0.13887598699489084, 2: 0.229447282861124}
```

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```
distances_2 = np.sqrt((fpr_2[1] - 0)**2 + (tpr_2[1] - 1)**2)

optimal_threshold_index_2 = np.argmin(distances_2)

optimal_threshold_2 = thresholds[optimal_threshold_index_2]

print("Optimal Threshold:", optimal_threshold_2)
```

```
Optimal Threshold: 0.18067812354853693
```

Compare and comment on the results you get from sampled data and original data distribution.

The results from the original and sampled data distributions reveal significant changes in the performance measures.

1. Precision, recall, and F1-score by class:
   - Precision increased from 0.59 to 0.32 in the sampled data, recall decreased from 0.26 to 0.49, while the F1-score remained stable.
   - For Class 1, precision fell from 0.69 to 0.81, recall from 0.97 to 0.51, and F1-score from 0.81 to 0.63.
   - For Class 2, precision increased from 1.00 to 0.26, recall from 0.02 to 0.48, and F1-score from 0.04 to 0.34.
2. Overall Metrics:
   - The sampled data had an accuracy of 0.50, down from 0.69.
   - The macro average F1-score increased slightly, while the weighted average F1-score dropped from 0.59 to 0.54.
3. Commentary:
   - The sampled data distribution improves precision, recall, and F1-score for Classes 0 and 2, but falls short for Class 1.

- Overall, the model's performance on the sampled data is weaker than on the original data, as seen by a fall in accuracy and weighted average F1 score.
  - The decision between original and sampled data is determined by the task's specific goals and priorities. If balanced performance across all classes is critical, using the original data may be preferable. However, if some classes are more essential than others, or if class imbalance is a major concern, sampling data may be considered.

In [ ]: