ARIGNAR ANNA GOVERNMENT ARTS COLLEGE

VILLUPURAM – 605 602.

DEPARTMENT OF COMPUTER SCIENCE

MACHINE LEARNING WITH PYTHON

Project Title : Identifying Patterns and Trends in Campus Placement Data using Machine Learning

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1. INTRODUCTION

1.1 OVERVIEW:

In Placement Prediction system predicts the probability of a undergrad students getting placed in a company by applying classification algorithms such as Decision tree and Random forest. The main objective of this model is to predict whether the student he/she gets placed or not in campus recruitment. For this the data consider is the academic history of student like overall percentage, backlogs, credits. The algorithms are applied on the previous years data of the students.

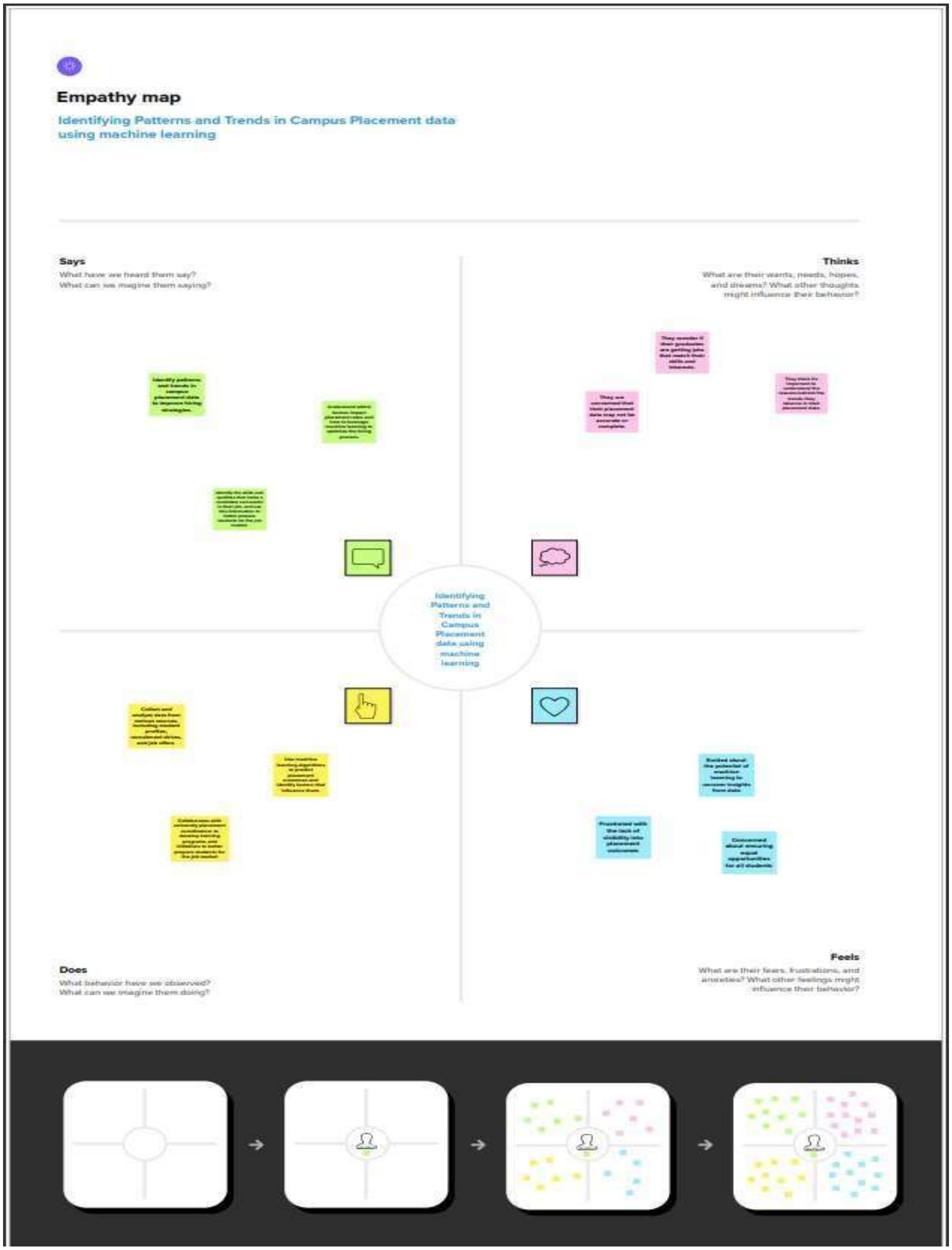
1.2 Purpose:

The objective is to predict the students getting placed for the current year by analyzing the data collected from previous year's students. This model is proposed with an algorithm to predict the same. These models help you to make a trend analysis of university placements data, to predict a placement rate for the students of an upcoming year which will help the university to analyze the performance during placements.

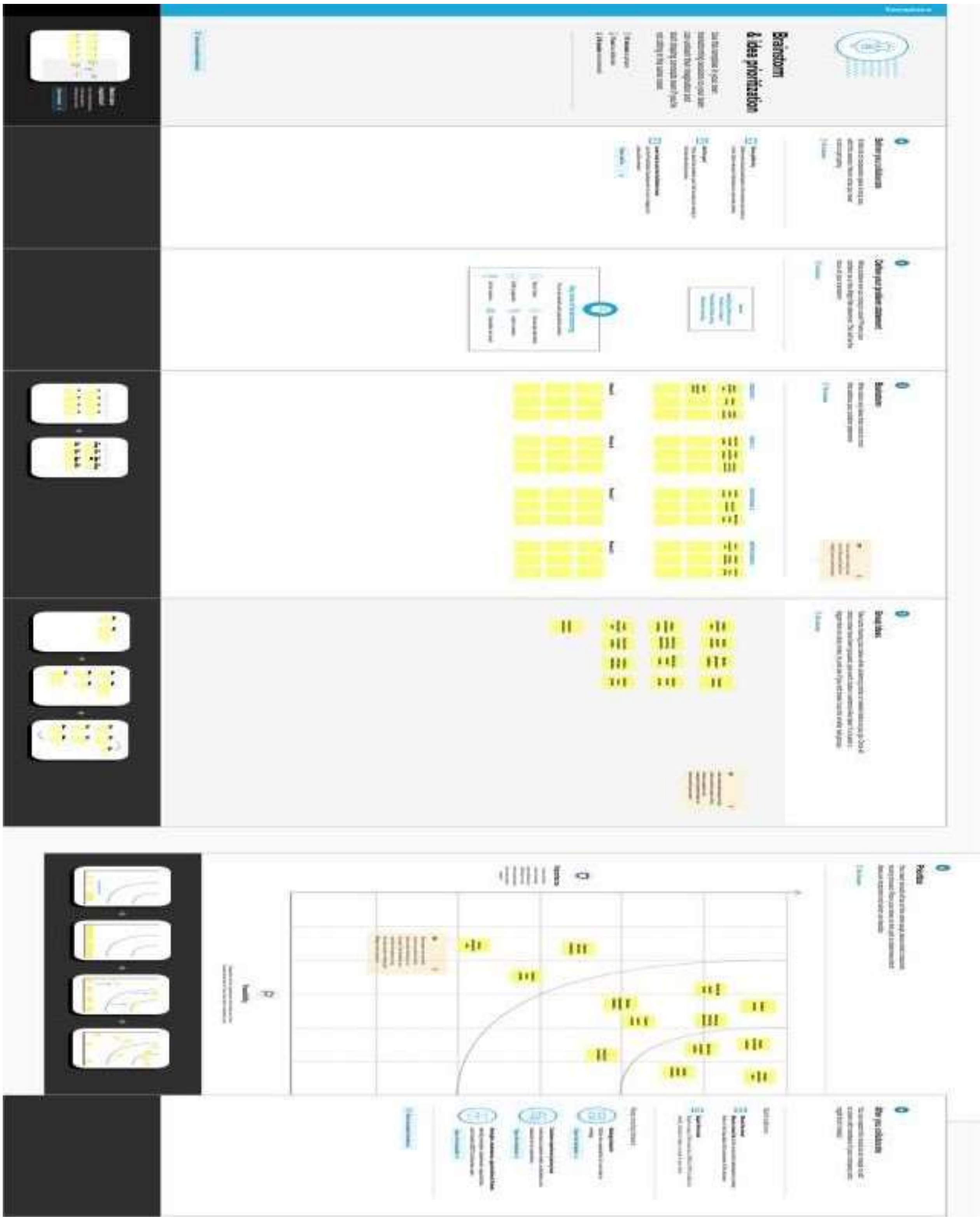
This proposed model is also compared with other traditional classification algorithms such as Decision tree and Random forest with respect to accuracy, precision and recall. From the results obtained it is found that the proposed algorithm performs significantly better in comparison with the other algorithms mentioned.

2. PROBLEM DEFINITION AND DESIGN THINKING

2.1 Empathy Map:



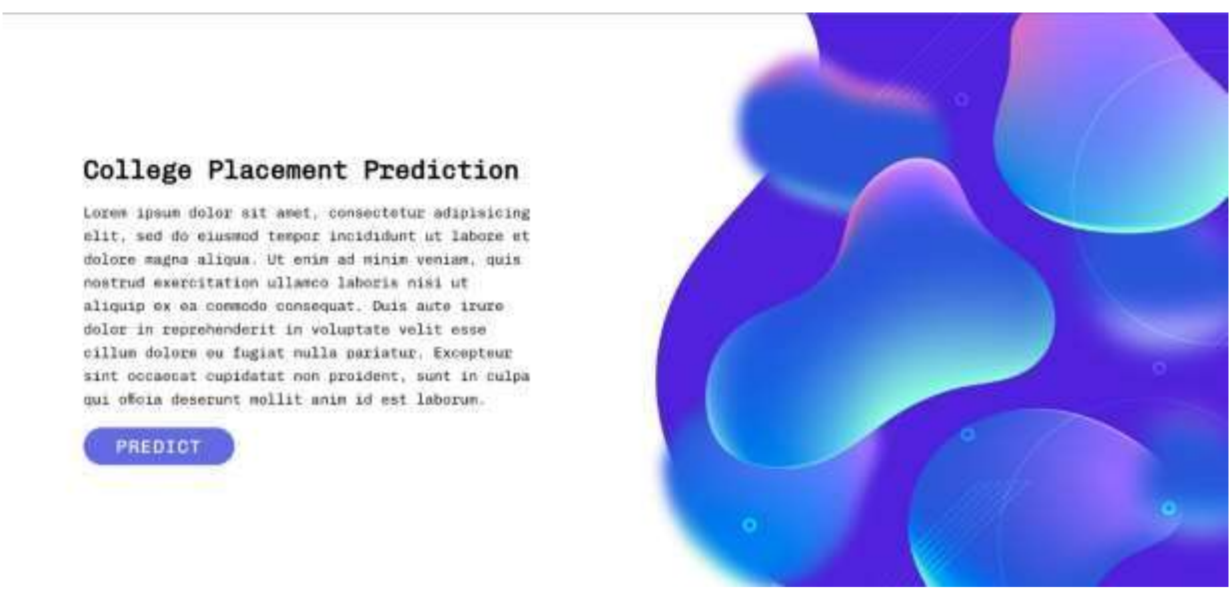
2.2 Ideation & Brainstorming Map:



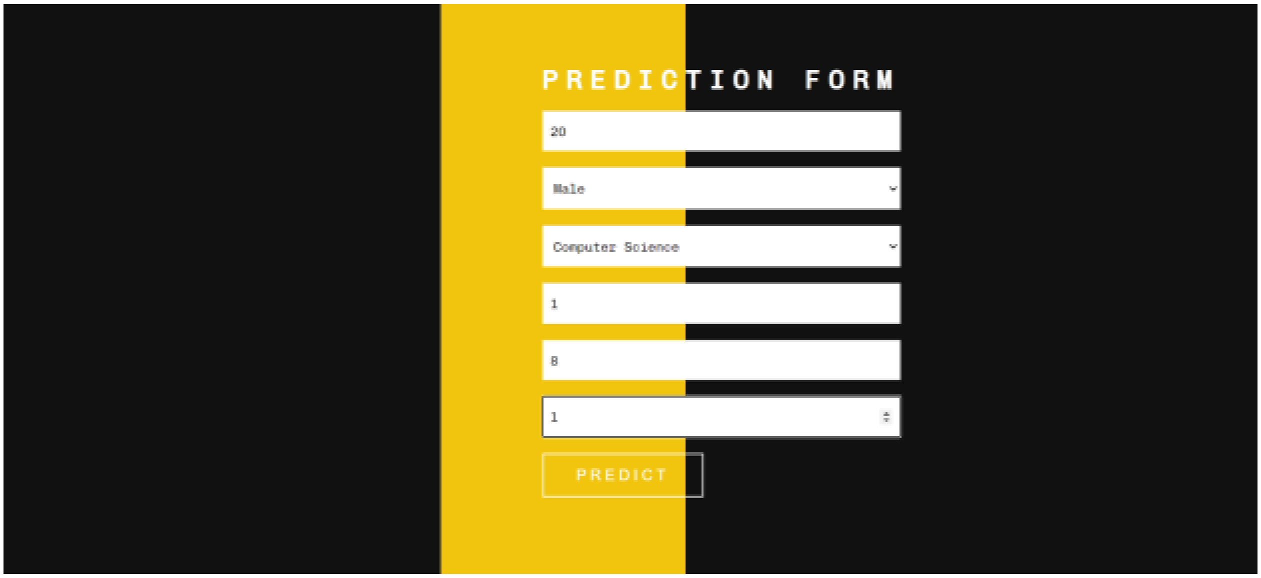
3. RESULT

The algorithms of machine learning we have discussed are can used to find the trend of placement, which will be helpful for university to get more admission in future.

Home Page:



Fill the Details:



Predicted page (Final output):

4. ADVANTAGES AND DISADVANTAGES

Advantages:

- ✓ By analyzing campus placement data, recruiters can identify which universities or program produces the most successful job candidates. This can help recruiters to focus their efforts on these institutions and programs, and to tailor their recruitment strategies accordingly.

- ✓ By examining the skills and qualifications of successful job candidates, employers can identify areas where their current workforce may be lacking. This can help employers to develop targeted training and development programs to address these skill gaps.

- ✓ Campus placement data can also be used to monitor diversity and inclusion efforts.

- ✓ Examining campus placement data over time can provide insights into industry trends and changes in the job market.

- ✓ By analyzing the success rates of graduates from different educational programs, employers can evaluate the effectiveness of those programs in preparing students for the job market.

Disadvantages:

- ✓ Campus placement may only represent a small sample of the overall job market.

- ✓ Campus placement data may be influenced by various biases, such as the preferences of recruiters or the characteristics of the universities or program being studied.

- ✓ Campus placement data may be incomplete or inaccurate due to factors such as incomplete reporting or data entry errors.

- ✓ Campus placement data may not provide enough context to fully understand the factors that contribute to job placement success.

- ✓ The collection and analysis of campus placement data may raise ethical concerns related to privacy and confidentially. Organizations must ensure that they are collecting and analyzing the data in a responsible and ethical manner.

5. APPLICATIONS

- ✓ Campus placement data can help organizations to develop more effective recruitment strategies.

- ✓ BY identifying which universities, programs, or majors produce the most successful job candidates, organizations can focus their recruitment efforts on these areas.

- ✓ Campus placement data can be used to identify skills gaps in the workforce.

- ✓ Campus placement data can be used to monitor diversity and inclusion efforts.

- ✓ Campus placement data can provide insights into industry trends and changes in the job market.

- ✓ Campus placement data can be used to identify potential future leaders within the organizations.

6. CONCLUSION

The campus placement activity is incredibly a lot of vital as institution point of view as well as student point of view. In this regard to improve the student's performance, a work has been analyzed and predicted using the classification algorithms Decision Tree and the Random forest algorithm to validate the approaches. The algorithms are applied on the data set and attributes used to build the model. The accuracy obtained after analysis for Decision tree is 84% and for the Random Forest is 86%. Hence, from the above said analysis and prediction it's better if the Random Forest algorithm is used to predict the placement results.

7. FUTURE SCOPE

Moreover from the study, the researcher concludes that most of the institutions' campus placement is not taken seriously. The awareness of such campus hiring should be taught to the students. The students also should consider the importance of campus placement as a part of academics and should have the ability to create academic balance. The significance of Off-campus drives should be taught to the students to crack the campus efficiently. The students should also develop the habit of reading books and journals to prepare themselves for campus placement. The organization should find ways to develop their process of recruitment which in turn helps in an increase in return on investment of campus hiring.

```
In [1]: from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

1.DATA COLLECTION AND PREPARATION :-

IMPORTING THE REQUIRED LIBRARIES :-

```
In [2]: import numpy as np
import pandas as pd
import os
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.metrics import accuracy_score
from  sklearn.neighbors  import  KNeighborsClassifier
from sklearn import metrics
from  sklearn.model_selection  import  cross_val_score
from sklearn import preprocessing
from  sklearn.model_selection  import  train_test_split
from sklearn.preprocessing import StandardScaler
import joblib
from sklearn.metrics import accuracy score
import tensorflow as tf
from tensorflow import keras
from keras.models import Sequential
from tensorflow.keras import layers
import warnings
warnings.filterwarnings('ignore')
from  sklearn.metrics  import  classification_report,confusion_matrix,RocCur
import pickle
```

READ THE DATASET :-

```
In [3]: df  =  pd.read_csv(r'/content/drive/MyDrive/Colab  Notebooks/collegePlace.cs
```

```
In [4]: df.head()
```

Out[4]:

	Age	Gender	Stream	Internships	CGPA	Hostel	HistoryOfBacklogs	PlacedOrNot
0	22	Male	Electronics And Communication	1	8	1	1	1
1	21	Female	Computer Science	0	7	1	1	1
2	22	Female	Information Technology	1	6	0	0	1
3	21	Male	Information Technology	0	8	0	1	1
4	22	Male	Mechanical	0	8	1	0	1

NUMERICAL ANALYSIS :-

In [5]:
```
df.describe()
```

Out[5]:

	Age	Internships	CGPA	Hostel	HistoryOfBacklogs	PlacedOrNot
count	2966.000000	2966.000000	2966.000000	2966.000000	2966.000000	2966.000000
mean	21.485840	0.703641	7.073837	0.269049	0.192178	0.552596
std	1.324933	0.740197	0.967748	0.443540	0.394079	0.497310
min	19.000000	0.000000	5.000000	0.000000	0.000000	0.000000
25%	21.000000	0.000000	6.000000	0.000000	0.000000	0.000000
50%	21.000000	1.000000	7.000000	0.000000	0.000000	1.000000
75%	22.000000	1.000000	8.000000	1.000000	0.000000	1.000000
max	30.000000	3.000000	9.000000	1.000000	1.000000	1.000000

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2966 entries, 0 to 2965
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Age                2966 non-null   int64
 1   Gender             2966 non-null   object
 2   Stream             2966 non-null   object
 3   Internships        2966 non-null   int64
 4   CGPA               2966 non-null   int64
 5   Hostel             2966 non-null   int64
 6   HistoryOfBacklogs  2966 non-null   int64
 7   PlacedOrNot        2966 non-null   int64
dtypes: int64(6), object(2)
memory usage: 185.5+ KB
```

No missing values ...

HANDLING CATEGORICAL VALUES :-

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2966 entries, 0 to 2965
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Age                2966 non-null   int64
 1   Gender             2966 non-null   object
 2   Stream             2966 non-null   object
 3   Internships        2966 non-null   int64
 4   CGPA               2966 non-null   int64
 5   Hostel             2966 non-null   int64
 6   HistoryOfBacklogs  2966 non-null   int64
 7   PlacedOrNot        2966 non-null   int64
dtypes: int64(6), object(2)
memory usage: 185.5+ KB
```

In [8]:
```
df.drop('Hostel',axis=1,inplace=True)
```

In [9]:
```
df.head()
```

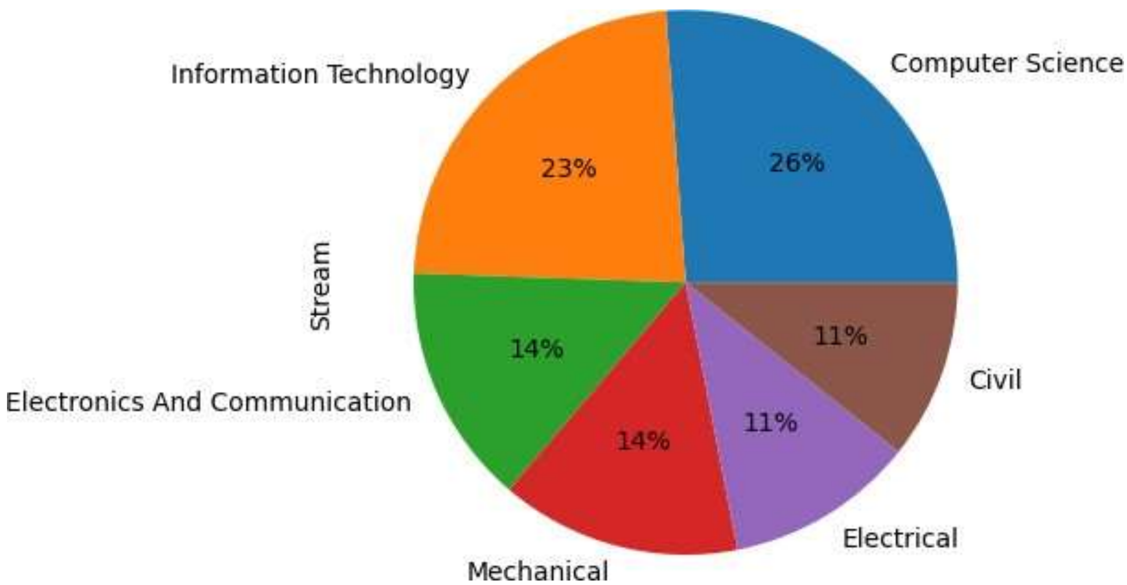
Out[9]:

	Age	Gender	Stream	Internships	CGPA	HistoryOfBacklogs	PlacedOrNot
0	22	Male	Electronics And Communication	1	8	1	1
1	21	Female	Computer Science	0	7	1	1
2	22	Female	Information Technology	1	6	0	1
3	21	Male	Information Technology	0	8	1	1
4	22	Male	Mechanical	0	8	0	1

EDA : Exploratory Data Analysis :-

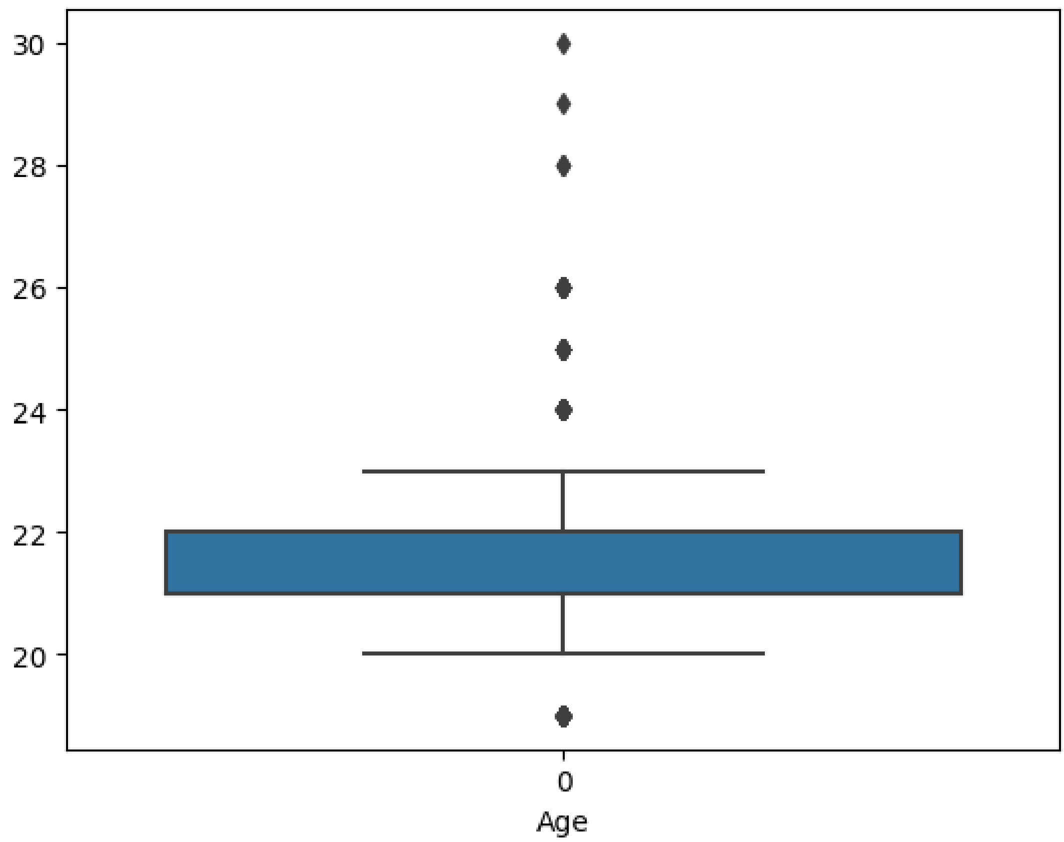
UNIVARIATE ANALYSIS :-

In [10]:
```
df['Stream'].value_counts().plot(kind='pie',autopct='%1.0f%%')
plt.show()
```



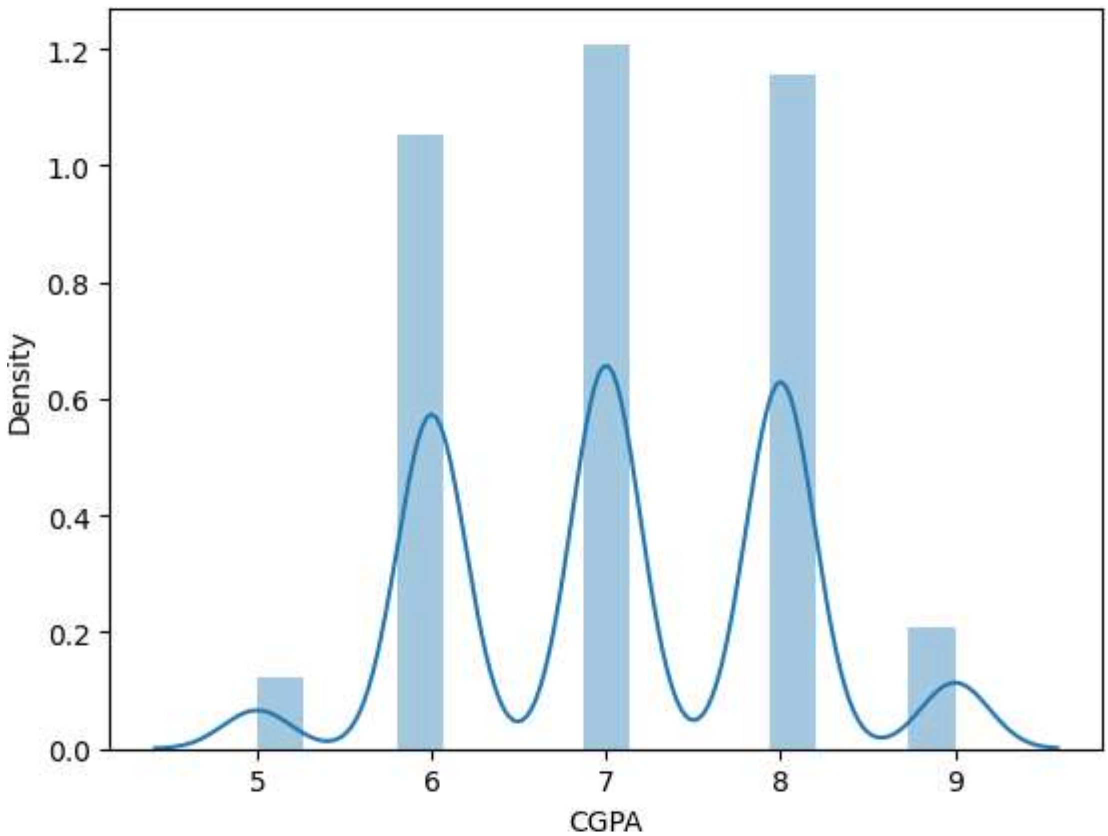
In [11]:
```
plt.xlabel('Age')
sns.boxplot(df['Age'])
```

Out[11]: <Axes: xlabel='Age'>



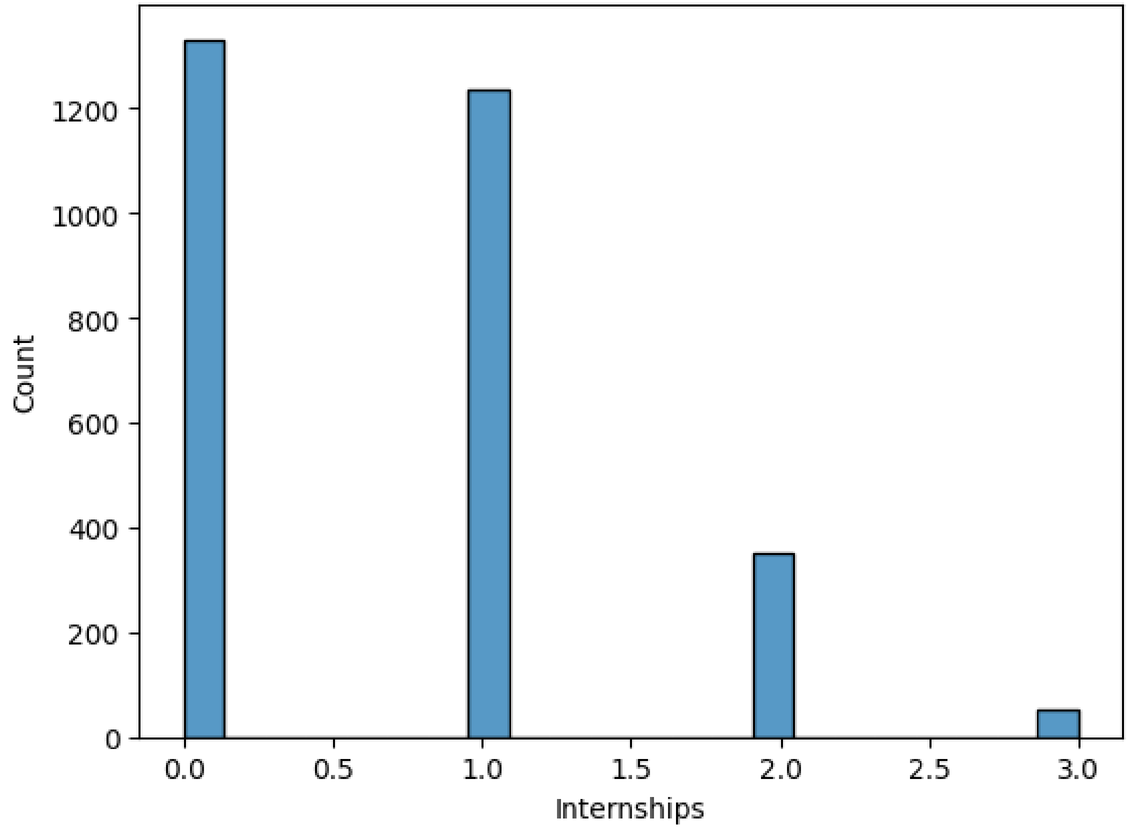

```
In [12]: sns.distplot(df['CGPA'])
```

```
Out[12]: <Axes: xlabel='CGPA', ylabel='Density'>
```




```
In [13]: sns.histplot(df,x='Internships')
```

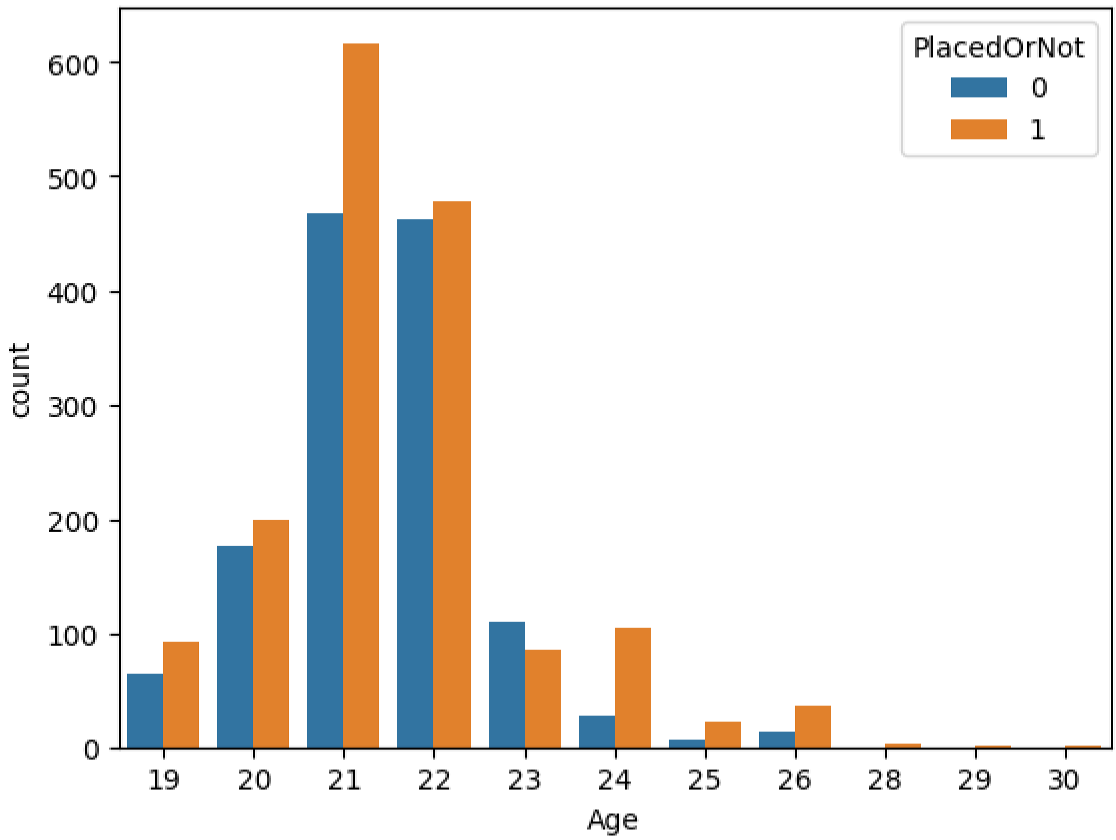
```
Out[13]: <Axes: xlabel='Internships', ylabel='Count'>
```



BIVARIATE ANALYSIS :-

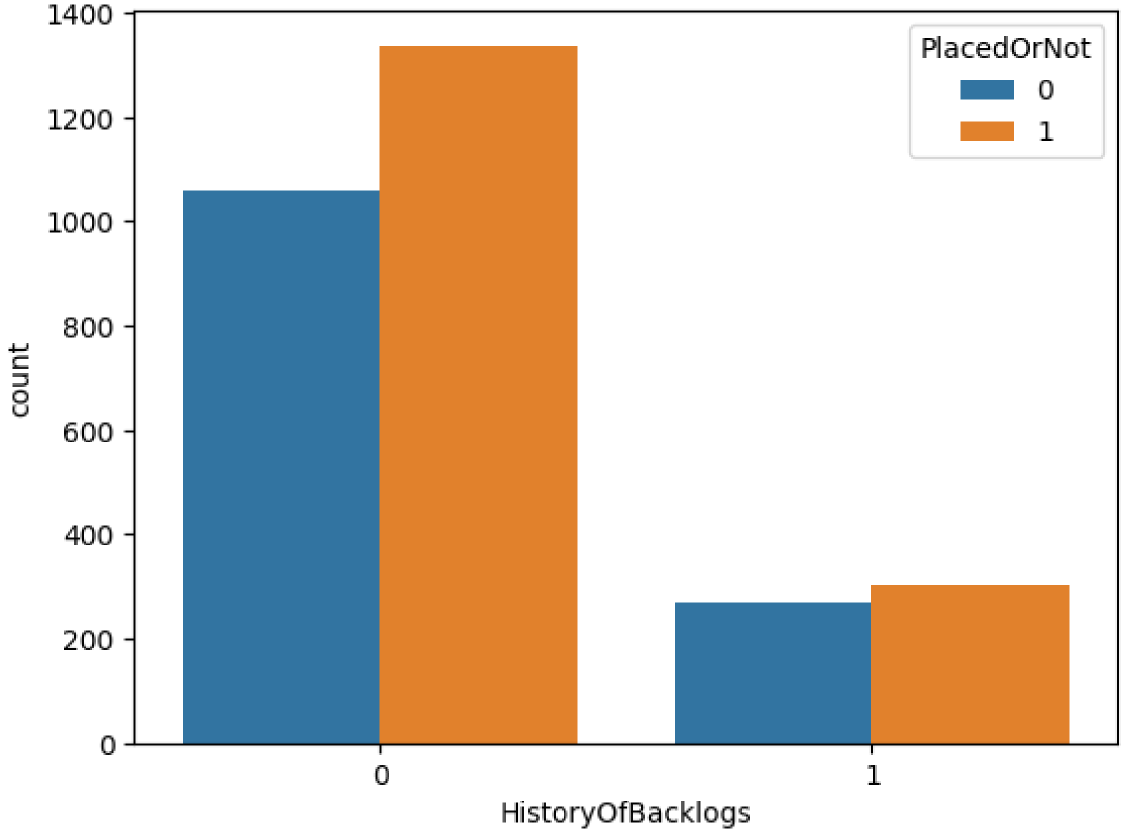
In [14]:
```
sns.countplot(df,x='Age',hue='PlacedOrNot')
```

Out[14]: <Axes: xlabel='Age', ylabel='count'>



In [15]:
```
sns.countplot(df,x='HistoryOfBacklogs',hue='PlacedOrNot')
```

Out[15]: <Axes: xlabel='HistoryOfBacklogs', ylabel='count'>

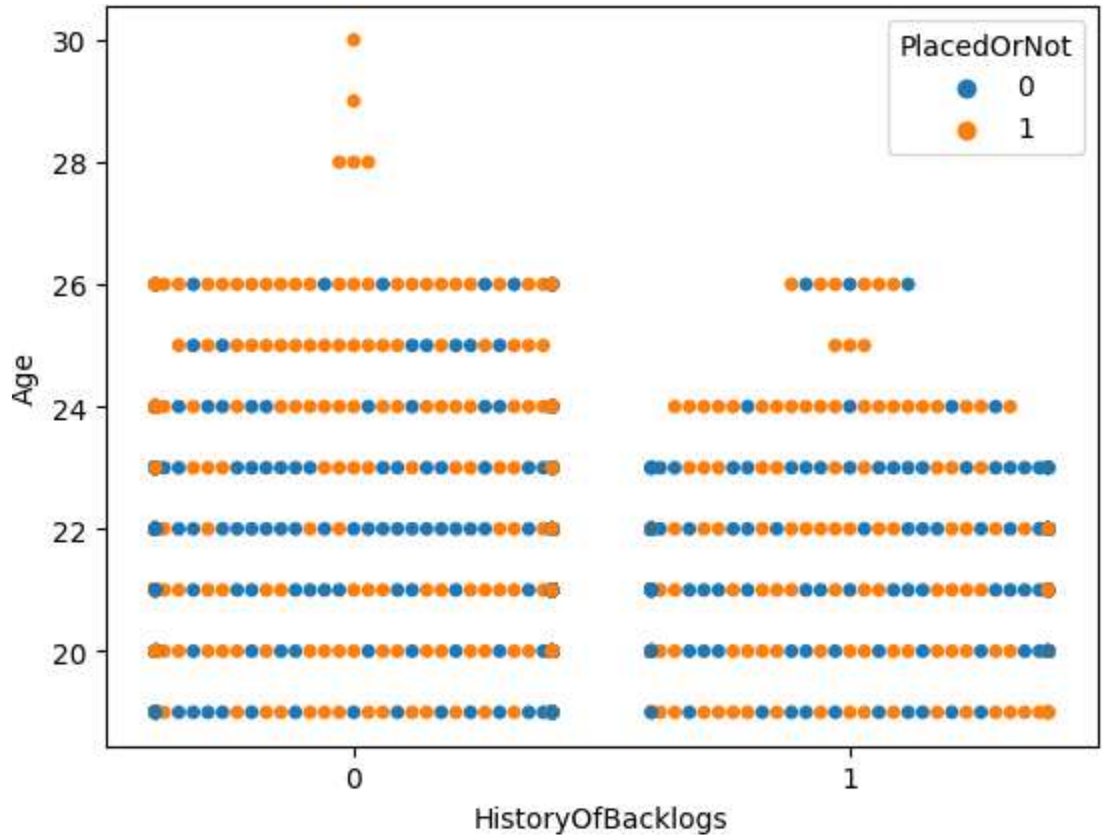


In [15]:

MULTIVARIATE ANALYSIS :-

In [16]:
```
sns.swarmplot(df,x='HistoryOfBacklogs',y='Age',hue='PlacedOrNot')
```

Out[16]: <Axes: xlabel='HistoryOfBacklogs', ylabel='Age'>



In [17]:
```
df['Gender'].value_counts()
```

Out[17]:
```
Male      2475
Female     491
Name: Gender, dtype: int64
```

In [18]:
```
df.Gender = df.Gender.replace({'Male':1,'Female':0})
```

In [19]:
```
df.Stream.value_counts()
```

Out[19]:
```
Computer Science                 776
Information Technology           691
Electronics And Communication    424
Mechanical                       424
Electrical                       334
Civil                            317
Name: Stream, dtype: int64
```

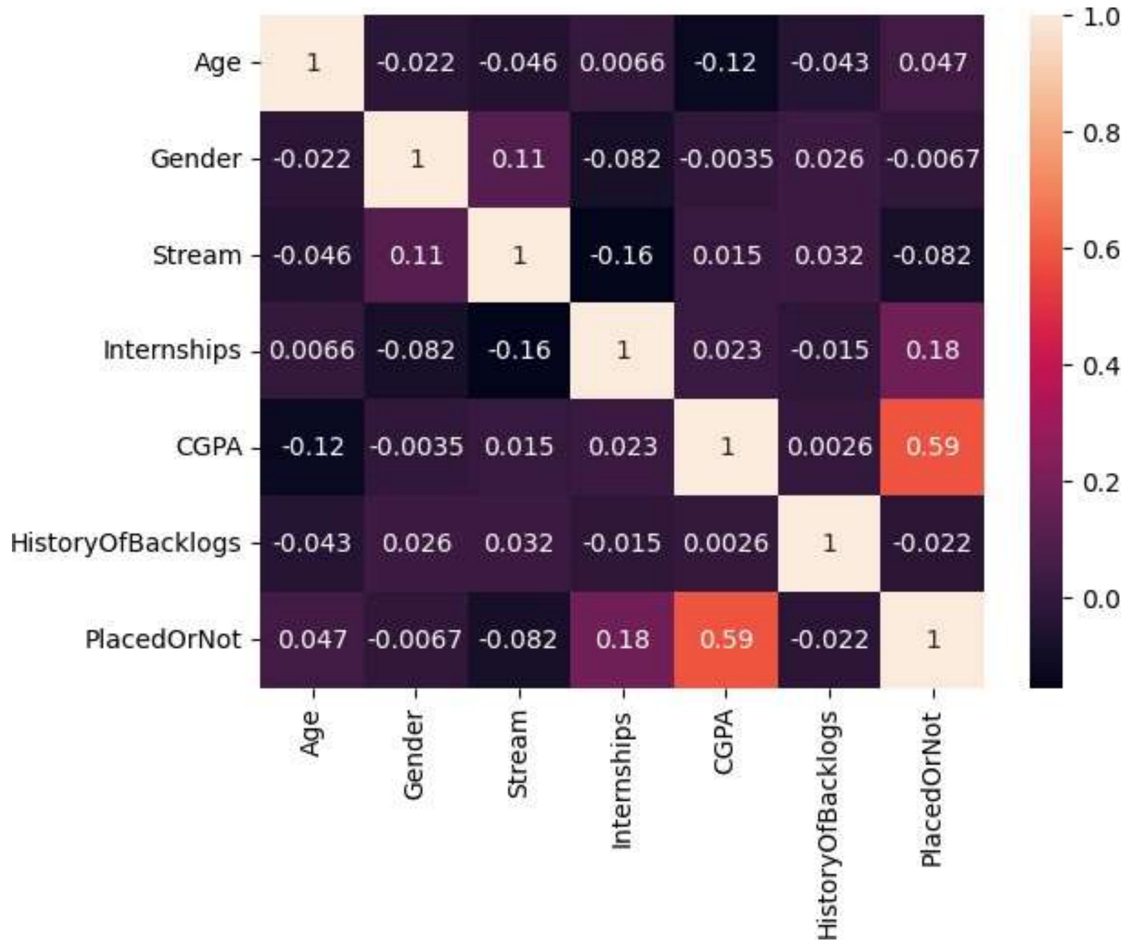
In [20]:
```
df['Stream'].replace({'Computer Science':0,'Information Technology':1,'El
```

In [21]:
```
df['CGPA'].value_counts()
```

Out[21]:
```
7    956
8    915
6    834
9    165
5     96
Name: CGPA, dtype: int64
```

In [22]:
```
sns.heatmap(df.corr(),annot=True)
```

Out[22]: <Axes: >



SEPARATING DEPENDENT AND INDEPENDENT VARIABLES :-

In [23]:
```
x = df.drop(columns ='PlacedOrNot', axis=1)
y = df['PlacedOrNot']
```

SCALING THE DATA:-

In [24]:
```
scaler = StandardScaler()
x = pd.DataFrame(scaler.fit_transform(x),columns=scaler.get_feature_names
print(x)
```

```
             Age    Gender    Stream  Internships      CGPA  HistoryOfBack
logs
0     0.388131  0.445403  0.040082     0.400445  0.957191             2.05
0246
1    -0.366752 -2.245158 -1.148743    -0.950773 -0.076310             2.05
0246
2     0.388131 -2.245158 -0.554331     0.400445 -1.109812            -0.48
7746
3    -0.366752  0.445403 -0.554331    -0.950773  0.957191             2.05
0246
4     0.388131  0.445403  0.634494    -0.950773  0.957191            -0.48
7746
...        ...       ...       ...          ...       ...
...
2961  1.143013  0.445403 -0.554331    -0.950773 -0.076310            -0.48
7746
2962  1.143013  0.445403  0.634494     0.400445 -0.076310            -0.48
7746
2963  0.388131  0.445403 -0.554331     0.400445 -0.076310            -0.48
7746
2964  0.388131  0.445403 -1.148743     0.400445 -0.076310            -0.48
7746
2965  1.143013  0.445403  1.823319    -0.950773  0.957191            -0.48
7746

[2966 rows x 6 columns]
```

In [25]:
```
pickle.dump(scaler,open('scaler.pkl','wb'))
```

SPLITTING THE DATA INTO TRAIN AND TEST

In [26]:
```
x_train, x_test , y_train, y_test = train_test_split(x,y, test_size=0.2,
print(x.shape, x_train.shape, x_test.shape )
```

```
(2966, 6) (2372, 6) (594, 6)
```

MODEL BUILDING :-

SVM MODEL :-

In [27]:
```
svc = svm.SVC(kernel ='linear')
svc.fit(x_train,y_train)

y_pred = svc.predict(x_train)
train_acc  =  accuracy_score(y_pred,y_train)
y_pred = svc.predict(x_test)
test_acc = accuracy_score(y_pred,y_test)
print('training data accuracy : ',train_acc)
print('testing data accuracy : ',test_acc)
```

```
training data accuracy :  0.7685497470489039
testing data accuracy :  0.7794612794612794
```

KNN MODEL :-

In [28]:
```
knn = KNeighborsClassifier()
knn.fit(x_train,y_train)

y_pred = knn.predict(x_train)
```

```
train_acc  =  accuracy_score(y_pred,y_train)
y_pred = knn.predict(x_test)
test_acc = accuracy_score(y_pred,y_test)
print('training data accuracy : ',train_acc)
print('testing data accuracy : ',test_acc)
```

```
training data accuracy :  0.8929173693086003
testing data accuracy :  0.8619528619528619
```

ARTIFICIAL NEURAL NETWORK :-

In [29]:

```
ann = Sequential()
ann.add(keras.layers.Dense(6,activation = 'selu'))
ann.add(keras.layers.Dense(24,activation  =  'selu'))
ann.add(keras.layers.Dense(12,activation  =  'selu'))

ann.add(keras.layers.Dense(1,activation='sigmoid'))
```

In [30]:

```
# compiting the model
loss_1 = tf.keras.losses.BinaryCrossentropy()
ann.compile(optimizer='Adam',loss=loss_1,metrics=['accuracy'])

# fitting the model-
ann.fit(x_train,y_train,batch_size  =20  ,epochs=100)
```

```
Epoch 1/100
119/119 [==============================] - 1s 2ms/step - loss: 0.5866 -
accuracy: 0.6838
Epoch 2/100
119/119 [==============================] - 0s 2ms/step - loss: 0.4540 -
accuracy: 0.7745
Epoch 3/100
119/119 [==============================] - 0s 2ms/step - loss: 0.4310 -
accuracy: 0.7774
Epoch 4/100
119/119 [==============================] - 0s 2ms/step - loss: 0.4141 -
accuracy: 0.7846
Epoch 5/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3880 -
accuracy: 0.8019
Epoch 6/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3680 -
accuracy: 0.8280
Epoch 7/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3534 -
accuracy: 0.8402
Epoch 8/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3453 -
accuracy: 0.8364
Epoch 9/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3395 -
accuracy: 0.8478
Epoch 10/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3335 -
accuracy: 0.8491
Epoch 11/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3314 -
accuracy: 0.8491
Epoch 12/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3274 -
accuracy: 0.8516
Epoch 13/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3243 -
accuracy: 0.8516
Epoch 14/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3218 -
accuracy: 0.8550
Epoch 15/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3188 -
accuracy: 0.8537
Epoch 16/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3167 -
accuracy: 0.8571
Epoch 17/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3142 -
accuracy: 0.8617
Epoch 18/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3106 -
accuracy: 0.8596
Epoch 19/100
119/119 [==============================] - 0s 2ms/step - loss: 0.3101 -
accuracy: 0.8588
Epoch 20/100
119/119 [==============================] - 0s 3ms/step - loss: 0.3058 -
accuracy: 0.8647
```

```
Epoch 21/100
119/119 [==============================] - 0s 3ms/step - loss: 0.3047 -
accuracy: 0.8655
Epoch 22/100
119/119 [==============================] - 0s 3ms/step - loss: 0.3040 -
accuracy: 0.8630
Epoch 23/100
119/119 [==============================] - 0s 3ms/step - loss: 0.3027 -
accuracy: 0.8676
Epoch 24/100
119/119 [==============================] - 0s 3ms/step - loss: 0.3012 -
accuracy: 0.8651
Epoch 25/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2984 -
accuracy: 0.8739
Epoch 26/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2955 -
accuracy: 0.8702
Epoch 27/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2973 -
accuracy: 0.8693
Epoch 28/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2968 -
accuracy: 0.8756
Epoch 29/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2942 -
accuracy: 0.8718
Epoch 30/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2942 -
accuracy: 0.8723
Epoch 31/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2905 -
accuracy: 0.8723
Epoch 32/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2904 -
accuracy: 0.8714
Epoch 33/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2895 -
accuracy: 0.8739
Epoch 34/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2889 -
accuracy: 0.8731
Epoch 35/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2880 -
accuracy: 0.8744
Epoch 36/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2871 -
accuracy: 0.8790
Epoch 37/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2861 -
accuracy: 0.8714
Epoch 38/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2860 -
accuracy: 0.8744
Epoch 39/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2849 -
accuracy: 0.8723
Epoch 40/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2848 -
accuracy: 0.8748
```

```
Epoch 41/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2825 -
accuracy: 0.8761
Epoch 42/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2829 -
accuracy: 0.8735
Epoch 43/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2814 -
accuracy: 0.8777
Epoch 44/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2816 -
accuracy: 0.8782
Epoch 45/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2817 -
accuracy: 0.8761
Epoch 46/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2805 -
accuracy: 0.8727
Epoch 47/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2783 -
accuracy: 0.8773
Epoch 48/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2783 -
accuracy: 0.8790
Epoch 49/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2794 -
accuracy: 0.8786
Epoch 50/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2790 -
accuracy: 0.8769
Epoch 51/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2766 -
accuracy: 0.8756
Epoch 52/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2783 -
accuracy: 0.8782
Epoch 53/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2768 -
accuracy: 0.8752
Epoch 54/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2772 -
accuracy: 0.8752
Epoch 55/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2774 -
accuracy: 0.8756
Epoch 56/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2749 -
accuracy: 0.8777
Epoch 57/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2737 -
accuracy: 0.8790
Epoch 58/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2767 -
accuracy: 0.8744
Epoch 59/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2753 -
accuracy: 0.8756
Epoch 60/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2736 -
accuracy: 0.8761
```

```
Epoch 61/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2740 -
accuracy: 0.8773
Epoch 62/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2738 -
accuracy: 0.8786
Epoch 63/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2738 -
accuracy: 0.8773
Epoch 64/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2717 -
accuracy: 0.8853
Epoch 65/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2742 -
accuracy: 0.8752
Epoch 66/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2733 -
accuracy: 0.8794
Epoch 67/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2734 -
accuracy: 0.8777
Epoch 68/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2731 -
accuracy: 0.8773
Epoch 69/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2723 -
accuracy: 0.8794
Epoch 70/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2715 -
accuracy: 0.8782
Epoch 71/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2724 -
accuracy: 0.8786
Epoch 72/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2718 -
accuracy: 0.8803
Epoch 73/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2710 -
accuracy: 0.8790
Epoch 74/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2700 -
accuracy: 0.8756
Epoch 75/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2684 -
accuracy: 0.8820
Epoch 76/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2694 -
accuracy: 0.8794
Epoch 77/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2675 -
accuracy: 0.8773
Epoch 78/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2703 -
accuracy: 0.8723
Epoch 79/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2691 -
accuracy: 0.8811
Epoch 80/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2676 -
accuracy: 0.8811
```

```
Epoch 81/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2686 -
accuracy: 0.8794
Epoch 82/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2683 -
accuracy: 0.8773
Epoch 83/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2662 -
accuracy: 0.8815
Epoch 84/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2685 -
accuracy: 0.8803
Epoch 85/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2676 -
accuracy: 0.8811
Epoch 86/100
119/119 [==============================] - 0s 3ms/step - loss: 0.2675 -
accuracy: 0.8811
Epoch 87/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2681 -
accuracy: 0.8777
Epoch 88/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2661 -
accuracy: 0.8820
Epoch 89/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2668 -
accuracy: 0.8777
Epoch 90/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2655 -
accuracy: 0.8773
Epoch 91/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2688 -
accuracy: 0.8777
Epoch 92/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2648 -
accuracy: 0.8820
Epoch 93/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2655 -
accuracy: 0.8836
Epoch 94/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2648 -
accuracy: 0.8790
Epoch 95/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2659 -
accuracy: 0.8811
Epoch 96/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2645 -
accuracy: 0.8849
Epoch 97/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2669 -
accuracy: 0.8798
Epoch 98/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2659 -
accuracy: 0.8777
Epoch 99/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2669 -
accuracy: 0.8794
Epoch 100/100
119/119 [==============================] - 0s 2ms/step - loss: 0.2644 -
accuracy: 0.8845
```

Out[30]: <keras.callbacks.History at 0x7f11bc0d7fd0>

In [31]:
```
#with the model

y_pred = ann.predict(x_train)
y_pred =(y_pred >0.5)
train_acc  =  accuracy_score(y_pred,y_train)

y_pred = ann.predict(x_test)
y_pred =(y_pred >0.5)
test_acc  =  accuracy_score(y_pred,y_test)

print('training data accuracy : ',train_acc)
print('testing data accuracy : ',test_acc)
```

```
75/75 [==============================] - 0s 2ms/step
19/19 [==============================] - 0s 2ms/step
training data accuracy :  0.8823777403035413
testing data accuracy :  0.8569023569023569
```

HYPER-PARAMETER TUNING :-

In [32]:
```
from sklearn.model_selection import RandomizedSearchCV
params = {'C': [0.1, 1, 10, 100],
              'kernel': ['rbf'],
              'gamma': [1, 0.1, 0.001],
              }

rscv  =  RandomizedSearchCV(svm.SVC(),  params)
rscv.fit(x_train, y_train)

print("Best  hyperparameters:  ",  rscv.best_params_)
```

```
Best hyperparameters:  {'kernel': 'rbf', 'gamma': 0.1, 'C': 10}
```

In [33]:
```
svc2  =  svm.SVC(kernel  ='rbf',gamma=0.1,C=100)
svc2.fit(x_train,y_train)

y_pred = svc2.predict(x_train)
train_acc  =  accuracy_score(y_pred,y_train)
y_pred = svc2.predict(x_test)
test_acc = accuracy_score(y_pred,y_test)
print('training data accuracy : ',train_acc)
print('testing data accuracy : ',test_acc)
```

```
training data accuracy :  0.8920741989881956
testing data accuracy :  0.8686868686868687
```

In [34]:
```
best_k = {'Regular':0}
best_score ={'Regular': 0}
for k in range(3,50,2):
  ##using Regular trainning set
  knn_temp =KNeighborsClassifier(n_neighbors=k)
  knn_temp.fit(x_train,y_train)
  knn_temp_pred=knn_temp.predict(x_test)
  score=metrics.accuracy_score(y_test, knn_temp_pred)*100
  if(score >= best_score['Regular'] and score<100):
    best_score['Regular'] = score
    best_k['Regular']=k
best_k['Regular']
```

Out[34]: 7

In [35]:
```
knn2  =  KNeighborsClassifier(n_neighbors=best_k['Regular'])
knn2.fit(x_train,y_train)

y_pred = knn2.predict(x_train)
train_acc  =  accuracy_score(y_pred,y_train)
y_pred = knn2.predict(x_test)
test_acc = accuracy_score(y_pred,y_test)
print('training data accuracy : ',train_acc)
print('testing data accuracy : ',test_acc)
```

```
training data accuracy :  0.887858347386172
testing data accuracy :  0.8636363636363636
```

EVALUATING THE MODEL :-

In [36]:
```
def  cl_res(name,model):
    y_pred = model.predict(x_test)
    if(name=='ANN'):
        y_pred = [0 if x<0.5 else 1 for x in y_pred]
    print(name,' :-\n-------------------------------------------------')
    print('accuracy score of ',name,' : ',accuracy_score(y_test,y_pred))
    print(classification_report(y_test,y_pred,target_names=['no delay','d
    print('confusion matrix : \n',confusion_matrix(y_test,y_pred))
    print('\n')
    #  plt.subplot(121)
    plt.figure(figsize=(3,2))
    sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
    # plt.subplot(122)
    plt.figure(figsize=(1,1))
    RocCurveDisplay.from_predictions(y_test,y_pred)
    plt.show()
    print('\n\n')
```

In [37]:
```
models  =  {'SVM':svc,'SVM2':svc2,'KNN':knn,'knn2':knn2,'ANN':ann}
```

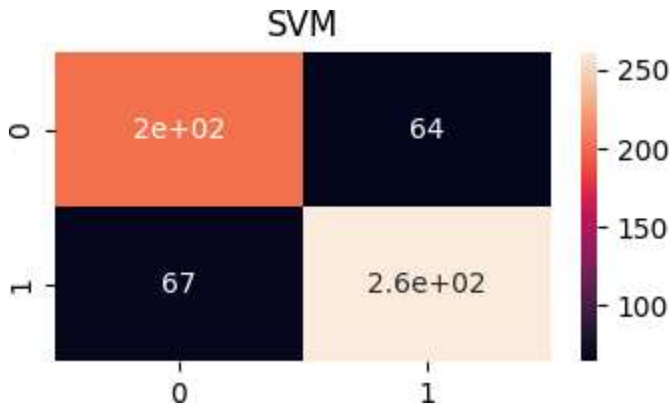
In [38]:
```
def prediction(model,input):
  output = model.predict(input)
  if  isinstance(model,Sequential):
    output = output > 0.5
  return output
```

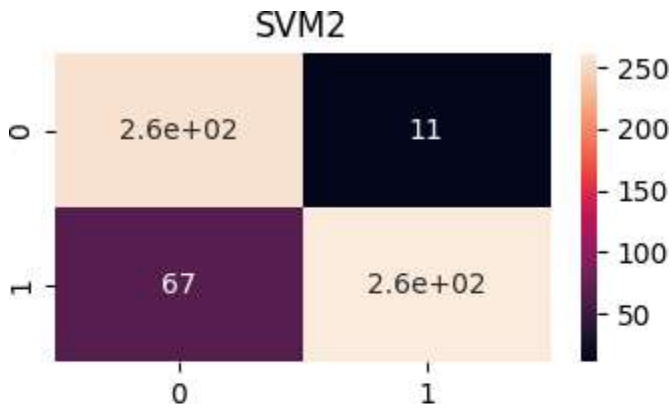
In [39]:
```
for name , model in models.items():
  y_pred  =  prediction(model,x_test)
  print('accuracy score of ',name,' : ',accuracy_score(y_test,y_pred))
```

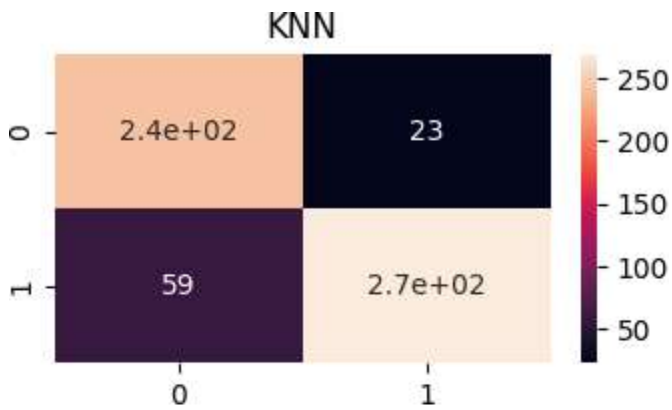
```
accuracy score of SVM : 0.7794612794612794
accuracy score of  SVM2  :  0.8686868686868687
accuracy score of KNN : 0.8619528619528619
accuracy score of  knn2  :  0.8636363636363636
19/19 [==============================] - 0s 1ms/step
accuracy score of  ANN  :  0.8569023569023569
```

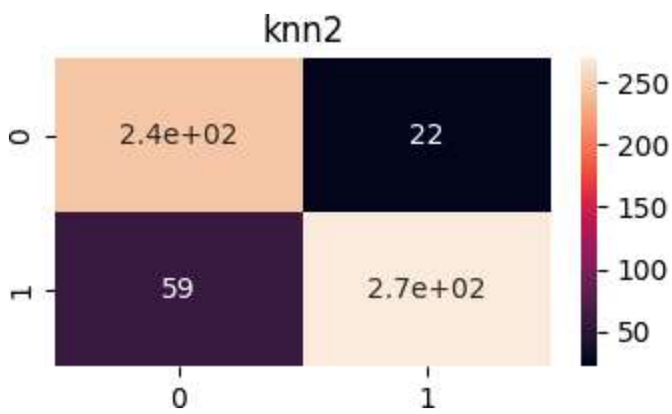
In [40]:
```
count = 1
for name , model in models.items():
  y_pred  =  prediction(model,x_test)
  plt.figure(figsize=(4,2))
  plt.title(name)
```

```
count+=1
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
plt.show()
```

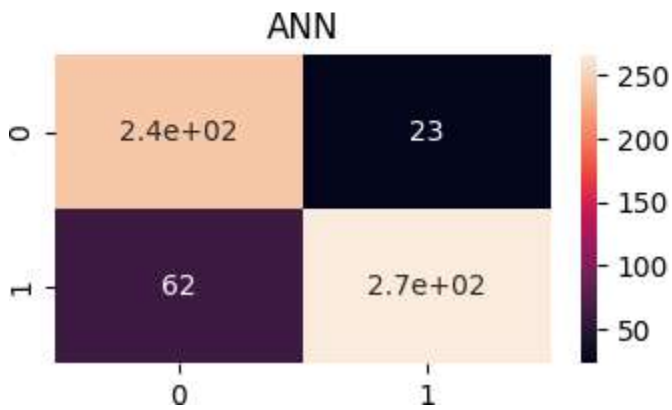








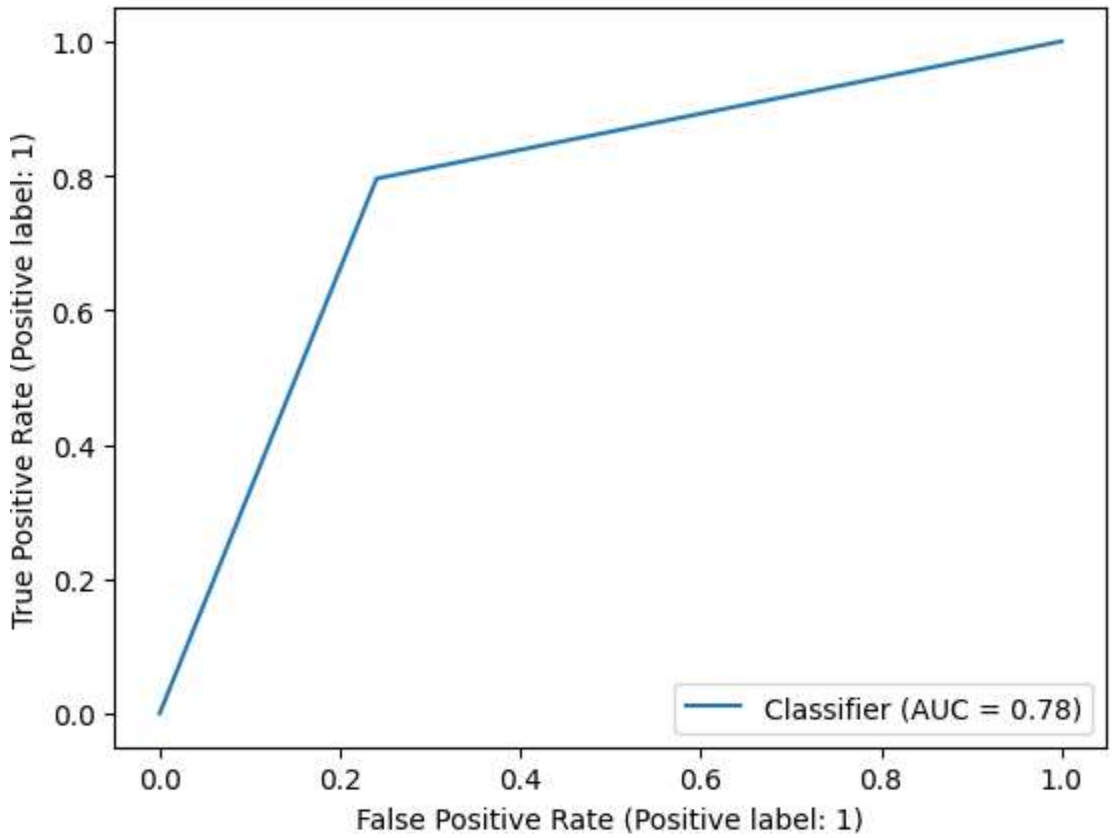

```
19/19 [==============================] - 0s 1ms/step
```



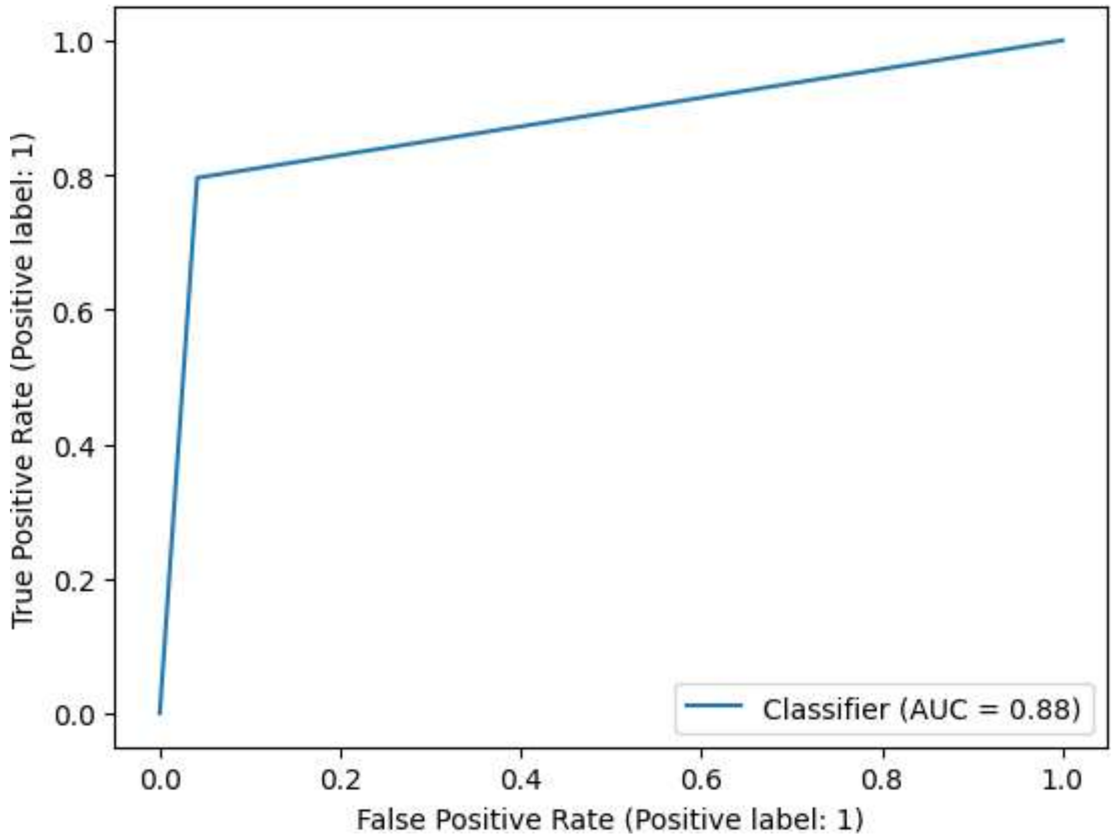
In [41]:

```
for name,model in models.items():
    y_pred = prediction(model,x_test)
    plt.figure(figsize=(2,1))
    print(name)
    RocCurveDisplay.from_predictions(y_test,y_pred)
```

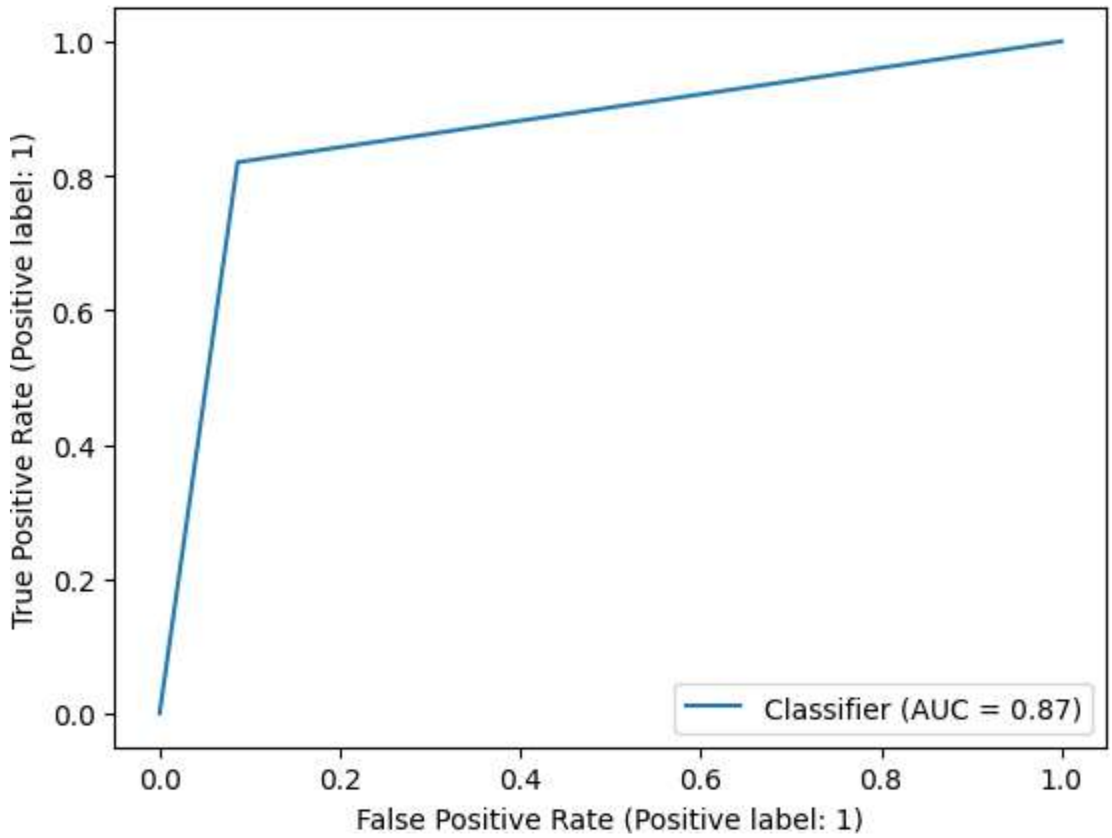
```
SVM
SVM2
KNN
knn2
19/19 [==============================] - 0s 1ms/step
ANN
<Figure size 200x100 with 0 Axes>
```



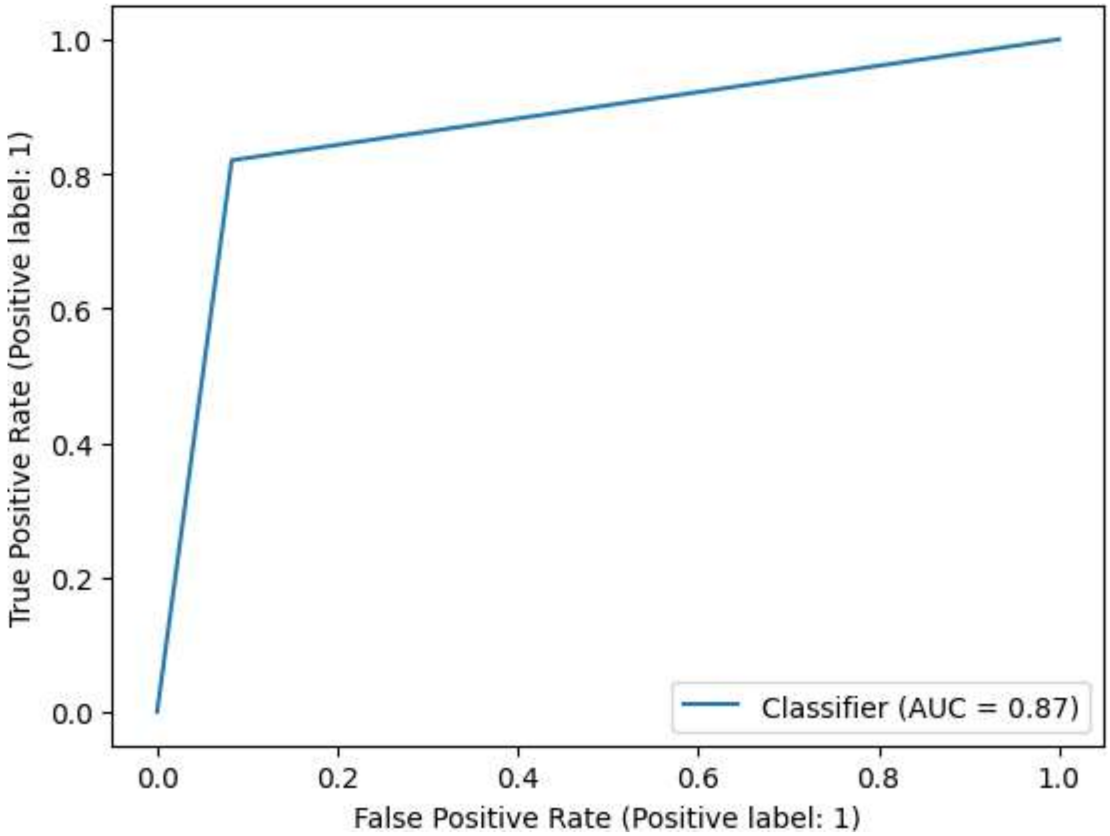

```
<Figure size 200x100 with 0 Axes>
```



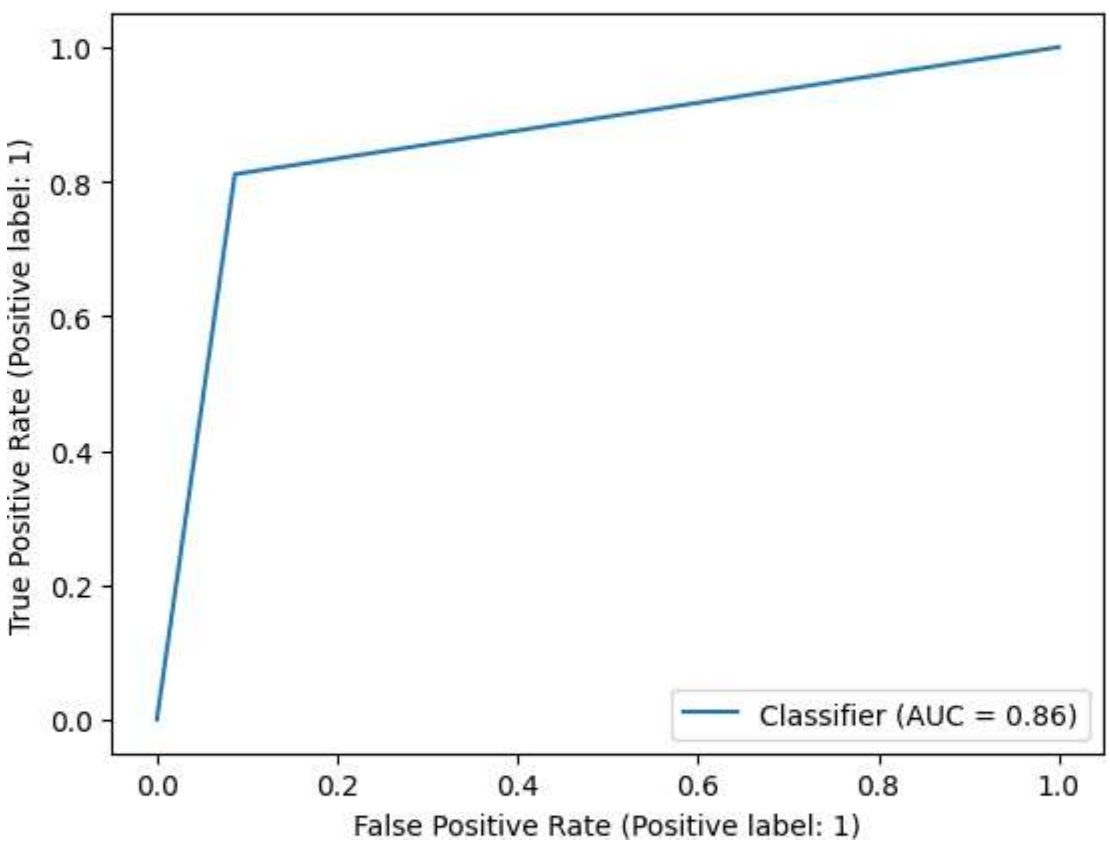
<Figure size 200x100 with 0 Axes>



<Figure size 200x100 with 0 Axes>



<Figure size 200x100 with 0 Axes>

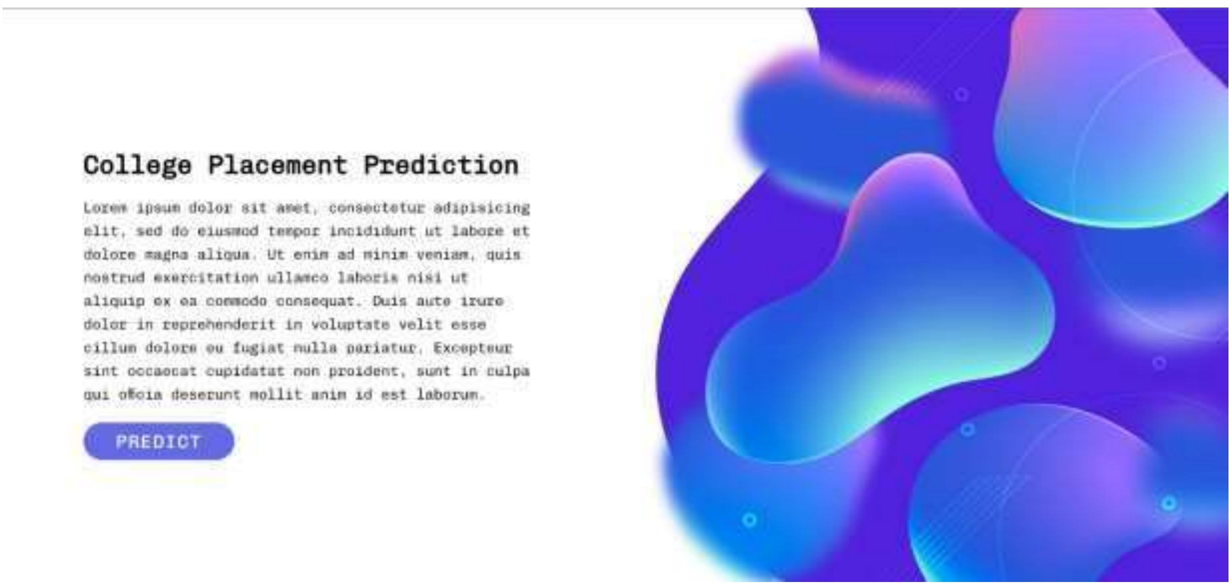


SAVING THE MODEL :-

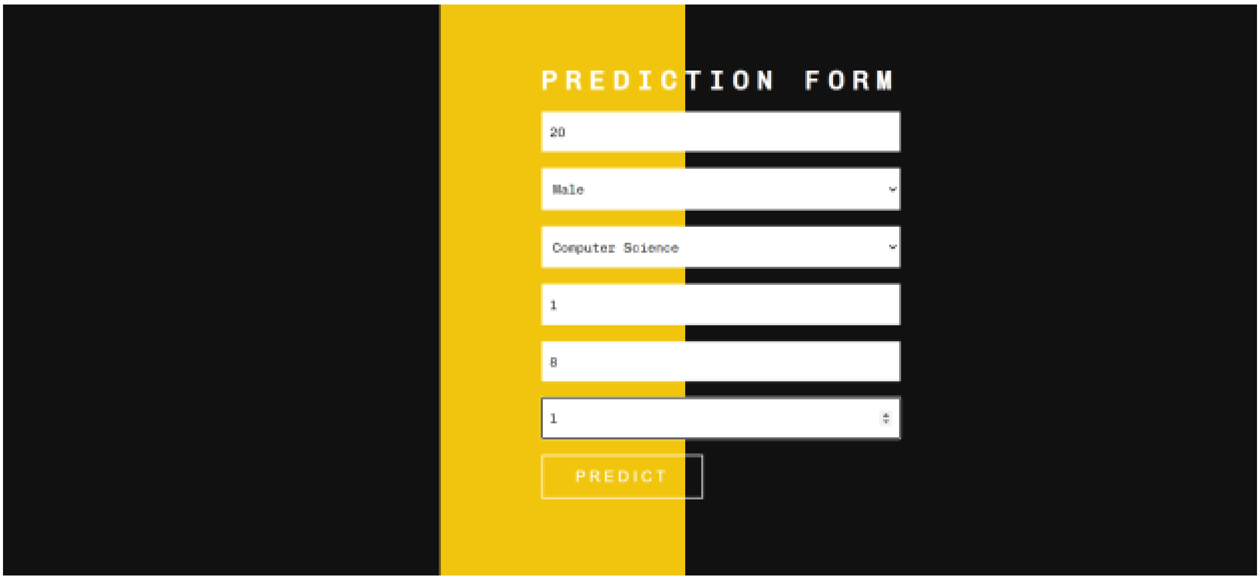
```
In [42]: pickle.dump(svc2,open('svc.pkl','wb'))
```

OUTPUT:

Home Page:



Fill the Details:



Predicted page (Final output):