ENGINEERING GRADUATE SALARY DATASET PREDICTION

GROUP -11 / BHAVANS VIVEKANANDA COLLEGE
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Abstract

This project develops a predictive model to estimate engineering graduates' salaries based on factors like academic performance, technical skills, work experience, and demographics. It offers insights into salary determinants, aiding educational institutions, recruiters, and students in making informed decisions, promoting transparency in hiring, and helping graduates understand their earning potential in the job market.

Objective

The goal is to create a predictive machine learning model that forecasts engineering graduates' salaries using academic, technical, and demographic data to promote equitable hiring and informed career planning.

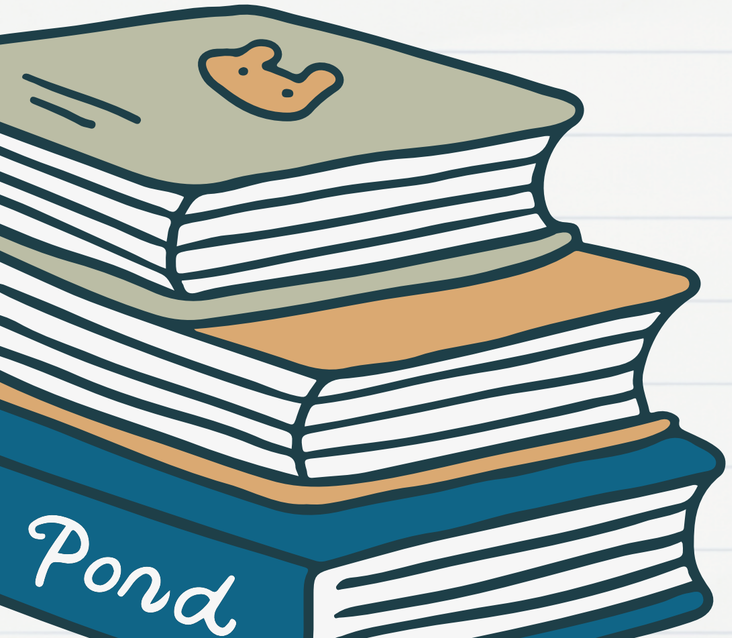
CONTENT

Introduction

Predicting salaries for engineering graduates is vital for understanding career opportunities. Accurate predictions help students, institutions, and employers align educational outcomes with industry needs. Factors like academic performance and work experience affect earning potential, making it essential for transparency and informed choices.

The rise of machine learning and data analytics enhances salary prediction by analyzing key data points, providing actionable insights for fair salary decisions and better career guidance in a changing job market.

Literature Review



Literature Review - 1

Author(s): Lee & Kumar
Title: Predicting Engineering Graduate Salaries with Machine Learning

This paper investigates machine learning methods for predicting engineering graduates' starting salaries using academic, demographic, and industry factors. Algorithms such as multiple linear regression, random forests, and support vector machines (SVMs) were employed to analyze the impact of attributes like GPA, specialization, and internship experience on salaries.

The study highlights the effectiveness of ensemble methods like random forests for processing diverse, nonlinear datasets and emphasizes the importance of feature selection for better model interpretability. It concludes that machine learning can help universities and recruiters align graduate skills with market demands.

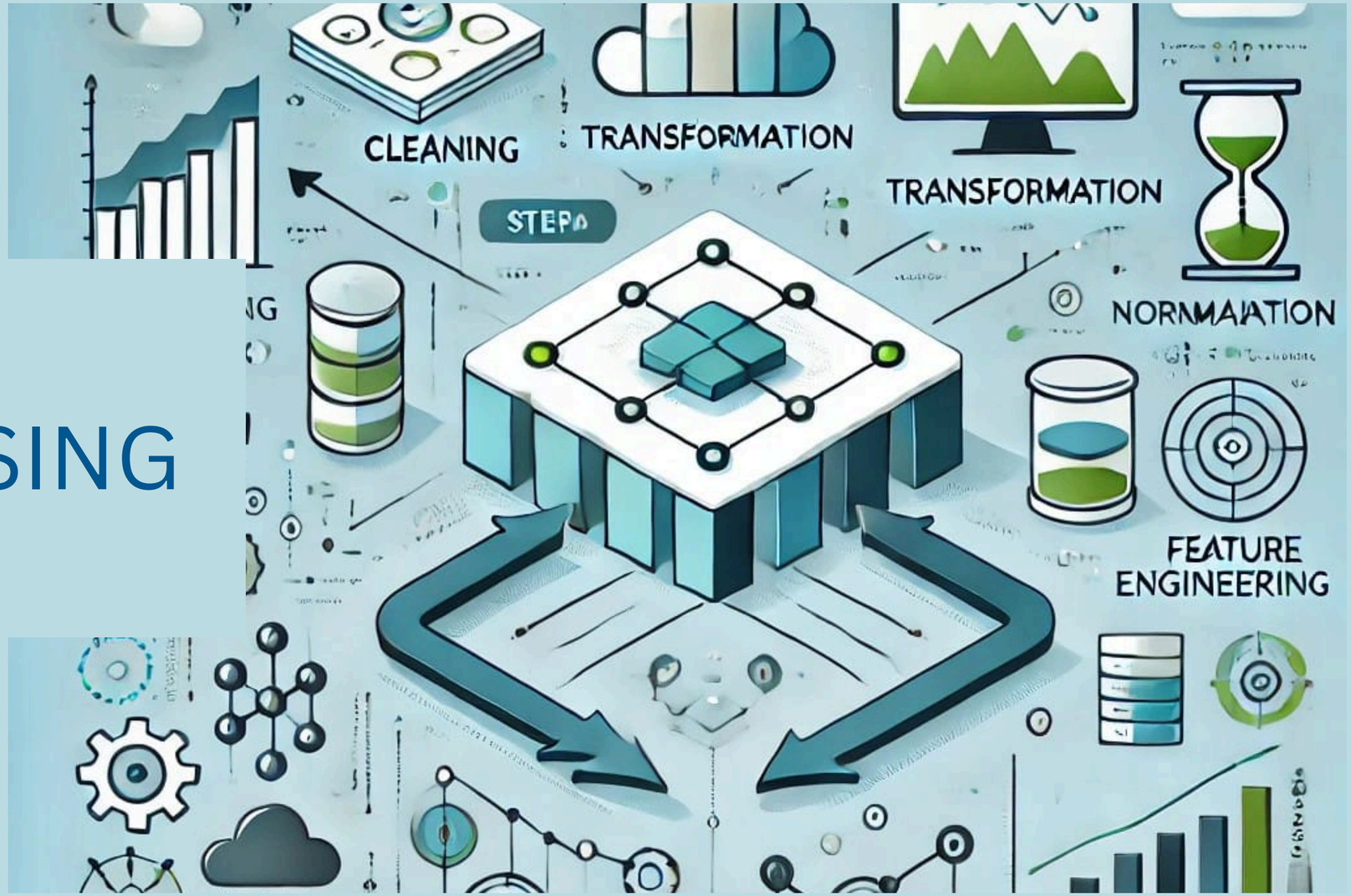
Literature Review - 2

Author(s): Smith & Zhang
Title: Machine Learning Models for Predicting Engineering Graduate Salaries
Published In: International Journal of Educational Data Science, 2021

This study examines the effectiveness of machine learning models in forecasting engineering graduates' salaries based on educational and experiential data. The authors implemented algorithms such as gradient boosting machines (GBM), neural networks, and k-nearest neighbors (KNN) to predict salaries using features like academic performance, certifications, job location, and industry type.

The research highlights the effectiveness of gradient boosting techniques in identifying complex patterns, surpassing traditional statistical models. It also examines the role of industry trends and market dynamics in enhancing prediction accuracy, recommending the integration of external economic indicators for better salary prediction frameworks.

DATA PREPROCESSING



DATA

Dataset: Our Dataset consists of 34 variables and 2998 records

Source: https://drive.google.com/drive/folders/1vGSRCnhqSxEH53BgLqhh32F1qNKqfOim?usp=drive_link

Variables:

ID	Gender	DOB	10percen	10board	12gradu	12percen	12board	CollegeII	College1	Degree	Specialit	collegeG	CollegeG	CollegeG	College%	Graduat	English	Logical	Quant	Domain	Computa	Electron	Computa	Mechan	Electrica	Telecom	CivilEng	conscie	agreeab	extraver	nuerotic	openess	Salary
604393	f	######	87.8	cbse	2009	84	cbse	6920	1	B.Techll	instrume	73.82	6920	1	Delhi	2013	650	665	810	0.6945	485	366	-1	-1	-1	-1	-1	-0.159	0.3789	1.2396	0.1453	0.2889	445000
988334	m	######	57	cbse	2010	64.5	cbse	6624	2	B.Techll	compute	65	6624	0	UttarPra	2014	440	435	210	0.3423	365	-1	-1	-1	-1	-1	-1	1.1336	0.0459	1.2396	0.5262	-0.286	110000
301647	m	######	77.33	maharas	2007	85.17	amravati	9084	2	B.Techll	electron	61.94	9084	0	Maharas	2011	485	475	505	0.8247	-1	400	-1	-1	-1	260	-1	0.51	-0.123	1.5428	-0.23	-0.288	255000
582313	m	######	84.3	cbse	2009	86	cbse	8195	1	B.Techll	compute	80.4	8195	1	Delhi	2013	675	620	635	0.99	655	-1	-1	-1	-1	-1	-1	-0.446	0.2124	0.3174	0.2727	0.4805	420000
339001	f	######	82	cbse	2008	75	cbse	4883	2	B.Techll	biotechn	64.3	4883	1	TamilNa	2012	575	495	365	0.2785	315	-1	-1	-1	-1	-1	-1	-1.493	-0.747	-1.07	0.0622	0.1864	200000
609356	f	######	83.16	icse	2007	77	cbse	10950	1	M.Tech.	instrume	99.93	10950	0	Punjab	2013	535	595	620	0.3761	455	300	-1	-1	-1	313	-1	0.8463	-0.62	-0.759	-0.995	-0.286	440000

Variables

Categorical variables
Gender
DOB
10board
12board
Degree
Specialization
College state

Continuous variables	
ID	Logical
10percentage	Quant
12graduation	Domain
12percentage	ElectricsAndSemicon
CollegeID	ComputerScience
Collegetier	MechanicalEngg
CollegeGPA	ElectricalEngg
CollegeCityID	TelecomEngg
CollegeCityTier	CivilEngg
Graduation Year	conscientiousness
English	agreebleness
Computer Programming	extraversion
nueroticism	openess_to_experience
salary	

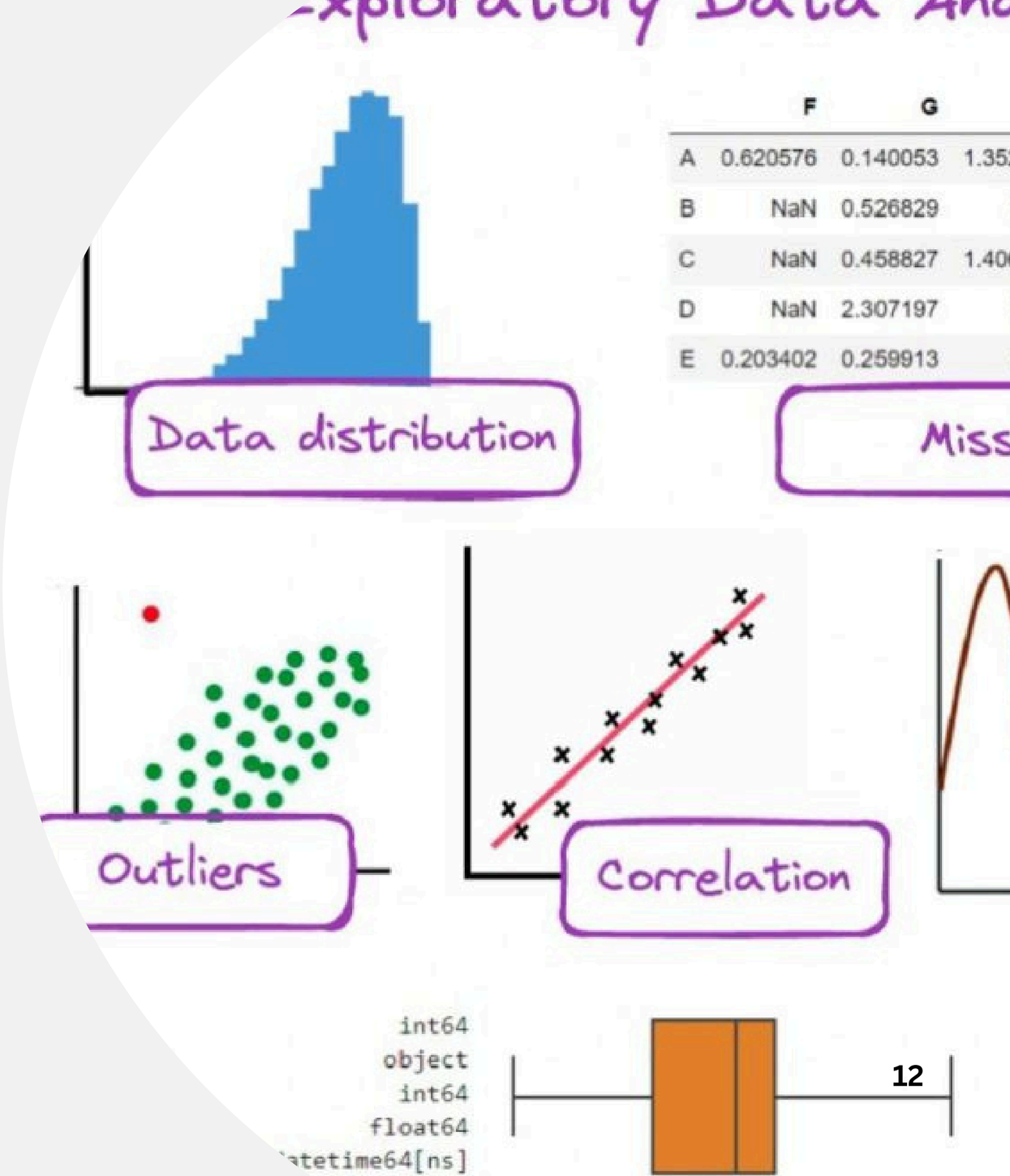
Data Cleaning

Data Cleaning is the process of identifying and correcting errors or inconsistencies in data to ensure it is accurate, complete, and usable for analysis. It involves tasks such as:

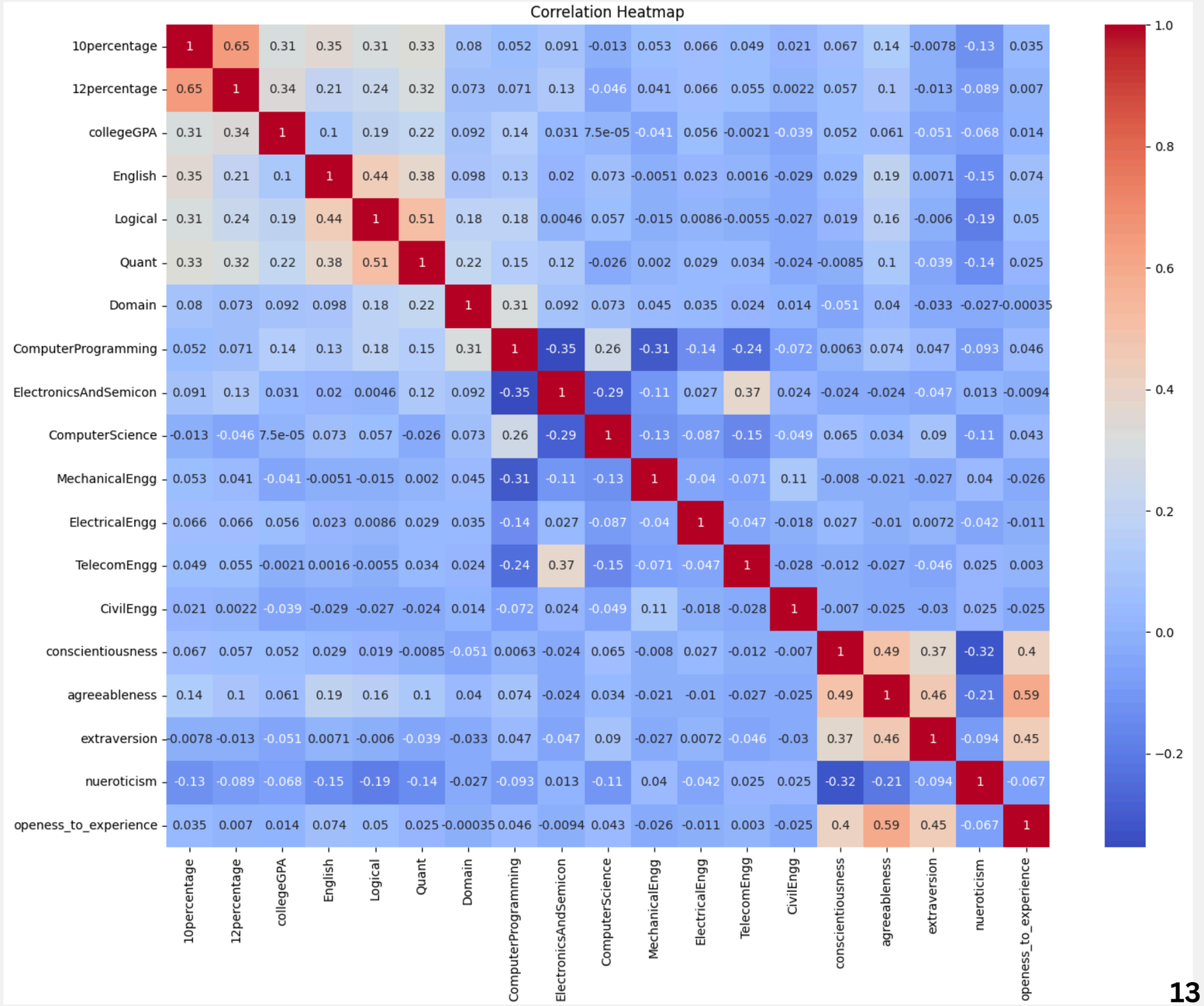
- *Handling missing values: Filling in or removing missing data points.*
- *Correcting errors: Identifying and fixing typos, incorrect formatting, or outliers.*
- *Standardizing data: Ensuring consistency in units, date formats, and categories.*
- *Removing duplicates: Identifying and eliminating redundant records.*
- *Data transformation: Converting data into a suitable format for analysis.*

Effective data cleaning improves the quality of the dataset, leading to more reliable insights and better decision-making.

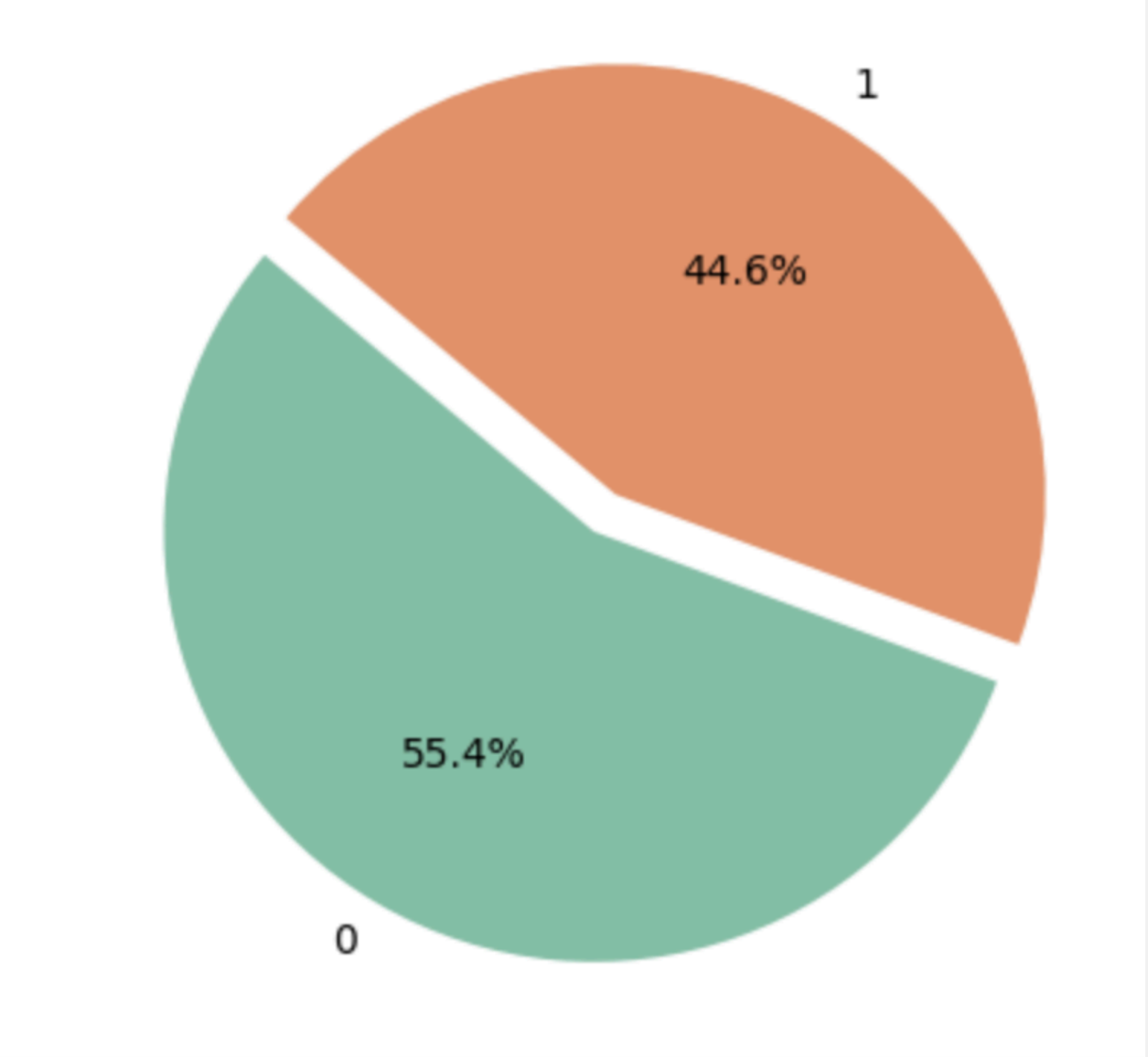
Exploratory Data Analysis



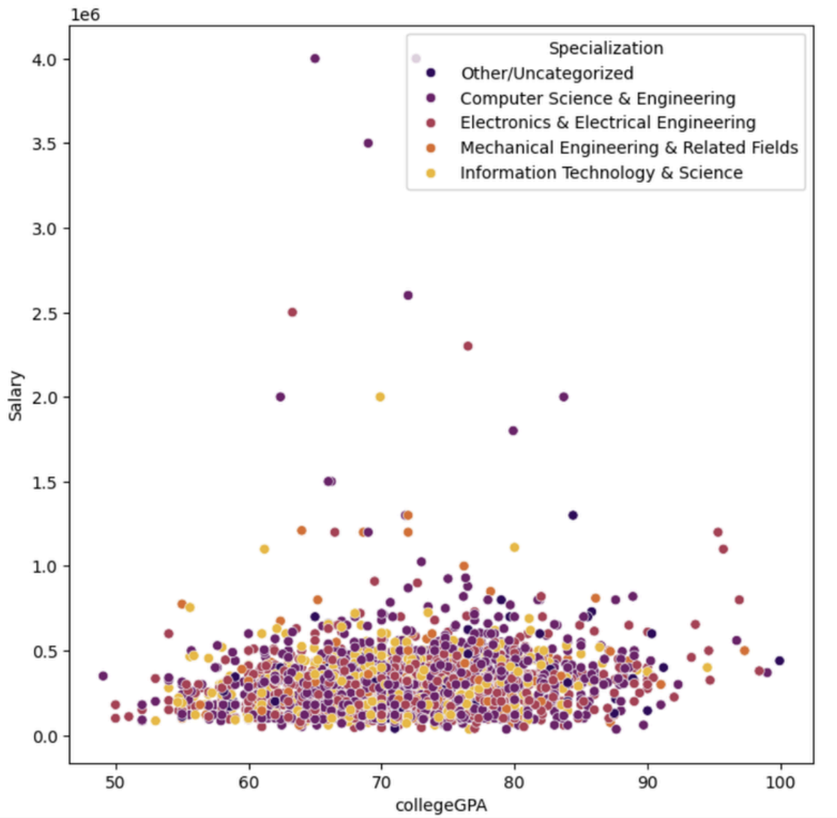
CORRELATION MATRIX

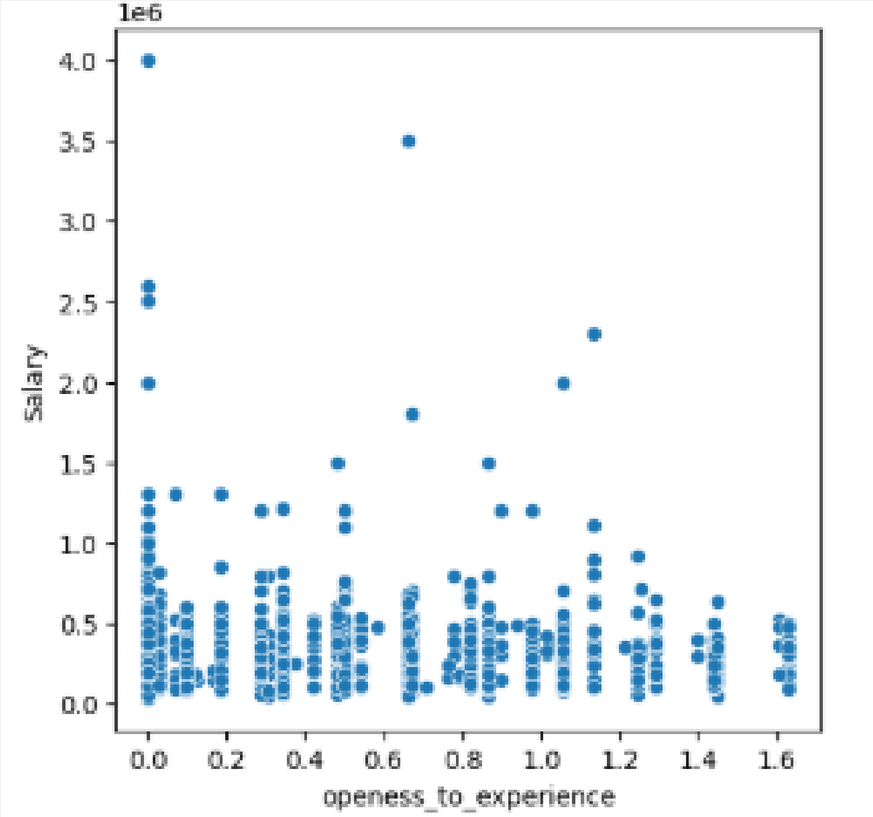


PIE CHART

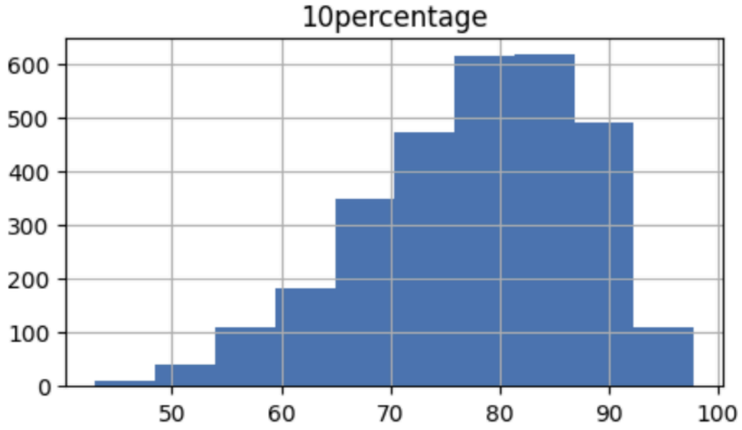


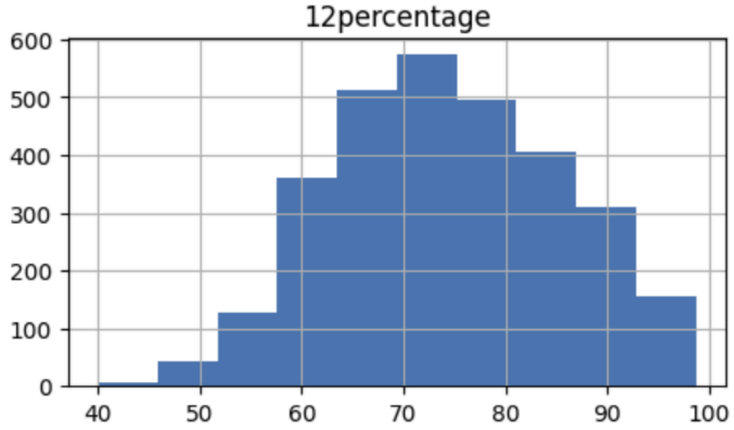
Scatter Plot

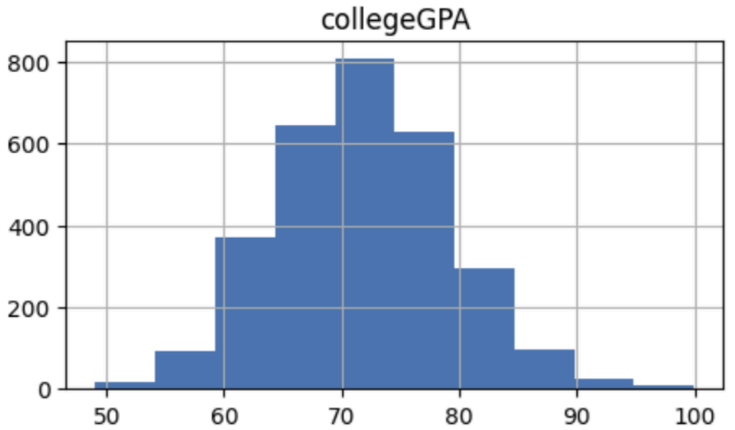


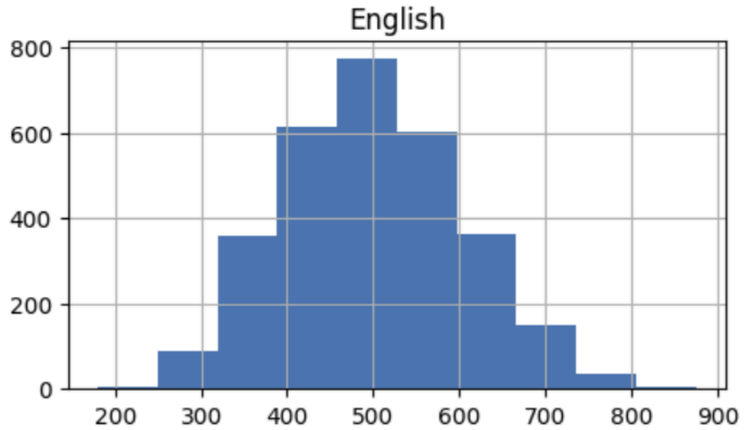


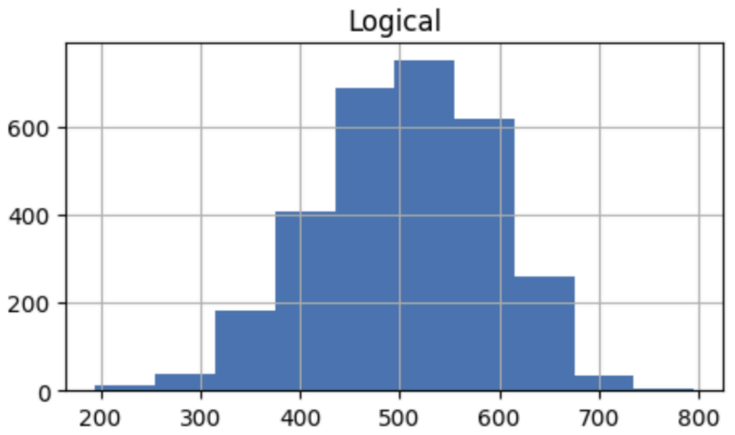
Histogram

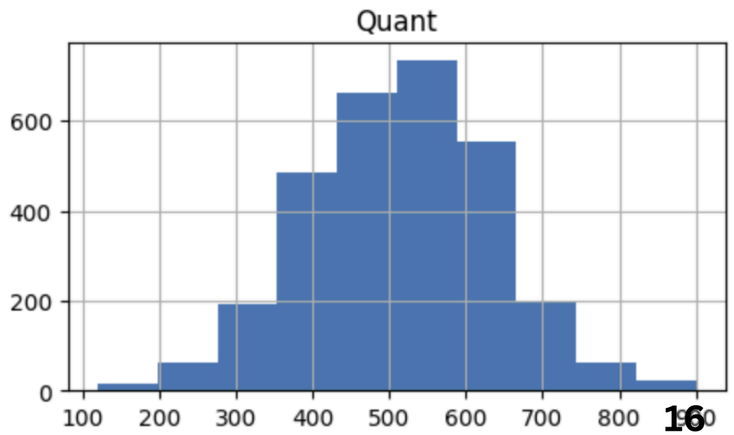

10percentage
600
500
400
300
200
100
0
50
60
70
80
90
100


12percentage
600
500
400
300
200
100
0
40
50
60
70
80
90
100

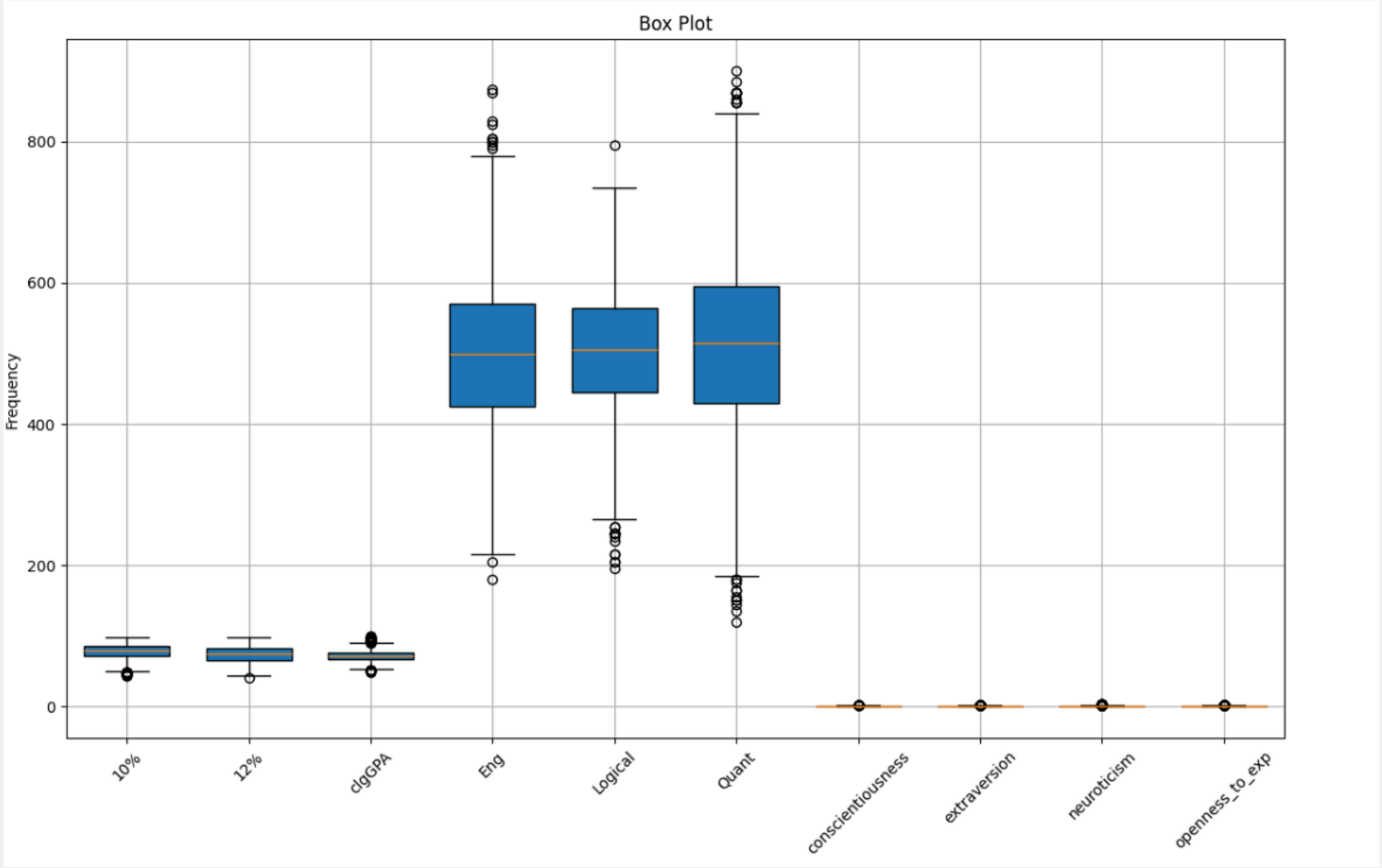

collegeGPA
800
600
400
200
0
50
60
70
80
90
100


English
800
600
400
200
0
200
300
400
500
600
700
800
900


Logical
600
400
200
0
200
300
400
500
600
700
800

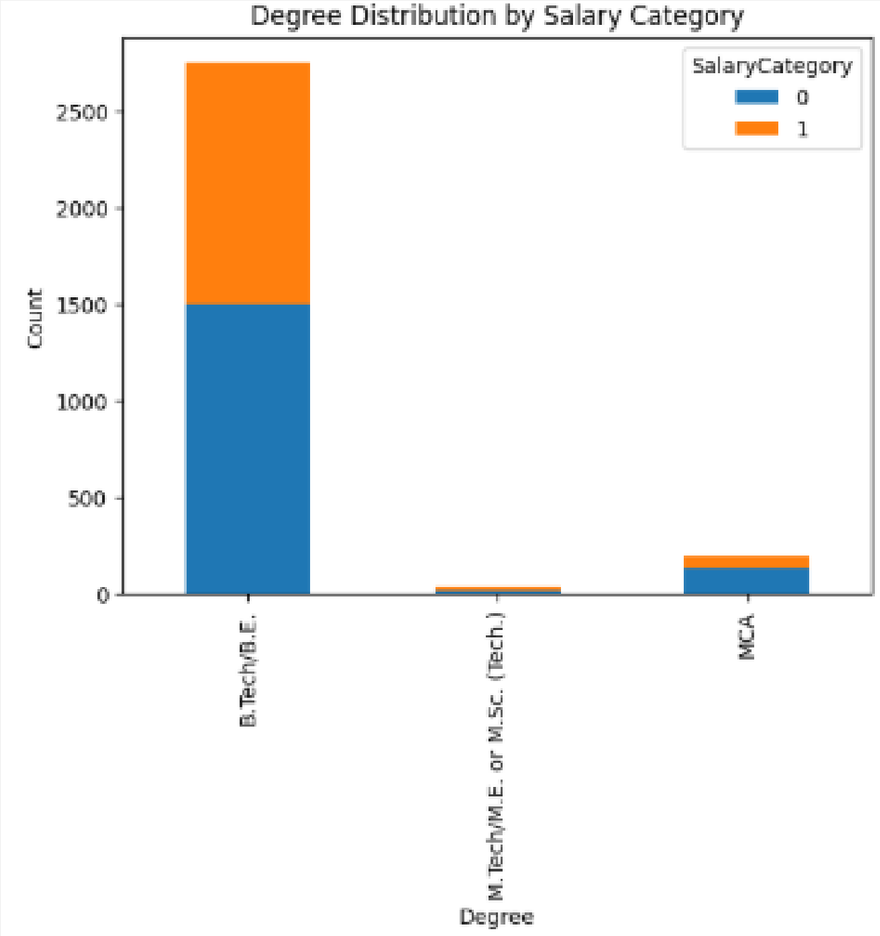

Quant
600
400
200
0
100
200
300
400
500
600
700
800

Boxplot


Box Plot
Frequency
800
600
400
200
0
10%
12%
clgGPA
Eng
Logical
Quant
conscientiousness
extraversion
neuroticism
openness_to_exp

Bar plot


Gender Distribution by Salary Category
SalaryCategory
0
1
count
1200
1000
800
600
400
200
0
f
m
Gender


Degree Distribution by Salary Category
SalaryCategory
0
1
Count
2500
2000
1500
1000
500
0
B.Tech/B.E.
M.Tech/M.E. or M.Sc. (Tech.)
MCA
Degree

Multicollinearity Check

variables with the greatest variance inflation factor (VIF>3) were removed

	variables	VIF
0	10percentage	117.7
1	12percentage	87.4
2	CollegeTier	37.5
3	collegeGPA	101.9
4	English	32.8
5	Logical	52.1
6	Quant	31.1
7	Domain	7.5
8	ComputerProgramming	7.7
9	ElectronicsAndSemicon	4.6
10	ComputerScience	1.6
11	MechanicalEngg	5.5
12	ElectricalEngg	1.4
13	TelecomEngg	1.4
14	CivilEngg	1.2
15	conscientiousness	2.0
16	agreeableness	2.6
17	extraversion	2.0
18	nueroticism	1.4
19	openess_to_experience	1.8
20	Gender_m	4.4
21	Degree_M.Tech/M.E. or M.Sc. (Tech.)	1.1
22	Degree_MCA	1.3
23	Specialization_Electronics & Electrical Engine...	7.3
24	Specialization_Information Technology & Science	1.5
25	Specialization_Mechanical Engineering & Relate...	5.9
26	Specialization_Other/Uncategorized	1.4

	variables	VIF
0	ComputerProgramming	3.5
1	ElectronicsAndSemicon	3.8
2	ComputerScience	1.5
3	MechanicalEngg	5.4
4	ElectricalEngg	1.3
5	TelecomEngg	1.4
6	CivilEngg	1.2
7	conscientiousness	2.0
8	agreeableness	2.5
9	extraversion	2.0
10	nueroticism	1.4
11	openess_to_experience	1.8
12	Gender_m	3.6
13	Degree_M.Tech/M.E. or M.Sc. (Tech.)	1.0
14	Degree_MCA	1.2
15	Specialization_Electronics & Electrical Engine...	5.2
16	Specialization_Information Technology & Science	1.4
17	Specialization_Mechanical Engineering & Relate...	5.5
18	Specialization_Other/Uncategorized	1.2

	variables	VIF
0	ComputerScience	1.4
1	ElectricalEngg	1.2
2	TelecomEngg	1.4
3	CivilEngg	1.1
4	conscientiousness	2.0
5	agreeableness	2.4
6	extraversion	2.0
7	nueroticism	1.3
8	openess_to_experience	1.8
9	Gender_m	2.8
10	Degree_M.Tech/M.E. or M.Sc. (Tech.)	1.0
11	Degree_MCA	1.1
12	Specialization_Electronics & Electrical Engine...	2.3
13	Specialization_Information Technology & Science	1.3
14	Specialization_Mechanical Engineering & Relate...	1.2
15	Specialization_Other/Uncategorized	1.2

ML Algorithms

- *Logistic Regression*
- *K-Nearest Neighbors(KNN)*
- *Decision Tree*
- *Random Forest*
- *XG Boosting*
- *ADA Boosting*
- *Support Vector Machine(SVM)*

80-20

Algorithms	Model -1 Before VIF Accuracy	Model -2 After VIF Accuracy
Logistic Regression	0.53	0.53
KNN	0.67	0.55
SVM	0.39	0.51
Decision Tree	0.63	0.55
Random Forest	0.69	0.55
XG Boost	0.70	0.56
ADA Boost	0.70	0.57

75-25

Algorithms	Model -1 Before VIF Accuracy	Model-2 After VIF Accuracy
Logistic Regression	0.64	0.55
KNN	0.69	0.55
SVM	0.38	0.53
Decision Tree	0.63	0.52
Random Forest	0.70	0.55
XG Boost	0.68	0.55
ADA Boost	0.70	0.57

70-30

Algorithms	Model -1 Before VIF Accuracy	Model -2 After VIF Accuracy
Logistic Regression	0.67	0.55
KNN	0.68	0.56
SVM	0.38	0.52
Decision Tree	0.63	0.53
Random Forest	0.70	0.56
XG Boost	0.70	0.58
ADA Boost	0.69	0.57

60-40

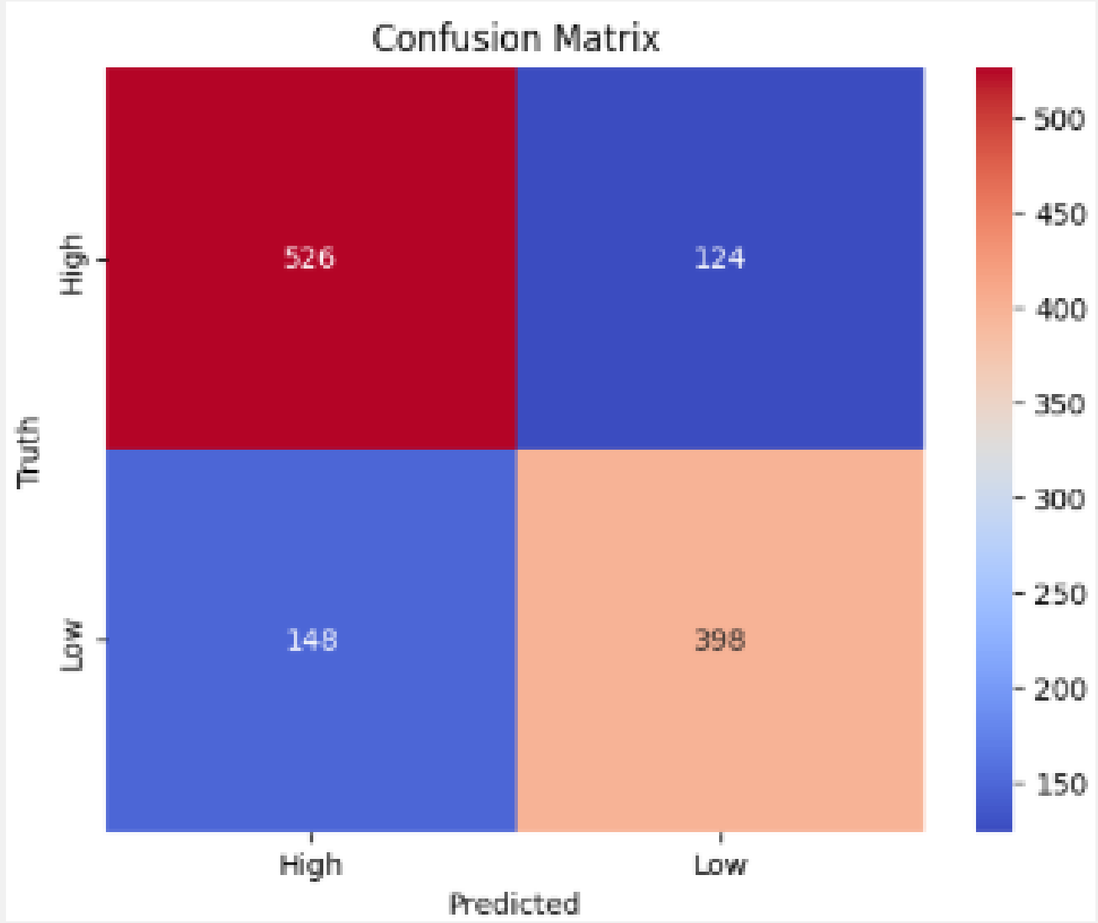
Algorithms	Model -1 Before VIF Accuracy	Model -2 After VIF Accuracy
Logistic Regression	0.64	0.58
KNN	0.68	0.58
SVM	0.38	0.54
Decision Tree	0.59	0.52
Random Forest	0.70	0.58
XG Boost	0.77	0.56
ADA Boost	0.67	0.59

Algorithms Comparision for MODEL-1

60-40 split before applying VIF

Algorithms	Model -1 Before VIF Accuracy
Logistic Regression	0.64
KNN	0.68
SVM	0.38
Decision Tree	0.59
Random Forest	0.70
XG Boost	0.77
ADA Boost	0.67

XG Boost(60-40)

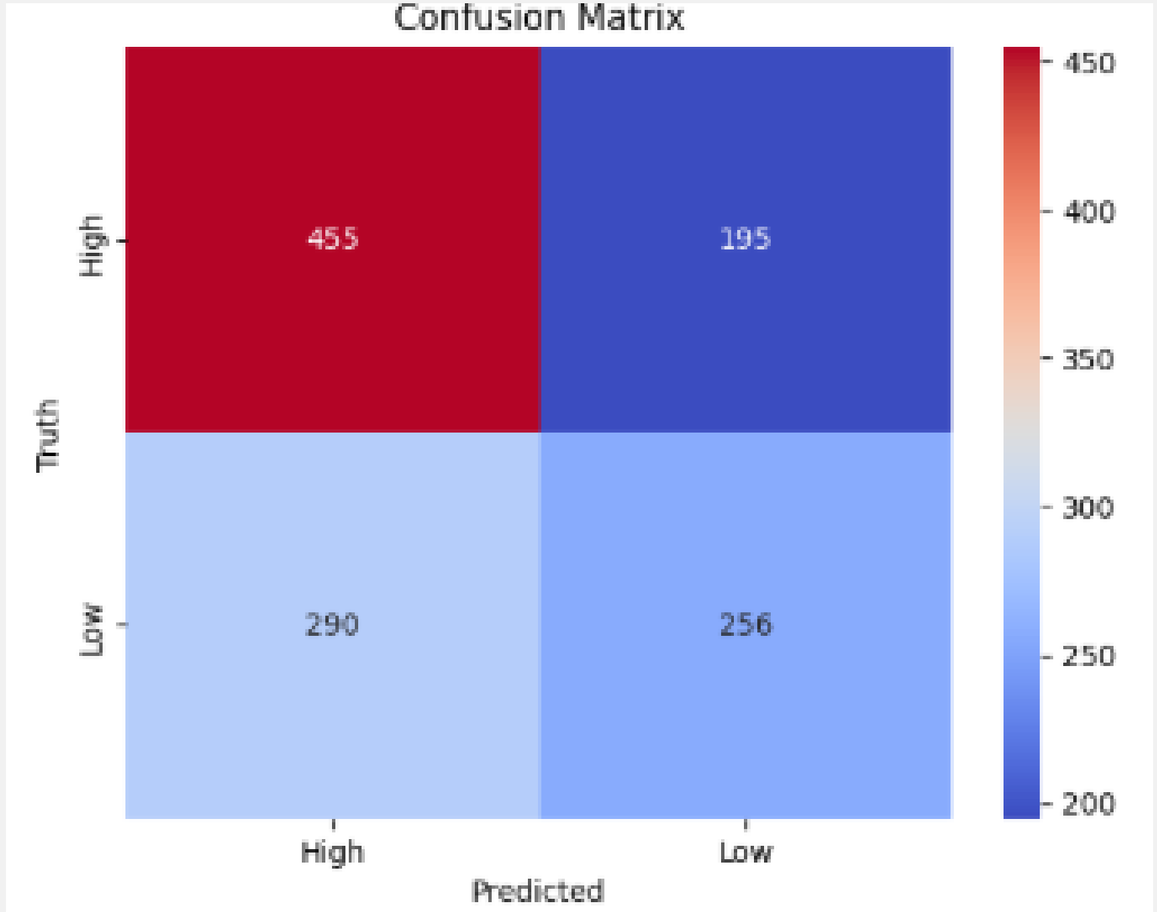


Algorithms Comparision for MODEL-2

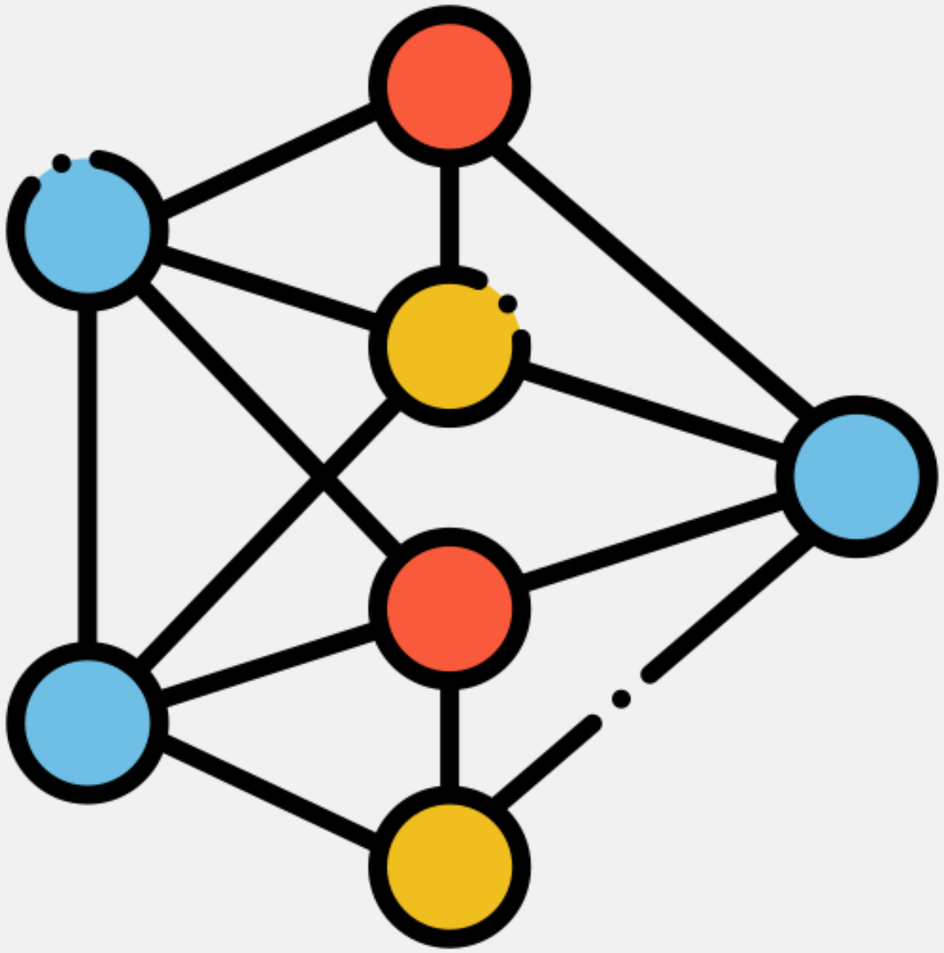
60-40 split before applying VIF

Algorithms	Model -2 After VIF Accuracy
Logistic Regression	0.58
KNN	0.58
SVM	0.54
Decision Tree	0.52
Random Forest	0.58
XG Boost	0.56
ADA Boost	0.59

ADA Boost (60-40)



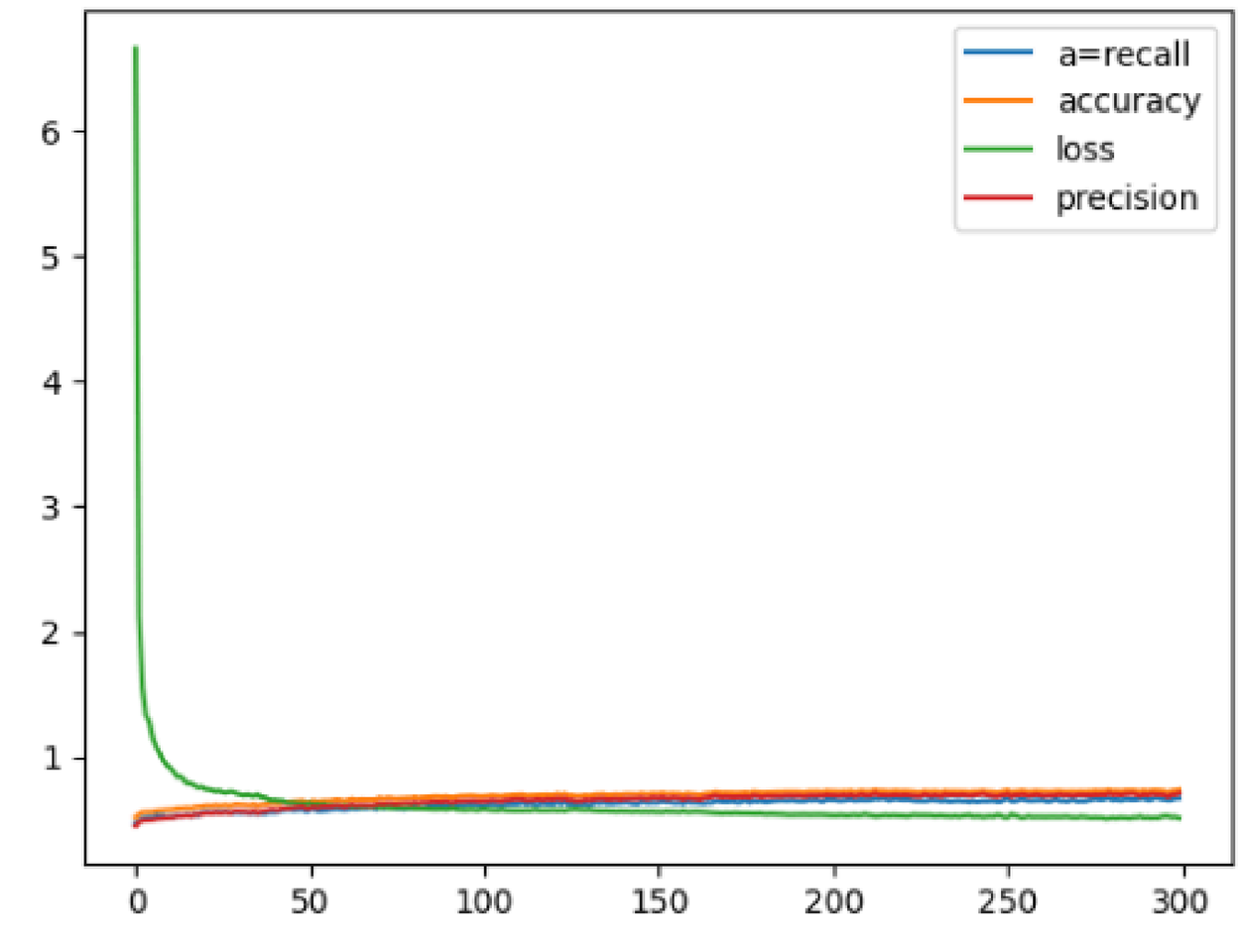
Neural Network



Neural Network

Train-Test	Architecture	Optimizer	Epochs	Precision	Recall	Accuracy	Loss
60-40	30-20-10-8-6-4-1	Adam	250	0.66	0.56	0.65	0.88
60-40	30-20-10-7-5-1	Adam	200	0.63	0.60	0.64	0.80
70-30	30-16-12-8-6-4-1	Adam	250	0.63	0.69	0.66	0.76
70-30	30-20-10-7-5-1	Adam	350	0.68	0.50	0.65	0.74
75-25	30-16-12-8-6-4-1	Adam	300	0.68	0.52	0.65	1.01
75-25	30-20-10-7-5-1	Adam	300	0.70	0.51	0.65	0.79
80-20	30-16-12-8-6-4-1	Adam	300	0.66	0.63	0.65	0.69
80-20	30-20-10-7-5-1	Adam	300	0.71	0.57	0.68	0.71

Neural Network plot for Observation



Train test split	**80-20**
Architecture	**30-20-10-7-5-1**
Optimizer	**Adam**
Epochs	**300**

SUMMARY

The purpose of this study is to develop a predictive model for estimating the salaries of engineering graduates.

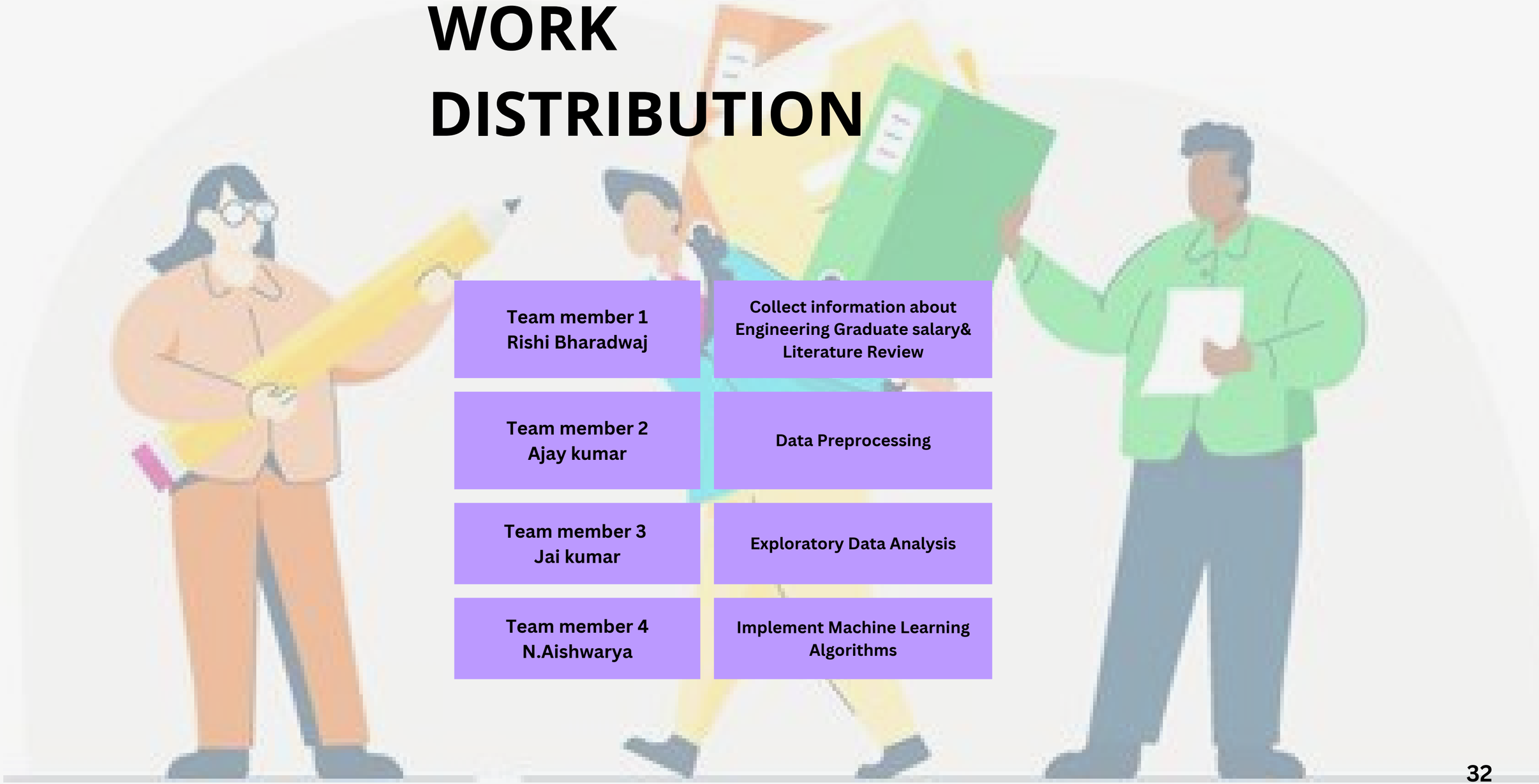
In Model 1, the best fit model is XG Boost with accuracy of 0.77, whereas in Model 2, the best fit model is ADA Boost with accuracy of 0.59

Thus, XG Boost is the best model for forecasting engineering graduates salaries utilizing an 60:40 train split ratio.

FUTURE SCOPE

- Include additional features like social media presence, online portfolios, and extracurricular activities in the dataset.
- Partner with recruitment platforms to predict salaries and educational platforms for tailored course recommendations.
- Implement advanced models like deep learning, ensemble methods, and explainable AI for better predictions.
- Develop gamified simulations to help students understand the impact of skill-building on salaries.

WORK DISTRIBUTION



Team member 1 Rishi Bharadwaj	Collect information about Engineering Graduate salary& Literature Review
Team member 2 Ajay kumar	Data Preprocessing
Team member 3 Jai kumar	Exploratory Data Analysis
Team member 4 N.Aishwarya	Implement Machine Learning Algorithms

Colab Notebook

Thank You

N.AISHWARYA
RISHI BHARADWAJ
AJAY KUMAR
JAI KUMAR

Appendix

Loading the Dataset

```
df= pd.read_csv('Engineering_graduate_salary.csv')
df.head()
```

	ID	Gender	DOB	10percentage	10board	12graduation	12percentage	12board	CollegeID	CollegeTier	...	MechanicalEngg	ElectricalEngg	TelecomEngg	CivilEngg	conscientiousness	agreeableness	extraversion	nueroticism	openess_to_experience	Salary
0	604399	f	1990-10-22	87.80	cbse	2009	84.00	cbse	6920	1	...	-1	-1	-1	-1	-0.1590	0.3789	1.2396	0.14590	0.2889	445000
1	988334	m	1990-05-15	57.00	cbse	2010	64.50	cbse	6624	2	...	-1	-1	-1	-1	1.1336	0.0459	1.2396	0.52620	-0.2859	110000
2	301647	m	1989-08-21	77.33	maharashtra state board,pune	2007	85.17	amravati divisional board	9084	2	...	-1	-1	260	-1	0.5100	-0.1232	1.5428	-0.29020	-0.2875	255000
3	582313	m	1991-05-04	84.30	cbse	2009	86.00	cbse	8195	1	...	-1	-1	-1	-1	-0.4463	0.2124	0.3174	0.27270	0.4805	420000
4	339001	f	1990-10-30	82.00	cbse	2008	75.00	cbse	4889	2	...	-1	-1	-1	-1	-1.4992	-0.7473	-1.0697	0.06223	0.1864	200000

5 rows × 34 columns

Null Values

```
df.isna().sum()
```

10percentage	0
10board	0
12graduation	0
12percentage	0
12board	0
CollegeID	0
CollegeTier	0
Degree	0
Specialization	0
collegeGPA	0
CollegeCityID	0
CollegeCityTier	0
CollegeState	0
GraduationYear	0
English	0
Logical	0
Quant	0
Domain	0
ComputerProgramming	0
ElectronicsAndSemicon	0
ComputerScience	0
MechanicalEngg	0
ElectricalEngg	0
TelecomEngg	0
CivilEngg	0
conscientiousness	0
agreeableness	0
extraversion	0
nueroticism	0
openess_to_experience	0
Salary	0

Checking for the data type

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2998 entries, 0 to 2997
Data columns (total 34 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   ID                     2998 non-null   int64  
 1   Gender                 2998 non-null   object 
 2   DOB                    2998 non-null   object 
 3   10percentage           2998 non-null   float64
 4   10board                2998 non-null   object 
 5   12graduation           2998 non-null   int64  
 6   12percentage           2998 non-null   float64
 7   12board                2998 non-null   object 
 8   CollegeID              2998 non-null   int64  
 9   CollegeTier            2998 non-null   int64  
 10  Degree                 2998 non-null   object 
 11  Specialization         2998 non-null   object 
 12  collegeGPA             2998 non-null   float64
 13  CollegeCityID          2998 non-null   int64  
 14  CollegeCityTier        2998 non-null   int64  
 15  CollegeState           2998 non-null   object 
 16  GraduationYear         2998 non-null   int64  
 17  English                2998 non-null   int64  
 18  Logical                2998 non-null   int64  
 19  Quant                  2998 non-null   int64  
 20  Domain                 2998 non-null   float64
 21  ComputerProgramming    2998 non-null   int64  
 22  ElectronicsAndSemicon  2998 non-null   int64  
 23  ComputerScience        2998 non-null   int64  
 24  MechanicalEngg         2998 non-null   int64  
 25  ElectricalEngg         2998 non-null   int64  
 26  TelecomEngg            2998 non-null   int64  
 27  CivilEngg              2998 non-null   int64  
 28  conscientiousness      2998 non-null   float64
 29  agreeableness          2998 non-null   float64
 30  extraversion           2998 non-null   float64
 31  nueroticism            2998 non-null   float64
 32  openess_to_experience  2998 non-null   float64
 33  Salary                 2998 non-null   int64  
dtypes: float64(9), int64(18), object(7)
memory usage: 796.5+ KB
```

checking unique Values

```
for i in range(df.shape[1]):
  print(df.iloc[:,i].unique())
  print(df.iloc[:,i].value_counts())
```

```
 -2.0105 -1.0524 -1.1169 -1.4356  1.4502 -1.2354 -0.4776 -0.169  -1.6273
 -0.8608 -0.6035  0.0973  0.4234  0.8973 -1.244   0.9763  1.0554  0.0284
  1.247  -1.8278  0.5024  1.6302 -0.9194 -1.8189 -0.7615  1.1343 -0.4392
 -2.0253  1.6082 -2.6572 -5.0763  0.5419  0.7788 -2.3412  0.1275 -2.2021
 -1.0774  0.1187 -0.643  -5.6512 -1.7093  0.7631 -0.0506 -0.9984  0.8183
  0.167  -2.1833 -0.5245 -2.3937 -0.8799 -1.8673 -6.8009 -3.763  -2.9686
 -2.3017 -5.2679 -0.4601  1.0158 -1.0872 -6.6092  0.3049 -1.5513 -0.406
 -3.9266  0.7906 -6.9925 -2.7769 -1.359  -3.735  -5.686   0.0679 -1.9234
 -2.7595 -2.9731 -3.1311  1.2528 -1.9463 -1.3539  1.3976  1.0395 -2.8152
 -3.1602 -1.4724 -3.6051 -2.0648 -1.1291  0.7941 -3.4471 -0.4229  0.0916
 -1.8386 -1.0458 -0.2511  1.4003 -0.0167 -3.5434  0.7104 -0.4139  0.585
 -3.3518 -0.8045  0.7657 -0.1521  0.9404 -3.9605  1.2121 -0.0844 -5.4595
 -1.6662 -0.8782  0.376  -7.3757 -4.3099]
openess_to_experience
 0.0973    142
 0.6721    140
 0.4805    136
-0.0943    134
 0.2889    133
          ...
 1.0395      1
-2.8152      1
-1.1291      1
-0.4229      1
-4.3099      1
Name: count, Length: 131, dtype: int64
[ 445000  110000  255000  420000  200000  440000  150000  105000  195000
  335000  300000  480000  550000  325000  405000  500000  210000  400000
  360000  240000  120000  430000  600000   80000  330000  450000  215000
  315000  220000  180000   60000  165000  370000  145000  100000  510000
  310000  380000  170000   95000   75000  140000  320000 1210000  700000
  305000  410000  375000  295000  260000  160000  475000  250000  465000
  720000  505000  290000  350000  230000  615000 1110000  340000  205000
  280000  190000  520000  235000  715000  390000  455000  385000  355000
  490000 2000000 1500000  275000  185000  225000  525000  515000  265000
  395000   90000  730000  485000  760000  820000  135000  460000  560000
  415000  435000  155000  425000  115000  345000  245000  495000   45000
  565000  660000   70000  470000   35000  270000 2600000 1025000  365000
  175000  570000  680000  785000  285000  870000  130000 1200000  650000
  144000  810000  880000 1100000  675000   65000  770000 2500000  125000
 1300000  610000  725000  775000   50000  555000  540000  705000  620000
  925000  800000   85000  545000  585000  590000 3500000  530000  535000
  630000  625000  605000  850000   40000  900000  640000  580000  690000
  930000  645000  655000  910000  750000 2300000 1800000 4000000  755000
   55000 1000000  575000]
Salary
300000    207
180000    189
200000    154
325000    134
120000    121
         ...
775000      1
705000      1
925000      1
585000      1
575000      1
Name: count, Length: 165, dtype: int64
```

Dropping few columns

```
df.drop(['ID','DOB','CollegeID','12graduation','10board','12board','CollegeState','CollegeCityID', 'CollegeCityTier','GraduationYear'], axis=1, inplace=True)
print(df)
```

```
2994      f         84.00         77.00           2  B.Tech/B.E.
2995      m         91.40         65.56           2  B.Tech/B.E.
2996      m         88.64         65.16           2  B.Tech/B.E.
2997      m         77.00         75.50           2  B.Tech/B.E.

                              Specialization  collegeGPA  English  Logical  \
0          instrumentation and control engineering       73.82      650      665
1                   computer science & engineering       65.00      440      435
2                 electronics & telecommunications       61.94      485      475
3                   computer science & engineering       80.40      675      620
4                                 biotechnology       64.30      575      495
...                                         ...         ...      ...      ...
2993  electronics and communication engineering       70.00      505      485
2994                      information technology       75.20      345      585
2995                      information technology       73.19      385      425
2996                        computer engineering       74.81      465      645
2997                      information technology       69.30      370      390

      Quant  ...  MechanicalEngg  ElectricalEngg  TelecomEngg  CivilEngg  \
0       810  ...             -1              -1           -1         -1
1       210  ...             -1              -1           -1         -1
2       505  ...             -1              -1          260         -1
3       635  ...             -1              -1           -1         -1
4       365  ...             -1              -1           -1         -1
...     ...  ...            ...             ...          ...        ...
2993    445  ...             -1              -1           -1         -1
2994    395  ...             -1              -1           -1         -1
2995    485  ...             -1              -1           -1         -1
2996    505  ...             -1              -1           -1         -1
2997    285  ...             -1              -1           -1         -1

      conscientiousness  agreeableness  extraversion  nueroticism  \
0               -0.1590         0.3789        1.2396      0.14590
1                1.1336         0.0459        1.2396      0.52620
2                0.5100        -0.1232        1.5428     -0.29020
3               -0.4463         0.2124        0.3174      0.27270
4               -1.4992        -0.7473       -1.0697      0.06223
...                 ...            ...           ...          ...
2993            -1.1901         0.9688       -1.0697      1.35490
2994            -0.1082         0.0328       -0.4891     -0.29020
2995            -0.8810         0.1888       -0.3440      0.06230
2996             1.4374         1.2808       -0.4891     -1.46537
2997            -0.5899        -1.9521        0.3174      1.16010

      openess_to_experience  Salary
0                    0.2889  445000
1                   -0.2859  110000
2                   -0.2875  255000
3                    0.4805  420000
4                    0.1864  200000
...                     ...     ...
2993                 0.0284  120000
2994                 0.5024  120000
2995                 0.6603  385000
2996                 0.5419  530000
2997                -2.3937  200000
```

Renaming and merging few columns

```
df['Degree'] = df['Degree'].replace({
    'M.Tech./M.E.': 'M.Tech/M.E. or M.Sc. (Tech.)',
    'M.Sc. (Tech.)': 'M.Tech/M.E. or M.Sc. (Tech.)'
})
print(df)
```

```
     Gender  10percentage  12percentage  CollegeTier       Degree  \
0         f         87.80         84.00            1  B.Tech/B.E.
1         m         57.00         64.50            2  B.Tech/B.E.
2         m         77.33         85.17            2  B.Tech/B.E.
3         m         84.30         86.00            1  B.Tech/B.E.
4         f         82.00         75.00            2  B.Tech/B.E.
...     ...           ...           ...          ...          ...
2993      f         75.00         73.00            2  B.Tech/B.E.
2994      f         84.00         77.00            2  B.Tech/B.E.
2995      m         91.40         65.56            2  B.Tech/B.E.
2996      m         88.64         65.16            2  B.Tech/B.E.
2997      m         77.00         75.50            2  B.Tech/B.E.

                          Specialization  collegeGPA  English  Logical  \
0      instrumentation and control engineering       73.82      650      665
1                computer science & engineering       65.00      440      435
2              electronics & telecommunications       61.94      485      475
3                computer science & engineering       80.40      675      620
4                                  biotechnology       64.30      575      495
...                                          ...         ...      ...      ...
2993  electronics and communication engineering       70.00      505      485
2994                     information technology       75.20      345      585
2995                     information technology       73.19      385      425
2996                       computer engineering       74.81      465      645
2997                     information technology       69.30      370      390

      Quant  ...  MechanicalEngg  ElectricalEngg  TelecomEngg  CivilEngg  \
0       810  ...             -1              -1           -1         -1
1       210  ...             -1              -1           -1         -1
2       505  ...             -1              -1          260         -1
3       635  ...             -1              -1           -1         -1
4       365  ...             -1              -1           -1         -1
...     ...  ...            ...             ...          ...        ...
2993    445  ...             -1              -1           -1         -1
2994    395  ...             -1              -1           -1         -1
2995    485  ...             -1              -1           -1         -1
2996    505  ...             -1              -1           -1         -1
2997    285  ...             -1              -1           -1         -1

      conscientiousness  agreeableness  extraversion  nueroticism  \
0               -0.1500         0.3789        1.2396      0.14590
```

```
specialization_mapping = {
    #'instrumentation and control engineering':'other',
    'computer science & engineering': 'Computer Science & Engineering',
    'electronics & telecommunications': 'Electronics & Electrical Engineering',
    #'biotechnology':'other',
    'mechanical engineering': 'Mechanical Engineering & Related Fields',
    'information technology': 'Information Technology & Science',
    'electronics and communication engineering': 'Electronics & Electrical Engineering',
    'computer engineering': 'Computer Science & Engineering',
    'computer application': 'Computer Science & Engineering',
    'computer science and technology': 'Computer Science & Engineering',
    'electrical engineering': 'Electronics & Electrical Engineering',
    'automobile/automotive engineering': 'Mechanical Engineering & Related Fields',
    'electronics and electrical engineering': 'Electronics & Electrical Engineering',
    'information science engineering': 'Information Technology & Science',
    #'chemical engineering':'other',
    #'instrumentation engineering':'other',
    'electronics & instrumentation eng': 'Electronics & Electrical Engineering',
    #'ceramic engineering': 'other',
    #'metallurgical engineering':'other',
    #'aeronautical engineering':'other',
    'electronics engineering': 'Electronics & Electrical Engineering',
    'electronics and instrumentation engineering': 'Electronics & Electrical Engineering',
    'applied electronics and instrumentation': 'Electronics & Electrical Engineering',
    #'civil engineering':'other',
    'computer and communication engineering': 'Computer Science & Engineering',
    #'industrial & production engineering':'other',
    'computer networking': 'Computer Science & Engineering',
    'electronics and computer engineering': 'Electronics & Electrical Engineering',
    #'control and instrumentation engineering':'other',
    'mechanical & production engineering': 'Mechanical Engineering & Related Fields',
    'mechanical and automation': 'Mechanical Engineering & Related Fields',
    #'industrial & management engineering':'other',
    #'biomedical engineering':'other',
    'electrical and power engineering': 'Electronics & Electrical Engineering',
    'telecommunication engineering': 'Electronics & Electrical Engineering',
    #'industrial engineering':'other',
    'mechatronics': 'Mechanical Engineering & Related Fields',
    'embedded systems technology': 'Computer Science & Engineering',
    'information & communication technology': 'Information Technology & Science',
    'information science': 'Information Technology & Science'
}
```

```
[16] df['Specialization'] = df['Specialization'].map(specialization_mapping)

    # Fill NaNs if any specialization was not in the mapping
    df['Specialization'].fillna('Other/Uncategorized', inplace=True)

    # Check the transformed data
    print(df['Specialization'].value_counts())
```

```
Specialization
Computer Science & Engineering            1180
Electronics & Electrical Engineering      1038
Information Technology & Science           526
Mechanical Engineering & Related Fields    168
Other/Uncategorized                         86
Name: count, dtype: int64
<ipython-input-16-c2a2de30c2c6>:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df['Specialization'].fillna('Other/Uncategorized', inplace=True)
```

Replacing columns with -1 to 0's

```
df.replace(-1, 0, inplace=True)

# Verify results
print(df)
```

```
     Gender  10percentage  12percentage  CollegeTier       Degree  \
0         f         87.80         84.00            1  B.Tech/B.E.
1         m         57.00         64.50            2  B.Tech/B.E.
2         m         77.33         85.17            2  B.Tech/B.E.
3         m         84.30         86.00            1  B.Tech/B.E.
4         f         82.00         75.00            2  B.Tech/B.E.
...     ...           ...           ...          ...          ...
2993      f         75.00         73.00            2  B.Tech/B.E.
2994      f         84.00         77.00            2  B.Tech/B.E.
2995      m         91.40         65.56            2  B.Tech/B.E.
2996      m         88.64         65.16            2  B.Tech/B.E.
2997      m         77.00         75.50            2  B.Tech/B.E.

                          Specialization  collegeGPA  English  Logical  \
0                    Other/Uncategorized       73.82      650      665
1          Computer Science & Engineering       65.00      440      435
2     Electronics & Electrical Engineering       61.94      485      475
3          Computer Science & Engineering       80.40      675      620
4                    Other/Uncategorized       64.30      575      495
...                                  ...         ...      ...      ...
2993  Electronics & Electrical Engineering       70.00      505      485
2994      Information Technology & Science       75.20      345      585
2995      Information Technology & Science       73.19      385      425
2996        Computer Science & Engineering       74.81      465      645
2997      Information Technology & Science       69.30      370      390

      Quant  ...  MechanicalEngg  ElectricalEngg  TelecomEngg  CivilEngg  \
0       810  ...              0               0            0          0
1       210  ...              0               0            0          0
2       505  ...              0               0          260          0
3       635  ...              0               0            0          0
4       365  ...              0               0            0          0
...     ...  ...            ...             ...          ...        ...
2993    445  ...              0               0            0          0
2994    395  ...              0               0            0          0
2995    485  ...              0               0            0          0
2996    505  ...              0               0            0          0
2997    285  ...              0               0            0          0

      conscientiousness  agreeableness  extraversion  nueroticism  \
0               -0.1590         0.3789        1.2396      0.14590
1                1.1336         0.0459        1.2396      0.52620
2                0.5100        -0.1232        1.5428     -0.29020
3               -0.4463         0.2124        0.3174      0.27270
4               -1.4992        -0.7473       -1.0697      0.06223
```

Converting salary to salary category

```
[25] max_value = df['Salary'].max()
     min_value = df['Salary'].min()
     print("Maximum value:", max_value)
     print("Minimum value:", min_value)
     mean_salary = df['Salary'].mean()
     print("Mean value:", mean_salary)
```

```
Maximum value: 4000000
Minimum value: 35000
Mean value: 305086.65105386416
```

```
salary_threshold = df['Salary'].mean()  # You can also use mean() or a custom threshold

# Apply categorization
df['SalaryCategory'] = df['Salary'].apply(lambda x: 1  if x > salary_threshold else 0)#High:1,low:0

# Define the mapping dictionary
mapping = {"High": 1, "Low": 0}

# Verify the new columns
print(df[['Salary', 'SalaryCategory']])

# Check the distribution of categories
print(df['SalaryCategory'].value_counts())
```

```
      Salary  SalaryCategory
0     445000               1
1     110000               0
2     255000               0
3     420000               1
4     200000               0
...      ...             ...
2993  120000               0
2994  120000               0
2995  385000               1
2996  530000               1
2997  200000               0

[2989 rows x 2 columns]
SalaryCategory
0    1657
1    1332
Name: count, dtype: int64
```

Dividing the dataset

```
X=df.drop(['SalaryCategory'],axis=1)

print(X)
y = df['SalaryCategory']
print(y)
```

```
2993  Electronics & Electrical Engineering       70.00      505      485
2994      Information Technology & Science       75.20      345      585
2995      Information Technology & Science       73.19      385      425
2996        Computer Science & Engineering       74.81      465      645
2997      Information Technology & Science       69.30      370      390

      Quant  ...  ComputerScience  MechanicalEngg  ElectricalEngg  \
0       810  ...                0               0               0
1       210  ...                0               0               0
2       505  ...                0               0               0
3       635  ...                0               0               0
4       365  ...                0               0               0
...     ...  ...              ...             ...             ...
2993    445  ...                0               0               0
2994    395  ...                0               0               0
2995    485  ...                0               0               0
2996    505  ...                0               0               0
2997    285  ...              376               0               0

      TelecomEngg  CivilEngg  conscientiousness  agreeableness  extraversion  \
0               0          0             0.0000         0.3789        1.2396
1               0          0             1.1336         0.0459        1.2396
2             260          0             0.5100         0.0000        1.5428
3               0          0             0.0000         0.2124        0.3174
4               0          0             0.0000         0.0000        0.0000
...           ...        ...                ...            ...           ...
2993            0          0             0.0000         0.9688        0.0000
2994            0          0             0.0000         0.0328        0.0000
2995            0          0             0.0000         0.1888        0.0000
2996            0          0             1.4374         1.2808        0.0000
2997            0          0             0.0000         0.0000        0.3174

      nueroticism  openess_to_experience
0         0.14590                 0.2889
1         0.52620                 0.0000
2         0.00000                 0.0000
3         0.27270                 0.4805
4         0.06223                 0.1864
...           ...                    ...
2993      1.35490                 0.0284
2994      0.00000                 0.5024
2995      0.06230                 0.6603
2996      0.00000                 0.5419
2997      1.16010                 0.0000

[2989 rows x 23 columns]
0       1
1       0
2       0
3       1
4       0
       ..
2993    0
2994    0
2995    1
2996    1
2997    0
Name: SalaryCategory, Length: 2989, dtype: int64
```

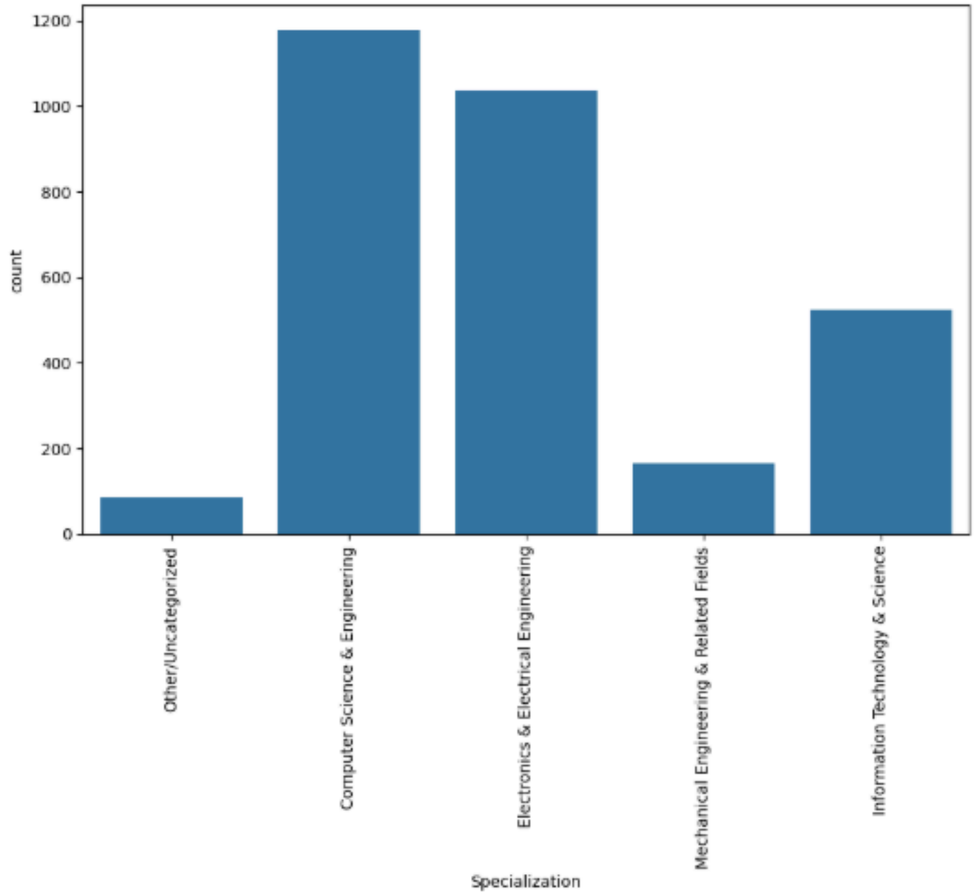
```
X= pd.get_dummies(X,dtype='int',drop_first=True)
print(X)
```

```
2994                                    0          0
2995                                    0          0
2996                                    0          0
2997                                    0          0

      Specialization_Electronics & Electrical Engineering  \
0                                                     0
1                                                     0
2                                                     1
3                                                     0
4                                                     0
...                                                 ...
2993                                                  1
2994                                                  0
2995                                                  0
2996                                                  0
2997                                                  0

      Specialization_Information Technology & Science  \
0                                                   0
1                                                   0
2                                                   0
3                                                   0
4                                                   0
...                                               ...
2993                                                0
2994                                                1
2995                                                1
2996                                                0
2997                                                1

      Specialization_Mechanical Engineering & Related Fields  \
0                                                     0
1                                                     0
2                                                     0
3                                                     0
4                                                     0
...                                                 ...
2993                                                  0
2994                                                  0
2995                                                  0
2996                                                  0
2997                                                  0

      Specialization_Other/Uncategorized
0                                      1
1                                      0
2                                      0
3                                      0
4                                      1
...                                  ...
2993                                   0
2994                                   0
2995                                   0
2996                                   0
2997                                   0

[2989 rows x 27 columns]
```

EDA

```
plt.figure(figsize=(10, 6))
sns.countplot(x=df['Specialization'])
plt.xticks(rotation=90)
```

```
([0, 1, 2, 3, 4],
 [Text(0, 0, 'Other/Uncategorized'),
  Text(1, 0, 'Computer Science & Engineering'),
  Text(2, 0, 'Electronics & Electrical Engineering'),
  Text(3, 0, 'Mechanical Engineering & Related Fields'),
  Text(4, 0, 'Information Technology & Science')])
```




```
sns.countplot(x='SalaryCategory', data=df)
plt.title('Distribution of Salary Categories')
plt.show()
```

Logistic Regression

```
[ ]  from sklearn.model_selection import train_test_split
     X_nomulti = X.drop(['10percentage','12percentage','CollegeTier','collegeGPA','English','Logical','Quant','Domain','ComputerProgramming','ElectronicsAndSemicon','Mechanica

     X_train1_nomulti, X_test1_nomulti, y_train1_nomulti, y_test1_nomulti = train_test_split(X_nomulti, y, test_size=0.20, train_size=0.80, random_state=1)
     X_train2_nomulti, X_test2_nomulti, y_train2_nomulti, y_test2_nomulti = train_test_split(X_nomulti, y, test_size=0.25, train_size=0.75, random_state=1)
     X_train3_nomulti, X_test3_nomulti, y_train3_nomulti, y_test3_nomulti = train_test_split(X_nomulti, y, test_size=0.30, train_size=0.70, random_state=1)
     X_train4_nomulti, X_test4_nomulti, y_train4_nomulti, y_test4_nomulti = train_test_split(X_nomulti, y, test_size=0.40, train_size=0.60, random_state=1)
     X_train5_nomulti, X_test5_nomulti, y_train5_nomulti, y_test5_nomulti = train_test_split(X_nomulti, y, test_size=0.50, train_size=0.50, random_state=1)
```

Logistic Regression after VIF

```
[ ]  from sklearn.linear_model import LogisticRegression
     logreg = LogisticRegression(C=1e9)

     logreg.fit(X_train1_nomulti, y_train1_nomulti)
     predictions1 = logreg.predict(X_test1_nomulti)
     print(predictions1)
```

```
[0 1 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 1 1 1 0
 0 1 1 1 0 1 0 0 1 0 1 0 0 0 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 0 1 0 0 0 0 0
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 0 0 0 0 1 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0
 1 0 0 0 0 0]
```

```
 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 1 1 1 1 0 1 0 0 1 0 1 0 0 0 1
 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 1 1 1 0 1 0 0 0 0 0 0 0 0 1 0 1
 0 1 0 0 0 1 1 0 1 1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
 0 0 0 0 1 1 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 1 0
 1 0 0 0 0 0 1 0 1 1 0 0 1 1 0 0 0 0 1 0 0 0 1 0 0 0 1 1 0 0 0 0
 1 0 1 1 0 1 0 0 0 1 1 1 0 0 0 0 0 1 1 0 0 0 0 1 0 0 0 1 1 0 0 1 0 0 0 1 0
 1 0 1 1 0 0 1 0 0 0 0 1 0 1 0 0 1 1 0 1 1 0 0 0 1 0 0 0 1 0 1 1 0 1 0 0 0
 0 0 0 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0
 0 1 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 1 1 0
 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 1 0 0 0 0 1 0 1 0 1 0 1 0 1 1
 0 0 0 0 0 1 0 0 0 1 1 0 1 0 0 0 0 1 0 0 1 1 1 0 0 0 1 0 1 0 1 0 0 0 0 0
 0 1 0 0 0 0 0 0 1 1 0 1 0 0 1 0 0 0 1 0 0 1 0 0 1 0 0 1 1 1 1 0 1 0 0 0 1
 0 0 0 0 1 1 0 0 0
```

```
[ ]  from sklearn.linear_model import LogisticRegression
     logreg = LogisticRegression(C=1e9)

     logreg.fit(X_train4_nomulti, y_train4_nomulti)
     predictions4 = logreg.predict(X_test4_nomulti)
     print(predictions4)
```

```
[0 1 1 ... 0 0 1]
```

```
[ ]  from sklearn.metrics import confusion_matrix
```

```
[ ]  z=confusion_matrix(y_test1_nomulti, predictions1)
     z
```

```
array([[228,  80],
       [203,  87]])
```

```
[ ]  z=confusion_matrix(y_test2_nomulti, predictions2)
     z
```

```
array([[288, 108],
       [231, 121]])
```

```
[ ]  z=confusion_matrix(y_test3_nomulti, predictions3)
     z
```

```
array([[349, 118],
       [285, 145]])
```

```
[ ]  z=confusion_matrix(y_test4_nomulti, predictions4)
     z
```

```
array([[503, 147],
       [348, 198]])
```

```
[ ]  from sklearn.metrics import accuracy_score
     accuracy_score(y_test1_nomulti,predictions1)
```

```
0.5267558528428093
```

KNN

```
[ ] from sklearn.neighbors import KNeighborsClassifier
    X_train1_nomulti, X_test1_nomulti, y_train1_nomulti, y_test1_nomulti = train_test_split(X_nomulti, y, test_size=0.20, train_size=0.80, random_state=1)
    X_train2_nomulti, X_test2_nomulti, y_train2_nomulti, y_test2_nomulti = train_test_split(X_nomulti, y, test_size=0.25, train_size=0.75, random_state=1)
    X_train3_nomulti, X_test3_nomulti, y_train3_nomulti, y_test3_nomulti = train_test_split(X_nomulti, y, test_size=0.30, train_size=0.70, random_state=1)
    X_train4_nomulti, X_test4_nomulti, y_train4_nomulti, y_test4_nomulti = train_test_split(X_nomulti, y, test_size=0.40, train_size=0.60, random_state=1)
    X_train5_nomulti, X_test5_nomulti, y_train5_nomulti, y_test5_nomulti = train_test_split(X_nomulti, y, test_size=0.50, train_size=0.50, random_state=1)
```

80-20

```
[ ] model=KNeighborsClassifier(n_neighbors=25)
    model.fit(X_train1_nomulti,y_train1_nomulti)
```

```
KNeighborsClassifier(n_neighbors=25)
```

```
    y_pred1_nomulti = model.predict(X_test1_nomulti)
    print(y_pred1_nomulti)
```

```
[0 1 0 0 0 1 1 0 0 1 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 1 0 1 1
 0 1 1 1 0 1 0 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1 1 1 0 0 0 0 1 1 1 0 0 1 0 0
 0 0 1 0 0 1 0 0 1 1 1 0 0 0 0 0 0 0 1 0 1 0 1 0 0 1 1 1 0 0 0 0 1 0 0 0 0 0 0
 0 1 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0
 1 0 1 1 0 0 1 0 0 0 1 1 0 1 0 1 1 1 1 0 1 0 0 0 0 0 1 0 1 0 0 0 0 1 0 1 0 0
 1 0 1 1 1 0 1 1 0 1 1 0 1 1 0 1 0 0 1 1 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0
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 1 0 0 0 0 1 0 0 1 1 1 1 1 0 1 1 0 1 0 1 0 1 1 1 0 0 0 1 0 0 0 0 1 1 1 0 0 0
 0 1 0 0 0 0 0 1 0 1 0 0 1 1 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1 1 0 1 0 1 1
 0 1 1 0 1 0 1 1 0 0 0 1 0 1 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 1 1 0 1 0 0 0 0
 0 1 0 0 0 0 0 0 1 1 1 1 0 1 0 0 0 1 0 1 0 0 1 1 1 0 1 1 0 0 0 0 1 1 1 1 0
 0 0 1 0 0 1 0 0 1 1 1 1 1 1 0 0 1 1 0 0 0 1 0 0 1 0 1 0 1 1 1 1 0 1 1 0 0 0 0 0 0
 0 0 0 0 0 1 1 1 0 1 1 0 1 1 0 0 0 0 1 1 0 0 1 0 1 0 1 1 0 1 1 0 0 1 0 0 1 0 1
 0 1 0 0 1 0 0 0 0 0 1 1 0 1 0 1 0 1 1 1 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1
 0 0 0 0 1 0 0 0 1 1 1 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 1 0 0
 0 0 0 0 1 1 0 1 0 0 1 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 1 0 0 1 0
 0 0 1 1 1 0]
```

```
[ ] df=pd.DataFrame({'Predicted':y_pred1_nomulti,'Actual':y_test1_nomulti})
    print(df)
```

```
      Predicted  Actual
1651          0       0
2828          1       1
383           0       1
1601          0       0
2376          0       1
...         ...     ...
303           0       1
1540          1       1
2210          1       1
2662          1       1
134           0       0

[598 rows x 2 columns]
```


```
[ ] df=pd.DataFrame({'Predicted':y_pred1_nomulti,'Actual':y_test1_nomulti})
    print(df)
```

```
      Predicted  Actual
1651          0       0
2828          1       1
383           0       1
1601          0       0
2376          0       1
...         ...     ...
303           0       1
1540          1       1
2210          1       1
2662          1       1
134           0       0

[598 rows x 2 columns]
```

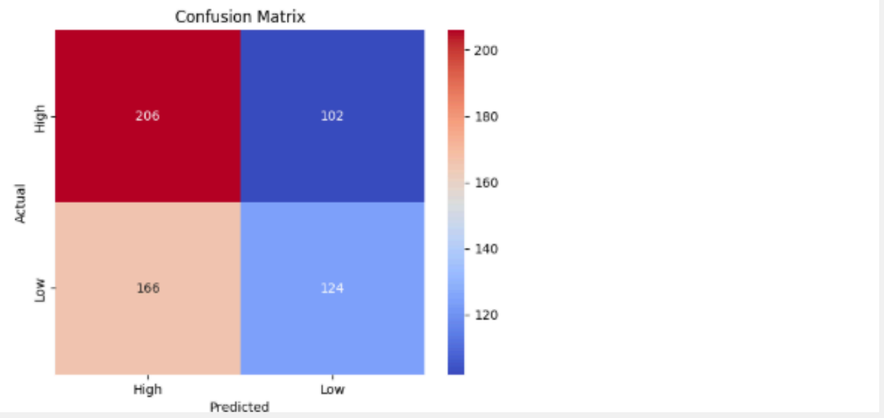

```
[ ] from sklearn.metrics import accuracy_score
    accuracy_score(y_test1_nomulti,y_pred1_nomulti)
```

```
0.5518394648829431
```

```
[ ] from sklearn.metrics import confusion_matrix
    cm1_nomulti = confusion_matrix(y_test1_nomulti,y_pred1_nomulti)
    cm1_nomulti
```

```
array([[206, 102],
       [166, 124]])
```

```
    sns.heatmap(cm1_nomulti, annot=True, fmt="d", cmap="coolwarm", xticklabels=["High", "Low"], yticklabels=["High", "Low"])
    plt.title('Confusion Matrix')
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()
```



SVM

```
from sklearn.svm import SVC
X_train1_nomulti, X_test1_nomulti, y_train1_nomulti, y_test1_nomulti = train_test_split(X_nomulti, y, test_size=0.20, train_size=0.80, random_state=1)
X_train2_nomulti, X_test2_nomulti, y_train2_nomulti, y_test2_nomulti = train_test_split(X_nomulti, y, test_size=0.25, train_size=0.75, random_state=1)
X_train3_nomulti, X_test3_nomulti, y_train3_nomulti, y_test3_nomulti = train_test_split(X_nomulti, y, test_size=0.30, train_size=0.70, random_state=1)
X_train4_nomulti, X_test4_nomulti, y_train4_nomulti, y_test4_nomulti = train_test_split(X_nomulti, y, test_size=0.40, train_size=0.60, random_state=1)
X_train5_nomulti, X_test5_nomulti, y_train5_nomulti, y_test5_nomulti = train_test_split(X_nomulti, y, test_size=0.50, train_size=0.50, random_state=1)
```

```
model = SVC(kernel='sigmoid')
model.fit(X_train1_nomulti, y_train1_nomulti)
```

```
SVC
SVC(kernel='sigmoid')
```

```
y_pred1_nomulti = model.predict(X_test1_nomulti)
print(y_pred1_nomulti)
```

```
[0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0
 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0
 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0]
```

```
df = pd.DataFrame({'Predicted':y_pred1_nomulti,'Actual':y_test1_nomulti})
print(df)
```

```
      Predicted  Actual
1651          0       0
2828          0       1
383           0       1
1601          0       0
2376          0       1
...         ...     ...
303           0       1
1540          0       1
2210          0       1
2662          0       1
134           0       0

[598 rows x 2 columns]
```

```
df = pd.DataFrame({'Predicted':y_pred1_nomulti,'Actual':y_test1_nomulti})
print(df)
```


```
      Predicted  Actual
1651          0       0
2828          0       1
383           0       1
1601          0       0
2376          0       1
...         ...     ...
303           0       1
1540          0       1
2210          0       1
2662          0       1
134           0       0

[598 rows x 2 columns]
```

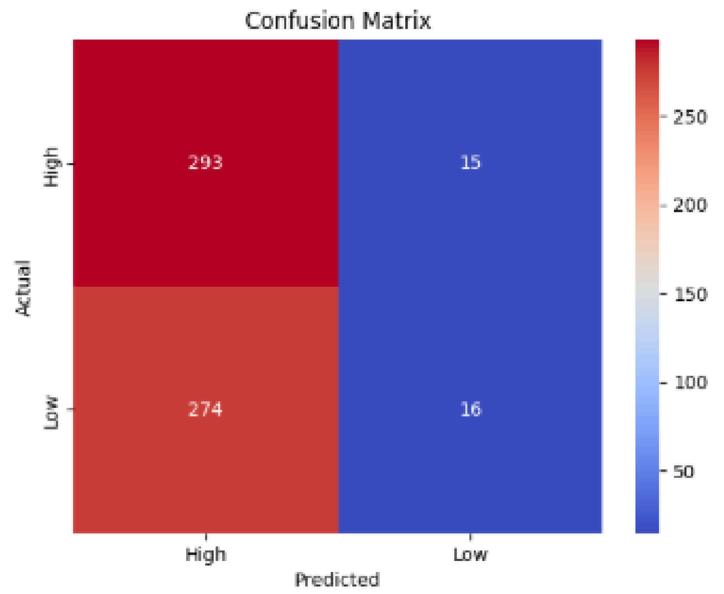

```
from sklearn.metrics import accuracy_score
accuracy_score(y_test1_nomulti,y_pred1_nomulti)
```

```
0.5167224080267558
```

```
from sklearn.metrics import confusion_matrix
cm1_nomulti = confusion_matrix(y_test1_nomulti,y_pred1_nomulti)
cm1_nomulti
```

```
array([[293,  15],
       [274,  16]])
```

```
sns.heatmap(cm1_nomulti, annot=True, fmt="d", cmap="coolwarm", xticklabels=["High", "Low"], yticklabels=["High", "Low"])
plt.title('Confusion Matrix')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



Decision tree classifier

```
[ ] import pandas as pd
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.model_selection import train_test_split
    from sklearn import metrics
    X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.20, train_size=0.80,random_state=1)
    X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.25, train_size=0.75,random_state=1)
    X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.30, train_size=0.70,random_state=1)
    X_train4, X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=0.40, train_size=0.60,random_state=1)
```

80-20

```
[ ] clf = DecisionTreeClassifier()
    clf1 = clf.fit(X_train1,y_train1)
    print(clf1)
```

```
DecisionTreeClassifier()
```

```
y_pred1 = clf.predict(X_test1)
print(y_pred1)
```

```
[1 1 1 1 0 1 1 0 0 0 1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0 1 1 1 1 0 1 0
 0 0 1 0 0 0 0 0 1 1 0 1 0 1 0 1 0 0 1 0 1 1 0 0 1 0 1 1 1 0 0 0 1 0 1 1 1
 1 0 0 1 0 1 0 1 0 0 1 1 0 0 0 1 1 0 1 1 0 0 1 1 0 0 0 1 1 0 0 1 0 1 0 0 1
 0 0 1 0 0 1 0 0 1 1 0 0 1 0 0 1 0 0 0 0 0 0 1 0 1 0 0 1 0 1 0 0 0 1 1 1 1
 0 0 1 0 1 1 1 1 0 1 1 1 1 1 1 0 0 1 1 1 0 0 0 1 0 0 0 1 1 0 1 0 1 0 0 1 0
 0 1 1 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0
 0 1 1 0 0 1 1 0 1 0 1 1 1 0 0 0 1 0 0 0 0 1 0 1 0 0 1 0 1 0 1 1 0 0 1 1 1
 0 0 0 1 1 0 0 0 1 1 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0 0 1 1 1 0 0 1 1 1 1 1 1
 1 1 0 1 1 1 0 1 1 1 0 1 0 0 1 0 0 1 1 0 0 1 0 0 0 1 0 1 1 0 1 0 1 1 0 0 0
 0 1 0 1 1 0 1 1 1 0 0 0 1 0 1 0 1 0 1 1 1 0 0 1 0 1 1 0 1 0 1 0 1 0 1 1 0 1 0
 1 0 1 1 0 1 0 0 0 0 1 0 0 0 0 0 1 0 1 0 1 1 1 0 0 0 0 1 1 0 1 0 0 0 0 0 1
 0 0 1 1 0 0 0 1 1 0 1 1 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 0 0 0 1 1 0 0 0 1 1
 1 1 0 0 1 1 0 1 1 1 0 0 0 0 0 1 0 1 0 1 0 1 0 0 1 1 0 1 1 0 0 1 0 0 0 0 1
 0 1 0 1 1 0 0 0 1 0 0 0 1 1 0 1 0 0 0 0 1 0 1 1 0 0 0 1 0 0 0 1 0 1 1 0 1
 1 1 1 0 1 0 0 0 0 1 0 0 1 1 0 1 1 0 1 0 0 0 1 0 1 0 1 0 0 1 1 0 1 0 0 1 1
 0 1 1 1 0 0 0 1 0 0 0 0 1 0 0 1 1 0 1 0 0 1 0 1 0 1 0 1 0 0 1 1 1 1 1 1 0
 0 1 1 1 1 1]
```

```
[ ] from sklearn.metrics import classification_report
    classification_metrics1 = classification_report(y_test1, y_pred1)
    print(classification_metrics1)
```

```
              precision    recall  f1-score   support

           0       0.62      0.67      0.64       308
           1       0.62      0.57      0.59       290

    accuracy                           0.62       598
   macro avg       0.62      0.62      0.62       598
weighted avg       0.62      0.62      0.62       598
```

Random Forest Classifier

```
from sklearn.tree import plot_tree
from matplotlib import pyplot as plt
X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.20, train_size=0.80,random_state=1)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.25, train_size=0.75,random_state=1)
X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.30, train_size=0.70,random_state=1)
X_train4, X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=0.40, train_size=0.60,random_state=1)
```

80-20

```
[ ] print(X_train1.shape)
    print(y_train1.shape)
    print(X_test1.shape)
    print(y_test1.shape)
```

```
(2391, 27)
(2391,)
(598, 27)
(598,)
```

```
[ ] rf = RandomForestClassifier()
    rf.fit(X_train1, y_train1)
```

```
RandomForestClassifier
RandomForestClassifier()
```

```
[ ] y_pred1 = rf.predict(X_test1)
    print(y_pred1)
```

```
[0 0 1 0 0 1 1 0 0 0 0 1 0 1 1 0 1 1 0 0 1 0 0 0 0 0 0 1 0 1 1 1 1 1 1 1 1 0
 0 1 0 0 1 1 0 0 1 0 1 1 0 0 0 1 0 0 1 1 1 1 0 0 0 1 0 1 1 1 1 0 0 0 1 1 1
 1 0 0 0 0 1 0 0 0 0 1 0 0 1 0 1 1 1 1 1 1 0 0 1 0 1 0 1 0 1 0 0 0 0 1 0 0 0 0 0
 1 0 0 0 0 1 0 0 1 0 0 0 0 1 1 0 0 1 0 0 1 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0 0 1 1 1
 0 0 1 0 1 1 1 1 0 1 1 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 1 1 1 0 1 0 0 0 0 1
 1 1 1 0 1 1 0 1 0 0 1 1 1 1 0 1 1 0 0 0 0 1 0 1 0 0 1 0 1 0 0 0 0 0 1 0 0
 0 1 1 0 0 1 1 0 1 1 1 1 1 1 0 1 1 0 0 0 0 1 1 1 0 1 0 0 0 0 1 1 0 0 1 1 1
 0 1 0 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 1 0 1 0 0 1 1 1 1 1 1 0
 0 1 1 1 0 1 0 0 0 1 0 1 0 0 1 0 0 1 1 0 0 1 0 0 0 1 0 1 1 0 0 0 1 0 0 0 1
 0 0 1 0 1 1 1 1 1 0 0 1 1 0 0 0 1 0 1 1 0 0 1 1 1 0 0 1 1 0 1 0 1 0 1 1 1 1 0
 1 1 1 1 0 1 0 0 1 0 1 0 0 1 1 0 0 0 1 0 1 1 1 0 0 0 0 0 1 0 1 0 1 0 1 0 0
 0 0 1 1 0 0 1 0 0 1 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1
 0 0 0 0 0 1 0 1 1 0 0 0 0 1 0 0 0 1 0 1 0 1 0 1 1 1 0 0 1 0 0 1 0 0 1 0 1
 0 1 0 0 0 0 1 0 1 0 0 0 0 1 1 1 0 0 1 0 1 0 1 0 0 1 0 0 0 0 1 0 1 1 0 0 0 1 1 1
 0 1 0 0 1 0 0 0 0 0 1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 1 1 1 1 0 1 0 0 1 0 0 1 1
 0 0 1 1 0 1 0 1 0 0 0 0 1 0 0 0 1 0 1 1 0 1 1 1 0 1 0 1 0 0 0 1 1 1 0 1 0
 1 1 0 1 1 1]
```

```
print(classification_report(y_test1, y_pred1))
print(confusion_matrix(y_test1, y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.70      0.78      0.74       308
           1       0.73      0.65      0.69       290

    accuracy                           0.71       598
   macro avg       0.72      0.71      0.71       598
weighted avg       0.72      0.71      0.71       598
```

XG Boost classifier

XG Boost

```
[ ] import numpy as np
    import pandas as pd
    import xgboost as xgb
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import classification_report
    from sklearn.metrics import accuracy_score
    X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.20, train_size=0.80,random_state=1)
    X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.25, train_size=0.75,random_state=1)
    X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.30, train_size=0.70,random_state=1)
    X_train4, X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=0.40, train_size=0.60,random_state=1)
```

```
[ ] model = xgb.XGBClassifier()
    model = model.fit(X_train1, y_train1)
```

```
    y_pred1 = model.predict(X_test1)
    print(y_pred1)
```

```
[0 1 1 1 0 1 1 0 0 0 1 0 1 1 0 1 1 0 1 1 0 0 0 0 0 0 1 0 1 0 1 1 1 1 1 0
 1 1 1 0 1 1 1 0 0 1 1 1 0 1 0 1 0 0 1 0 1 1 1 0 0 0 0 1 1 1 1 0 0 0 0 1 1
 1 0 0 0 0 1 0 0 0 0 1 0 0 1 0 1 1 1 1 1 1 0 1 1 0 1 0 1 0 0 0 0 1 1 0 1 0 0 0 0 0
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 1 1 1 0 1 1 1 0 1 0 0 1 1 1 1 0 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 1 0 0
 0 1 1 0 0 1 1 1 1 1 0 1 1 0 0 1 0 0 0 0 0 1 1 1 1 0 1 0 0 0 0 1 1 0 0 1 1 1
 0 0 0 1 1 1 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 0 0 1 1 1 1 1
 0 1 1 0 1 0 0 1 0 0 0 1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 1 1 0 1 0 1 1 1 1 0 0 1
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 0 1 0 0 1 0 0 0 0 1 1 0 0 1 0 1 1 1 0 1 0 0 0 0 0 1 0 0 1 0 1 0 0 1 0 0 1 1
 0 0 1 1 0 1 0 1 0 0 0 0 1 0 0 0 1 0 1 1 0 1 0 1 0 0 0 1 0 0 0 0 1 1 0 1 0
 1 1 0 1 1 0]
```

```
[ ] print(classification_report(y_test1, y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.69      0.75      0.72       308
           1       0.71      0.65      0.68       290

    accuracy                           0.70       598
   macro avg       0.70      0.70      0.70       598
weighted avg       0.70      0.70      0.70       598
```

```
[ ] print("Accuracy:",metrics.accuracy_score(y_test1, y_pred1))
```

```
Accuracy: 0.7006688963210702
```

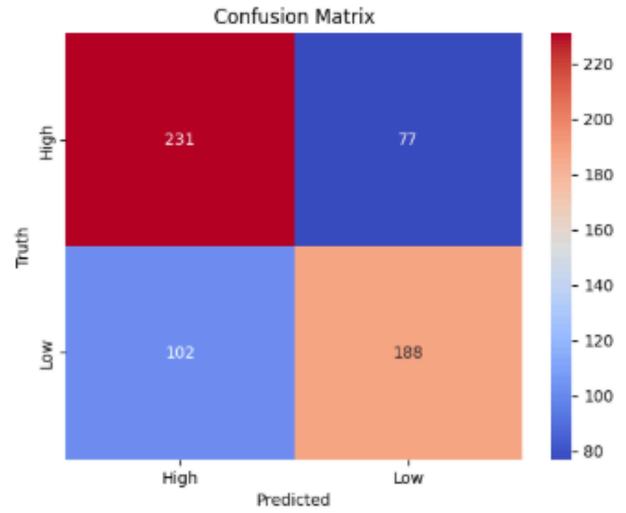

```
[ ] print("Accuracy:",metrics.accuracy_score(y_test1, y_pred1))
```


```
Accuracy: 0.7006688963210702
```

```
[ ] cm1 = confusion_matrix(y_test1, y_pred1)
    cm1
```

```
array([[231,  77],
       [102, 188]])
```

```
    sns.heatmap(cm1, annot=True, fmt="d", cmap="coolwarm", xticklabels=["High", "Low"], yticklabels=["High", "Low"])
    plt.title('Confusion Matrix')
    plt.xlabel("Predicted")
    plt.ylabel("Truth")
    plt.show()
```



ADA Boost Classifier

```
[ ] import pandas as pd
    import seaborn as sns
    from sklearn.tree import DecisionTreeClassifier
    import numpy as np
    import matplotlib.pyplot as plt
    from sklearn.ensemble import AdaBoostClassifier
    from sklearn.metrics import accuracy_score, classification_report
    X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.20, train_size=0.80,random_state=1)
    X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.25, train_size=0.75,random_state=1)
    X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.30, train_size=0.70,random_state=1)
    X_train4, X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=0.40, train_size=0.60,random_state=1)
```

30-20

```
[ ] model = AdaBoostClassifier(n_estimators=50, random_state=42)
    model.fit(X_train1, y_train1)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_weight_boosting.py:527: FutureWarning: The SAMME.R algorithm (the default) is deprecat
  warnings.warn(
AdaBoostClassifier(random_state=42)
```

```
[ ] y_pred1 = model.predict(X_test1)
    print(y_pred1)
```

```
[0 0 1 0 0 1 1 0 0 0 0 1 0 1 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 1 1 1 1 0
 0 1 1 0 1 1 0 0 1 0 1 1 0 1 0 1 1 1 0 1 0 1 1 1 0 0 0 1 1 0 1 1 1 0 0 0 1 1
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 1 1 1 0 0 1 0 0 1 0 1 0 0 1 1 0 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 1 0 1 0 1 0 0
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 0 1 0 0 1 0 1 0 0 1 1 0 0 1 0 0 1 0 1 0 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 1 1
 0 0 1 1 0 1 0 1 0 0 0 0 1 1 0 1 0 0 0 0 0 1 0 1 1 0 0 1 0 1 0 1 1 0 0 1 0
 1 1 0 1 1 0]
```

```
[ ] accuracy = accuracy_score(y_test1, y_pred1)
    print(f"Accuracy: {accuracy:.2f}")
    print(classification_report(y_test1, y_pred1))
```

```
Accuracy: 0.70
              precision    recall  f1-score   support

           0       0.69      0.77      0.73       308
           1       0.72      0.62      0.67       290

    accuracy                           0.70       598
   macro avg       0.70      0.70      0.70       598
weighted avg       0.70      0.70      0.70       598
```

Neural Networks :

```
[ ] import tensorflow as tf
    import pandas as pd
    import matplotlib.pyplot as plt
```

```
[ ] from sklearn.model_selection import train_test_split
    X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.20, train_size=0.80,random_state=1)
    X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.25, train_size=0.75,random_state=1)
    X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.30, train_size=0.70,random_state=1)
    X_train4, X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=0.40, train_size=0.60,random_state=1)
```

80-20

```
[ ] tf.random.set_seed(42)

    # STEP1: Creating the model

    model_nom1= tf.keras.Sequential([

                              tf.keras.layers.Dense(30 ,activation='relu'),
                              tf.keras.layers.Dense(20, activation='relu'),
                              tf.keras.layers.Dense(10, activation='relu'),
                              tf.keras.layers.Dense(7, activation='relu'),
                              tf.keras.layers.Dense(5, activation='relu'),
                              tf.keras.layers.Dense(1, activation='sigmoid')
    ])

    # STEP2: Compiling the model

    model_nom1.compile(loss= tf.keras.losses.binary_crossentropy,
                optimizer= tf.keras.optimizers.Adam(learning_rate=0.001),
                metrics= [tf.keras.metrics.BinaryAccuracy(name='accuracy'),
                          tf.keras.metrics.Precision(name='precision'),
                          tf.keras.metrics.Recall(name='a=recall')
                ]
                )

    # STEP1: Fit the model

    history= model_nom1.fit(X_train1, y_train1, epochs= 300)
```

```
Epoch 1/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - a=recall: 0.4825 - accuracy: 0.5300 - loss: 10.1588 - precision: 0.4577
Epoch 2/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - a=recall: 0.4778 - accuracy: 0.5541 - loss: 2.4216 - precision: 0.4832
Epoch 3/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - a=recall: 0.5086 - accuracy: 0.5671 - loss: 1.6361 - precision: 0.4980
Epoch 4/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - a=recall: 0.5172 - accuracy: 0.5729 - loss: 1.3974 - precision: 0.5058
Epoch 5/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - a=recall: 0.5306 - accuracy: 0.5701 - loss: 1.3800 - precision: 0.5022
Epoch 6/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - a=recall: 0.5215 - accuracy: 0.5710 - loss: 1.1996 - precision: 0.5046
Epoch 7/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - a=recall: 0.5351 - accuracy: 0.5703 - loss: 1.1305 - precision: 0.5022
Epoch 8/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - a=recall: 0.5342 - accuracy: 0.5740 - loss: 1.0641 - precision: 0.5065
Epoch 78/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - a=recall: 0.5770 - accuracy: 0.6723 - loss: 0.5843 - precision: 0.6372
Epoch 79/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - a=recall: 0.5899 - accuracy: 0.6712 - loss: 0.5879 - precision: 0.6275
Epoch 80/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - a=recall: 0.5917 - accuracy: 0.6631 - loss: 0.5900 - precision: 0.6141
Epoch 81/300
75/75 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - a=recall: 0.5948 - accuracy: 0.6723 - loss: 0.5822 - precision: 0.6276
```

```
[ ] model_nom1.evaluate(X_test1, y_test1)
```

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - a=recall: 0.5724 - accuracy: 0.6751 - loss: 0.7090 - precision: 0.7065
[0.7448945641517639,
 0.6638795733451843,
 0.6995515823364258,
 0.5379310250282288]
```

```
pd.DataFrame(history.history).plot()
```

```
<Axes: >
```