MEDICAL INSURANCE PREMIUM PREDICTION USING ML ALGORITHMS

BHAVANS VIVEKANANDA COLLEGE

Group-11

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Abstract

This project seeks to create a predictive model for estimating medical insurance premiums based on factors like age, BMI, smoking status, and region.

Utilizing machine learning, the model aids insurance companies in determining fair premiums and helps consumers understand the financial effects of their health choices, promoting transparency in healthcare insurance.

Objective

To develop a strong machine learning framework to predict medical insurance premiums using health and demographic data for fair, data-driven calculations.

CONTENT

Introduction

Medical insurance is vital for financial security, covering healthcare costs. As medical expenses rise, accurately predicting insurance premiums is crucial for affordability and transparency for both insurers and policyholders.

Advancements in data analytics and machine learning are transforming healthcare by enabling insurance providers to predict premiums based on health and demographic factors. This allows for fair, personalized premiums and helps customers make informed health and financial choices.

LITERATURE REVIEW

Literature Review - 1

Author(s): Smith & Johnson
Title: Predictive Modeling of Medical Insurance Premiums Using Machine Learning
Published In: Journal of Health Economics, 2021

This study investigates machine learning models for predicting medical insurance premiums. The authors evaluated algorithms, including linear regression, decision trees, and deep learning, to assess their effectiveness in forecasting costs. It emphasizes the influence of factors like age, medical history, and demographics on premium calculations.

The paper highlights the advantages of machine learning techniques in improving the accuracy of premium predictions over traditional actuarial methods. The authors emphasize that machine learning models can help insurance companies personalize premium structures, thereby enhancing customer satisfaction and operational efficiency

Literature Review - 2

Authors: Satyabrata Dash, Bhawani Sankar Panigrahi, B K Madhavi, Susanta Kumar Sahoo, Vijay Venkata Bhaskar Reddy Sanikomu
Title: A Comparative Analysis of Different Machine Learning Techniques for Medical Insurance Premium Prediction
Published in : International Conference on Advances in Computing , Communication and Applied Informatics (ACCAI),IEEE -2023

To create predictive models, the study combined various regression approaches, including logistic regression, Random Forest Regression, Decision Tree Regression, Gradient Boosting Regression, and linear regression.

The predictive models were highly accurate, with a mean absolute error of less than 5% across all examined samples. The findings have significant implications for both insurers and customers, as accurate premium pricing is essential for insurers to maintain their financial health and offer customers coverage at reasonable prices.

Data Preprocessing

DATA

- **Dataset :** *Our Dataset consists of 7 variables and 1338 records*
- **Source :** https://drive.google.com/drive/folders/1vGSRCnhqSxEH53BgLqhh32F1qNKqfOim?usp=drive_link
- ***About the dataset:***

A medical insurance company aims to deepen its understanding of the determinants impacting individual health insurance costs. They have gathered a dataset featuring diverse individual profiles, encompassing details such as age, gender, BMI, number of children, smoking status, and region.

Age (Age of the person)
Sex (Gender of the person)
BMI (Body Mass Index)
Children (Number of children)
Smoker (smoker or non smoker)
Region
Charges (Insurance price)

- **Data Variables :**

Categorical variables	Continuous variables
smoker	age
region	bmi
sex	children
	charges

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

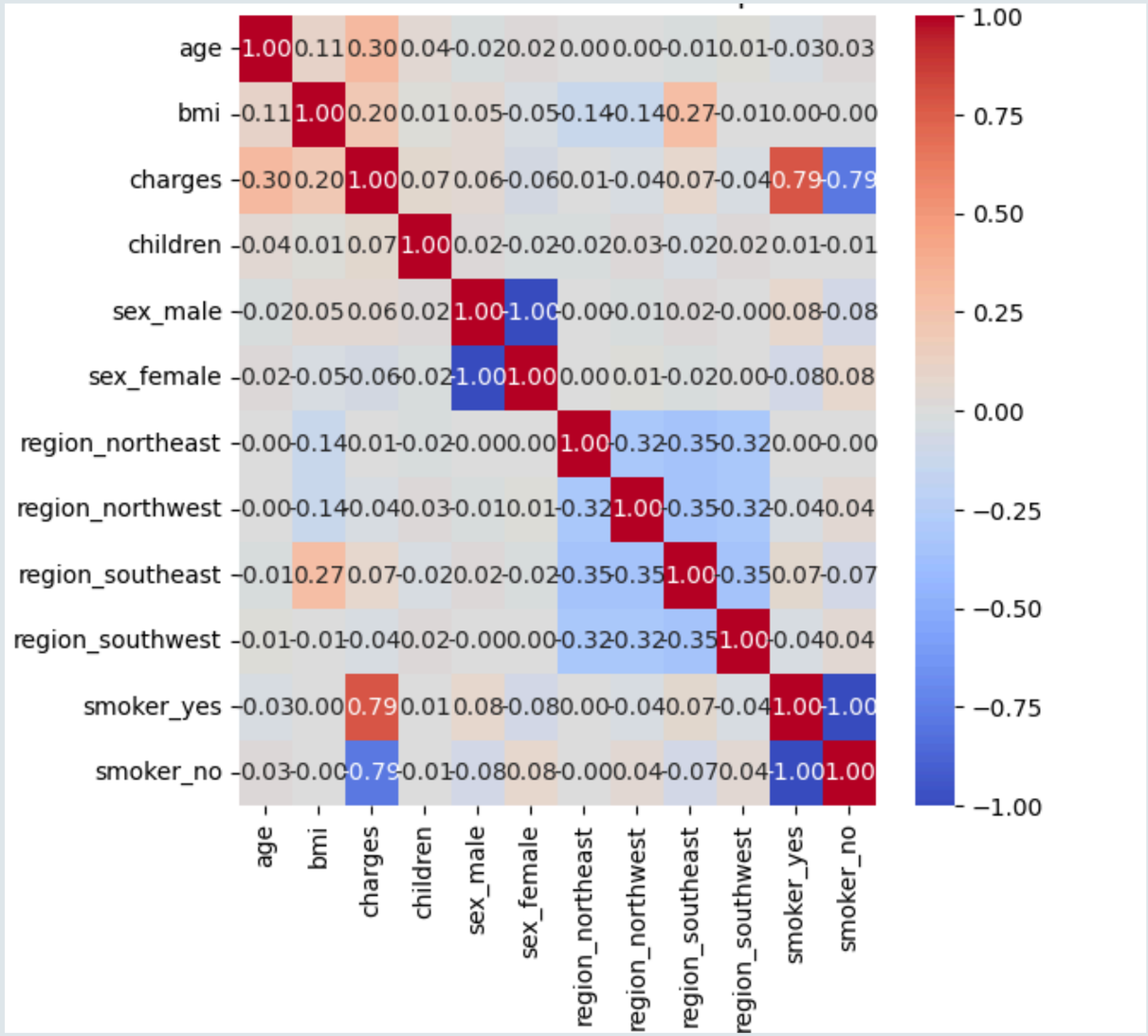
1338 rows × 7 columns

Data Cleaning

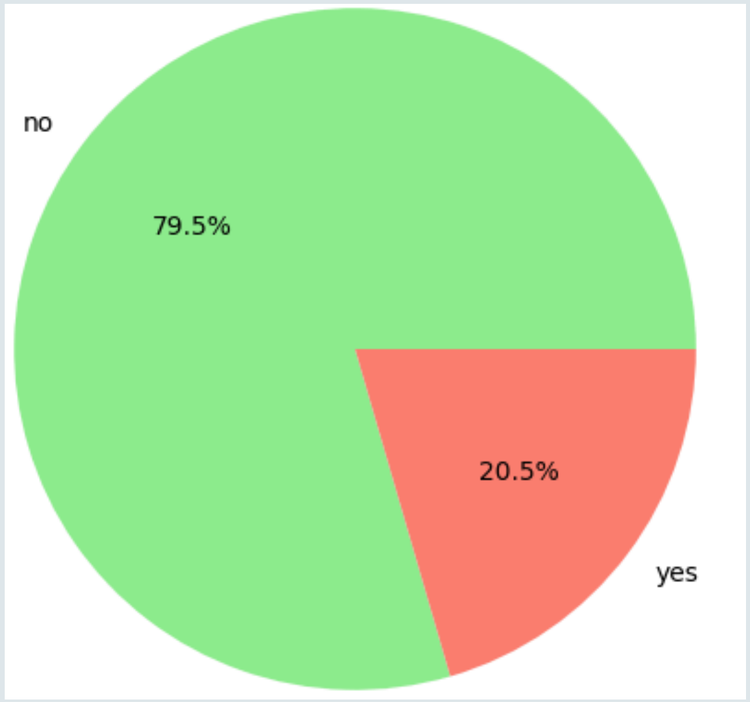
- ***Removed duplicate row from the data.***
- ***Checked for missing and unique values.***
- ***Dummified categorical variables:***
  - ***Sex as sex_male and sex_female.***
  - ***Region as region_northeast, region_northwest, region_southeast, and region_southwest.***
  - ***Smoker column in binary format (0 and 1).***

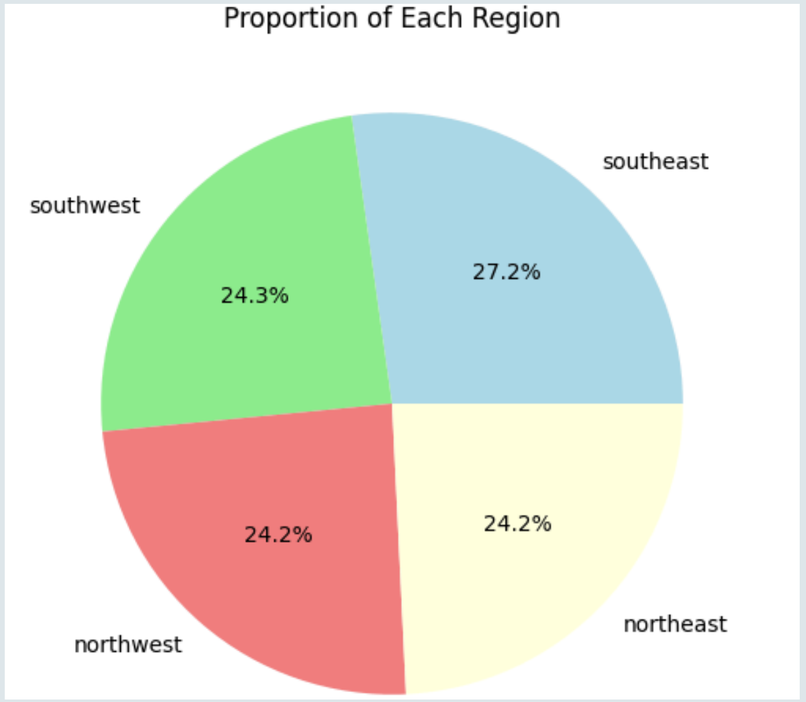
Exploratory Data Analysis

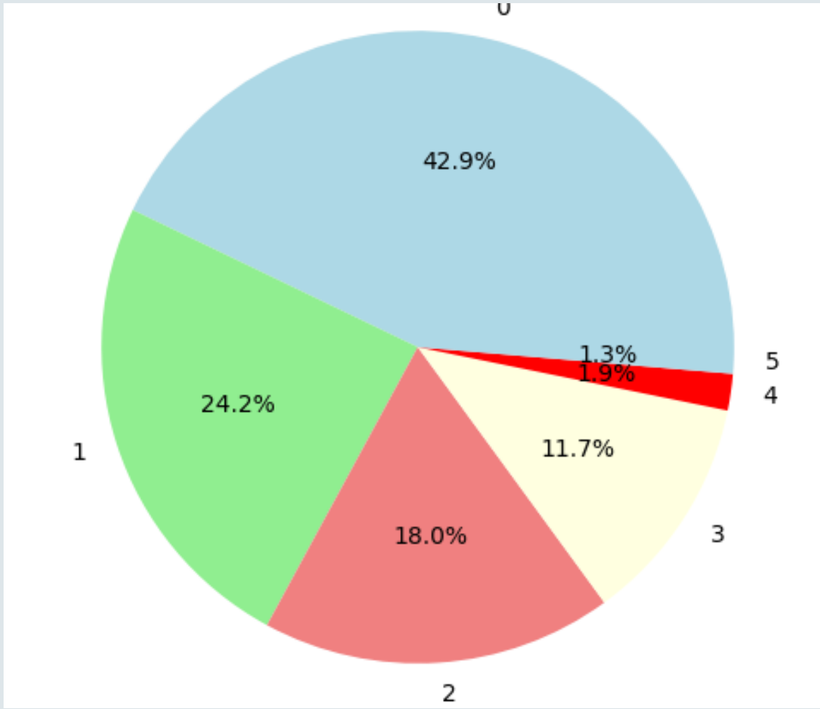
CORRELATION MATRIX



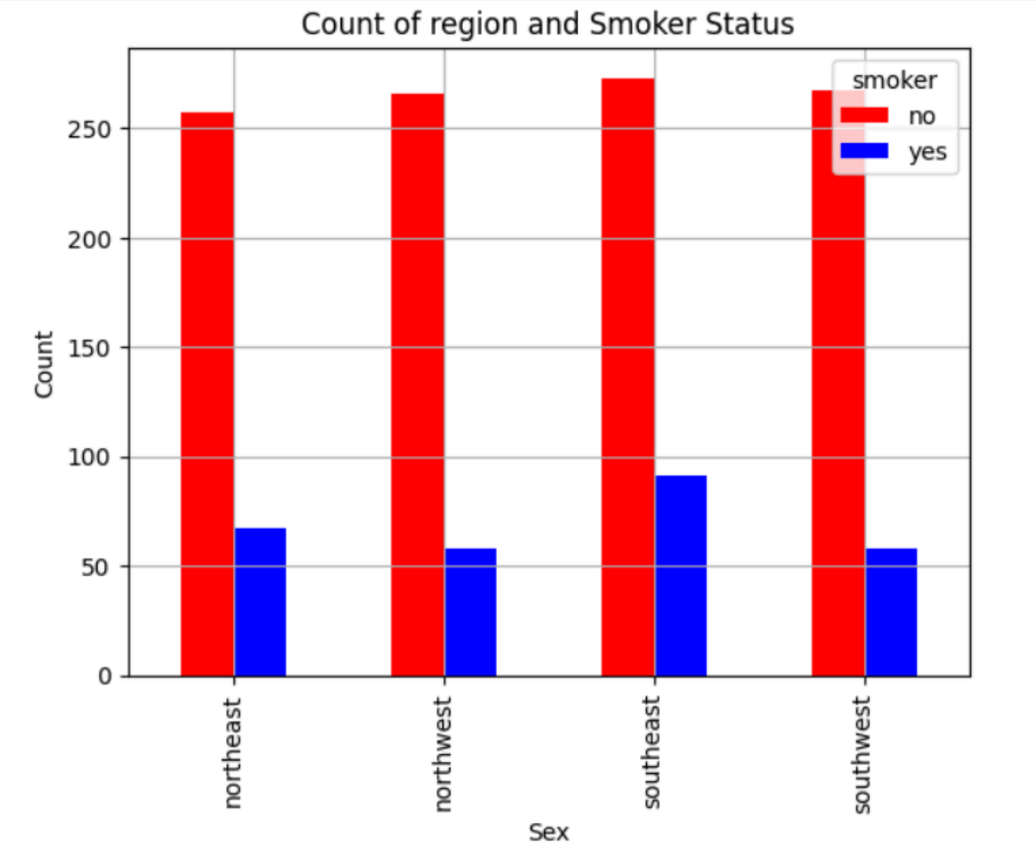
PIE CHART

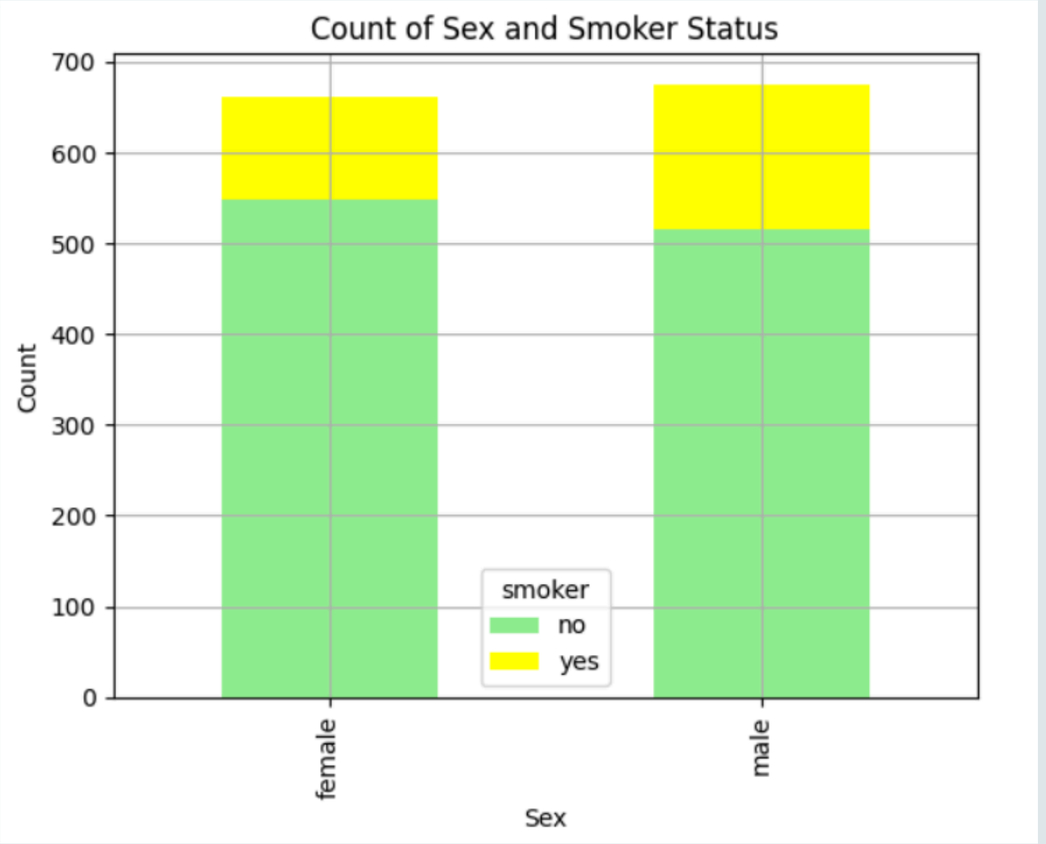

no
79.5%
20.5%
yes


Proportion of Each Region
southeast
southwest
24.3%
27.2%
24.2%
24.2%
northwest
northeast

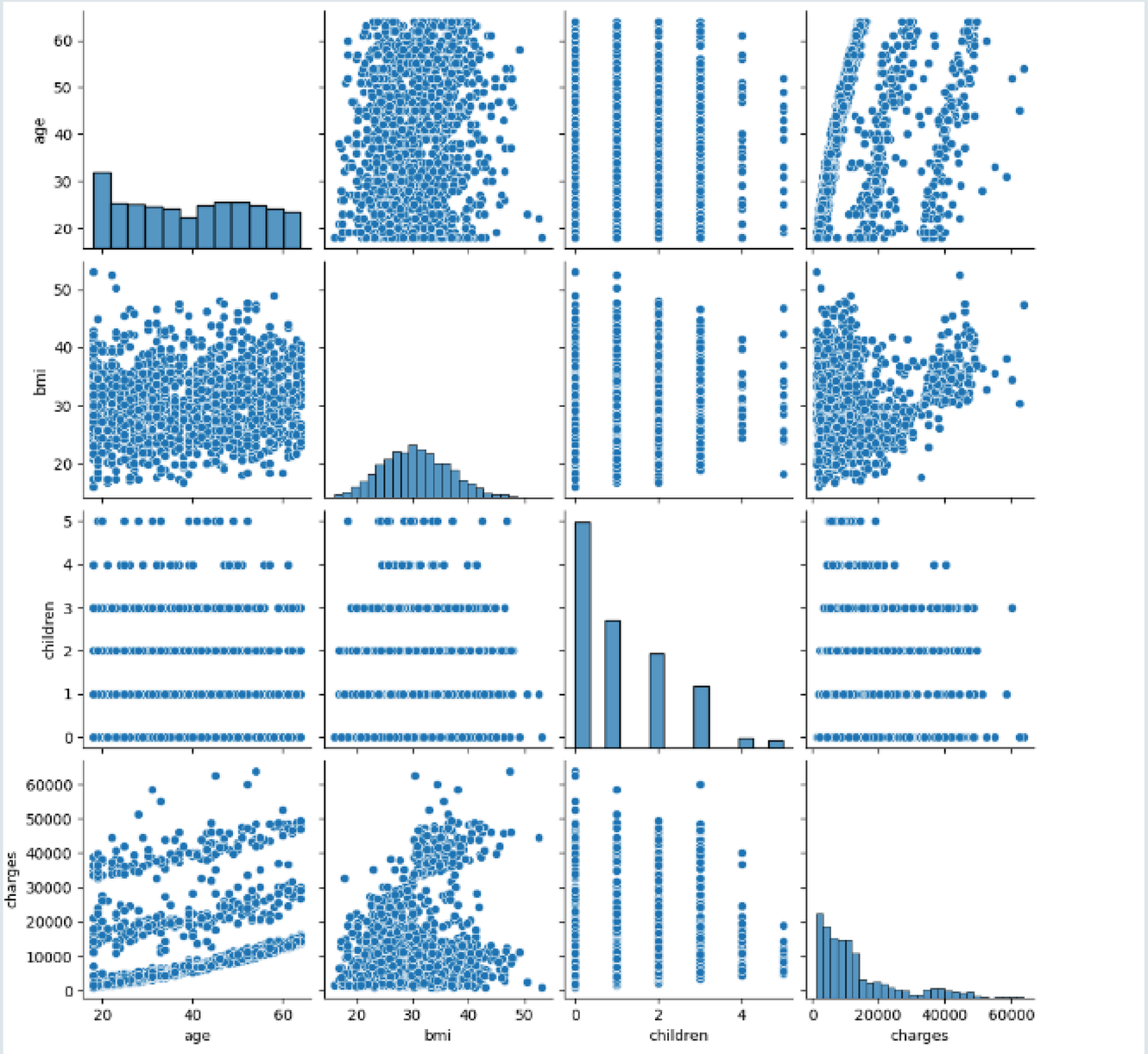

0
42.9%
1.3%
1.9%
5
4
24.2%
1
11.7%
18.0%
3
2

BAR PLOT

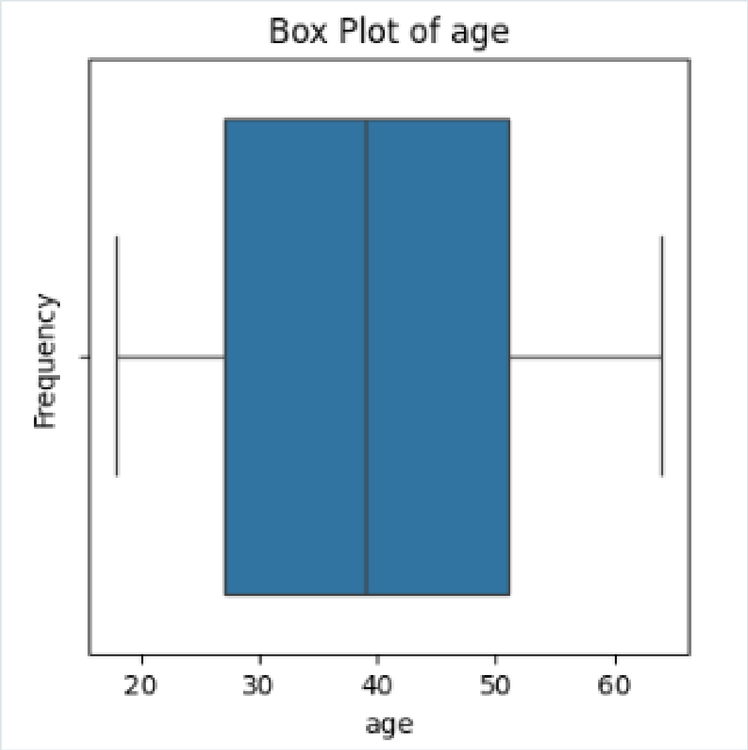

Count of region and Smoker Status
smoker
no
yes
Count
0
50
100
150
200
250
northeast
northwest
southeast
southwest
Sex

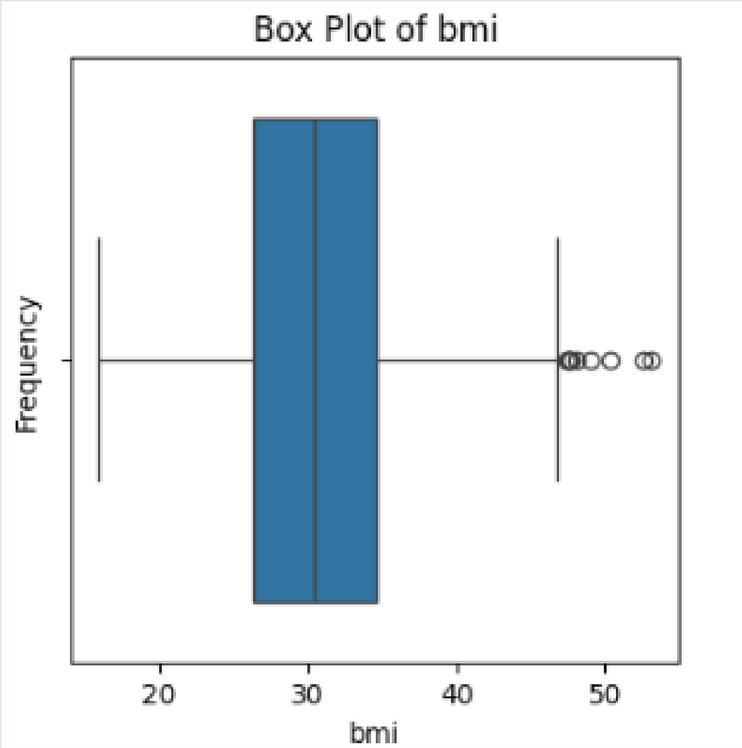

Count of Sex and Smoker Status
Count
0
100
200
300
400
500
600
700
smoker
no
yes
female
male
Sex

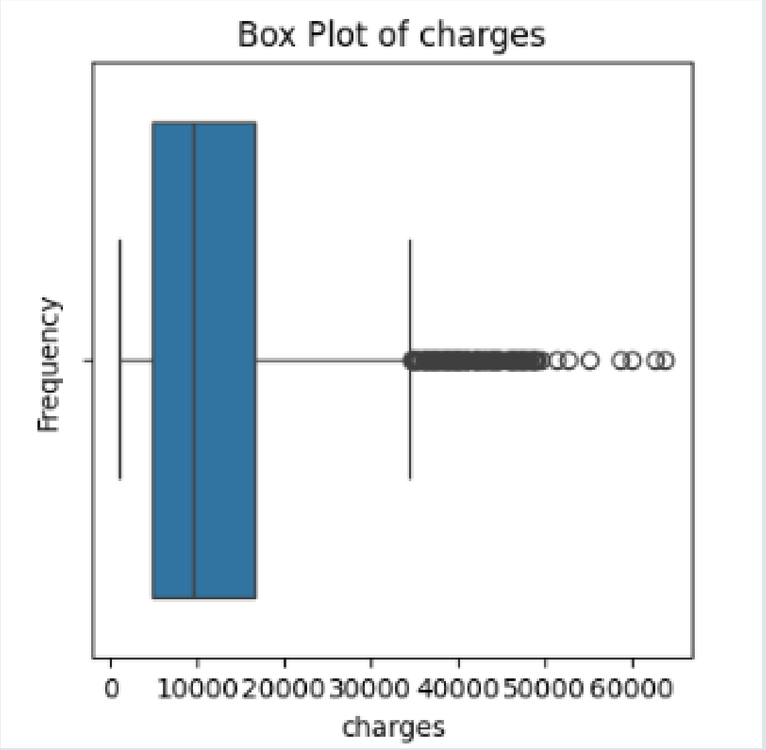
PAIR PLOT


age
bmi
children
charges
20
40
60
20
30
40
50
0
2
4
0
20000
40000
60000
0
10000
20000
30000
40000
50000
60000

BOX PLOT


Box Plot of age
Frequency
20
30
40
50
60
age


Box Plot of bmi
Frequency
20
30
40
50
bmi


Box Plot of charges
Frequency
0
10000
20000
30000
40000
50000
60000
charges

Multicollinearity Check

Variables with the greatest variance inflation factor (VIF > 2) were removed

	variables	VIF
0	age	7.7
1	bmi	11.4
2	children	1.8
3	sex_male	2.0
4	smoker_yes	1.3
5	region_northwest	1.9
6	region_southeast	2.3
7	region_southwest	2.0

	variables	VIF
0	age	3.9
1	children	1.8
2	sex_male	1.9
3	smoker_yes	1.2
4	region_northwest	1.7
5	region_southeast	1.8
6	region_southwest	1.7

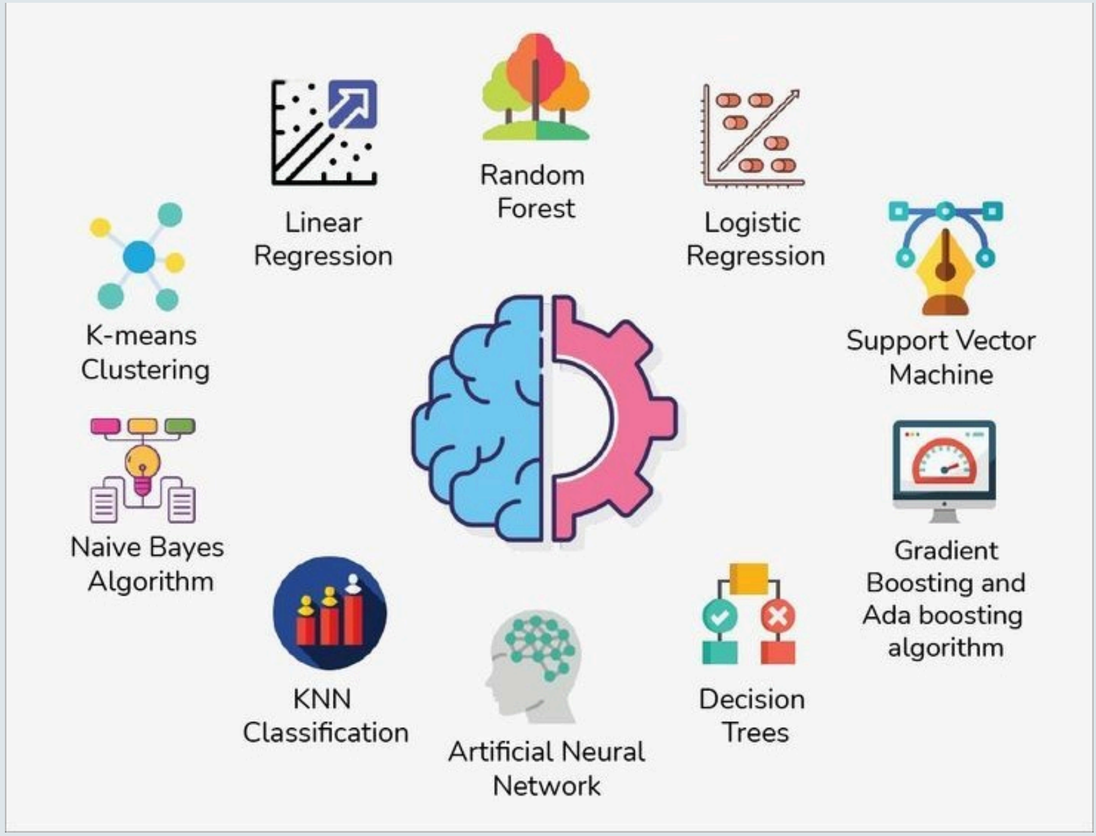
bmi was removed

	variables	VIF
0	children	1.6
1	sex_male	1.7
2	smoker_yes	1.2
3	region_northwest	1.3
4	region_southeast	1.4
5	region_southwest	1.3

age was removed

ML Algorithms

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



80-20

Algorithms	Model-1 (r2 score)	Model-2 (r2 score)	Model-1 (MAE)	Model-2 (MAE)
Linear Regression	0.750	0.647	3924.64	5184.0847
KNN	0.164	0.586	7452.49	5464.843
Decision Tree	0.632	0.635	3251.76	5126.588
Random Forest	0.829	0.638	2631.44	5080.645
XGBoost	0.794	0.638	3030.09	5080.645
ADABoost	0.820	0.640	3928.00	5080.65
SVM	-0.037	-0.037	7409.86	7450.926

Model 1: With all features | Model 2: After removing multi-collinear variables

r2 score- represents goodness of fit of a model

MAE- absolute difference b/w predicted and actual values

75-25

Algorithms	Model-1 (r2 score)	Model-2 (r2 score)	Model-1 (MAE)	Model-2 (MAE)
Linear Regression	0.720	0.811	4151.721	3954.255
KNN	0.160	0.546	7430.074	5628.108
Decision Tree	0.628	0.606	3216.599	5346.590
Random Forest	0.816	0.592	2769.744	5367.993
XGBoost	0.793	0.592	3010.910	5367.993
ADABoost	0.810	0.59	3954.25	5367.99
SVM	-0.046	-0.045	7420.140	7454.331

Model 1: With all features | Model 2: After removing multi-collinear variables

r2 score- represents goodness of fit of a model

MAE- absolute difference b/w predicted and actual values

70-30

Algorithms	Model-1 (r2 score)	Model-2 (r2 score)	Model-1 (MAE)	Model-2 (MAE)
Linear Regression	0.733	0.811	4207.80	3987.05
KNN	0.125	0.559	7821.08	5723.50
Decision Tree	0.656	0.615	3296.05	5388.69
Random Forest	0.825	0.606	2817.397	5417.70
XGBoost	0.815	0.607	2995.79	5417.70
ADABoost	0.810	0.610	3987.05	5417.70
SVM	-0.056	-0.055	7753.014	7781.744

Model 1: With all features | Model 2: After removing multi-collinear variables

r2 score- represents goodness of fit of a model

MAE- absolute difference b/w predicted and actual values

60-40

Algorithms	Model-1 (r2 score)	Model-2 (r2 score)	Model-1 (MAE)	Model-2 (MAE)
Linear Regression	0.720	0.799	4274.29	4148.44
KNN	0.078	0.493	7949.71	6018.83
Decision Tree	0.622	0.573	3523.32	5583.30
Random Forest	0.819	0.573	2782.36	5583.30
XGBoost	0.785	0.573	3034.98	5583.31
ADABoost	0.800	0.570	4148.44	5583.31
SVM	-0.054	-0.053	7754.86	7778.46

Model 1: With all features | Model 2: After removing multi-collinear variables

r2 score- represents goodness of fit of a model

MAE- absolute difference b/w predicted and actual values

Algorithms Comparison :

80-20 Model-1

Algorithms	r2 score	MAE
Linear Regression	0.750	3924.64
K- nearest numbers	0.164	7452.49
Decision tree	0.632	3251.76
Random forest	0.829	2631.44
XG Boosting	0.794	3030.09
ADA Boosting	0.820	3928.00
SVM	-0.037	7409.86

75-25 Model -2

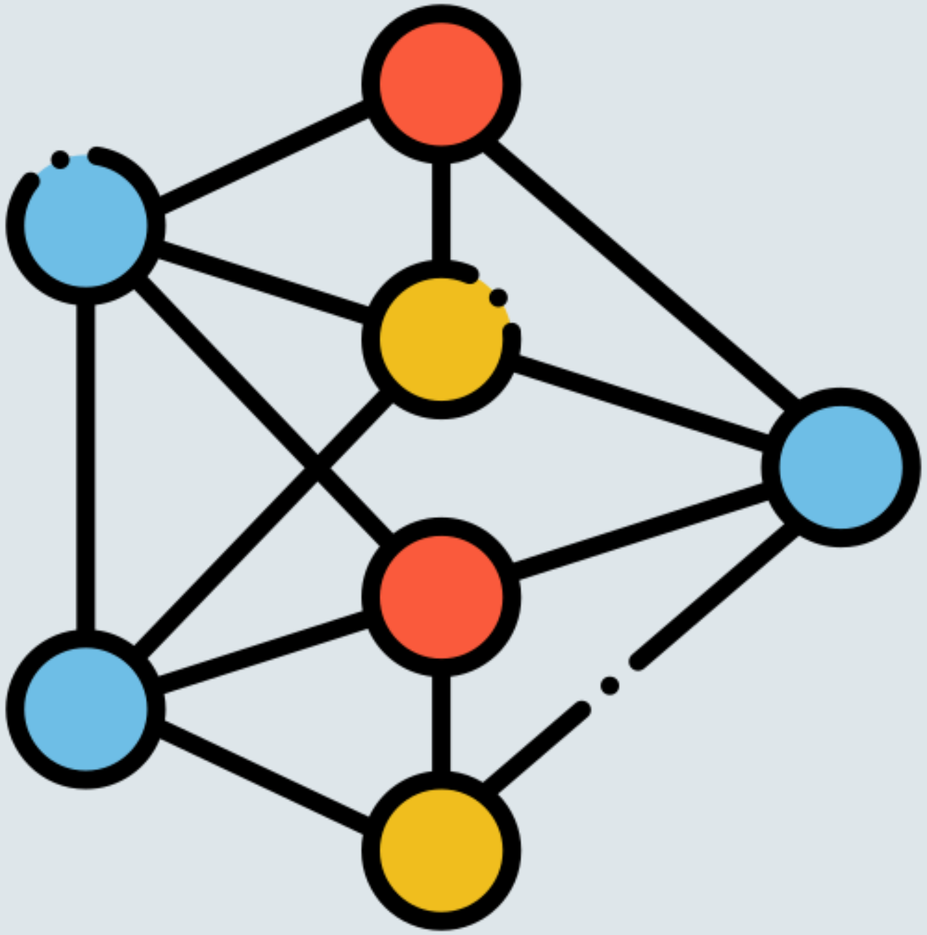
Algorithms	r2 score	MAE
Linear Regression	0.811	3954.26
K- nearest numbers	0.546	5628.11
Decision tree	0.606	5346.59
Random forest	0.592	5367.993
XG Boosting	0.592	5367.993
ADA Boosting	0.590	5367.99
SVM	-0.045	7454.33

r2 score- represents goodness of fit of a model

MAE- absolute difference b/w predicted and actual values

Model 1: With all features | Model 2: After removing multi-collinear variables

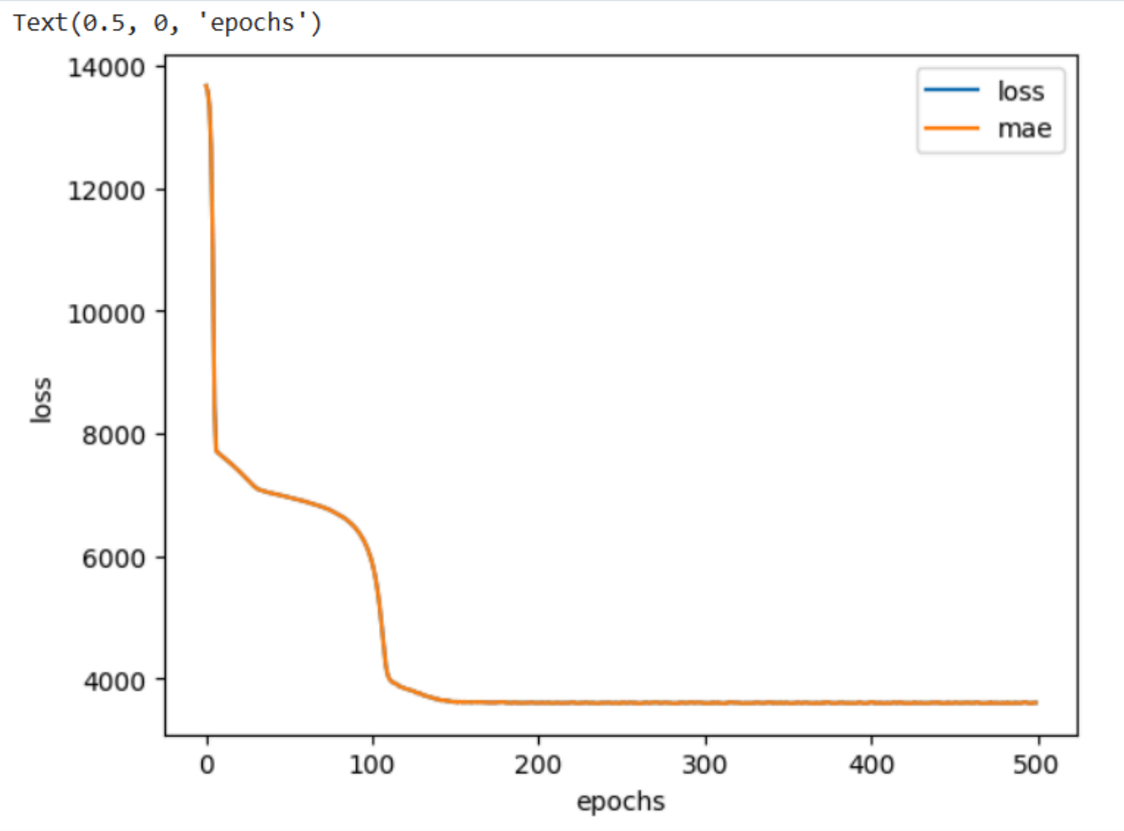
Neural Network



Neural Network

Train-Test	Architecture	Optimizer	Epochs	MAE
60-40	16-8-6-4-2-1	Adam	300	4131.75
60-40	16-8-6-4-2-1	Adam	600	2818.14
70-30	16-8-6-4-2-1	Adam	300	3596.79
70-30	16-8-6-4-2-1	Adam	250	2714.46
75-25	16-8-6-4-2-1	Adam	300	3516.62
75-25	16-8-6-4-2-1	Adam	500	2678.48
80-20	16-8-6-4-2-1	Adam	300	3483.99
80-20	16-8-6-4-2-1	Adam	400	2702.36

Neural Network plot for Observation



Train test split	**75-25**
Architecture	**16-8-6-4-2-1**
Optimizer	**Adam**
Epochs	**500**

SUMMARY

The research aims to identify factors increasing insurance costs to aid in pricing and risk assessment.

In Model 1, Random Forest outperformed with an r^2 score of 0.829 and MAE of 2631.44. Model 2, using Linear Regression, had an r^2 score of 0.811 and MAE of 3954.26.

Thus, Random Forest is the best model for forecasting medical insurance premiums, utilizing an 80:20 train split ratio.

KEY INSIGHTS

- Health Factors
- Unhealthy lifestyle
- Regional Variation
- Cost for family coverage
- Healthier behaviors

FUTURE SCOPE

- custom Premiums
- Improved Accuracy
- Adaptive Pricing
- Transparent Models

WORK DISTRIBUTION

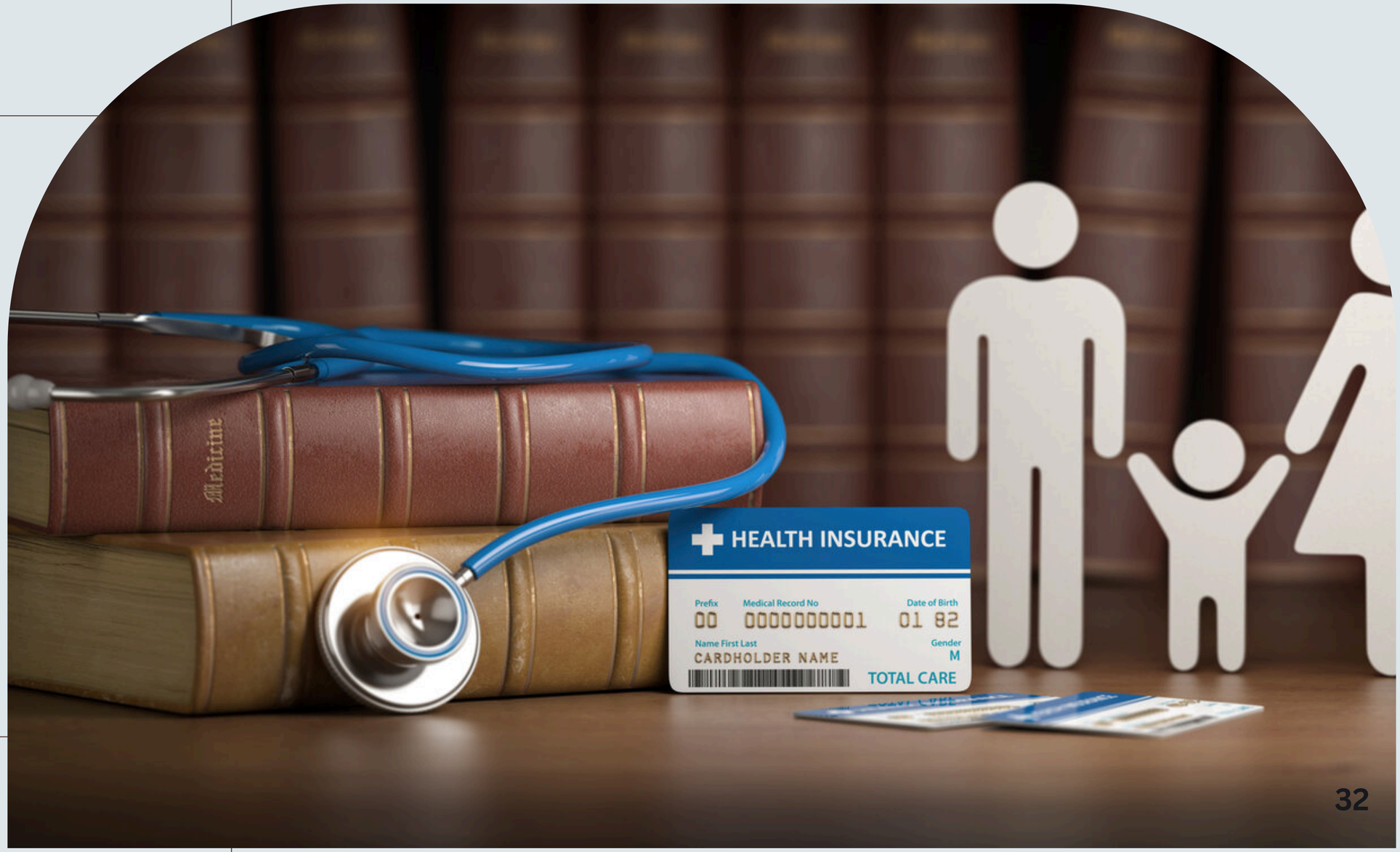
Team member 1 Rishi Bharadwaj	Collect information about medical insurance premium & Literature Review
Team member 2 Ajay kumar	Data Preprocessing
Team member 3 Jai kumar	Exploratory Data Analysis
Team member 4 N.Aishwarya	Implement Machine Learning Algorithms

Colab Notebook

Thank You

N.AISHWARYA
RISHI BHARADWAJ
AJAY KUMAR
JAI KUMAR

APPENDIX


Medicine
HEALTH INSURANCE
Prefix
00
Medical Record No
0000000001
Date of Birth
01 82
Name First Last
CARDHOLDER NAME
Gender
M
TOTAL CARE

Loading the Dataset

```
data= pd.read_csv('Insurance.csv')
data
```

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

Null Values

```
[ ] data.isna().sum()
```

	0
age	0
sex	0
bmi	0
children	0
smoker	0
region	0
charges	0

dtype: int64

Checking for the data type

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1338 non-null   int64  
 1   sex       1338 non-null   object 
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64  
 4   smoker    1338 non-null   object 
 5   region    1338 non-null   object 
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

checking unique Values

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

```
[19 18 28 33 32 31 46 37 60 25 62 23 56 27 52 30 34 59 63 55 22 26 35 24
 41 38 36 21 48 40 58 53 43 64 20 61 44 57 29 45 54 49 47 51 42 50 39]
age
18    69
19    68
50    29
51    29
47    29
46    29
45    29
20    29
48    29
52    29
22    28
49    28
54    28
53    28
21    28
26    28
24    28
25    28
28    28
27    28
23    28
43    27
29    27
```

```
data.describe()
```

	age	bmi	children	charges
count	1337.000000	1337.000000	1337.000000	1337.000000
mean	39.222139	30.663452	1.095737	13279.121487
std	14.044333	6.100468	1.205571	12110.359656
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.290000	0.000000	4746.344000
50%	39.000000	30.400000	1.000000	9386.161300
75%	51.000000	34.700000	2.000000	16657.717450
max	64.000000	53.130000	5.000000	63770.428010

Replacing Duplicate Rows:

```
[147] num_duplicates = data.duplicated().sum()
      print(f"Number of duplicate rows: {num_duplicates}")
```

```
Number of duplicate rows: 1
```

```
[148] data[data.duplicated()]
```

	age	sex	bmi	children	smoker	region	charges
581	19	male	30.59	0	no	northwest	1639.5631

```
data_cleaned=data.drop_duplicates()
```

```
[150] data.drop_duplicates(inplace=True)
```

```
[151] num_duplicates = data.duplicated().sum()
      print(f"Number of duplicate rows: {num_duplicates}")
```

```
Number of duplicate rows: 0
```

Dividing the data set

```
X=data.drop(['charges'],axis=1)

print(X)
y = data['charges']
print(y)
```

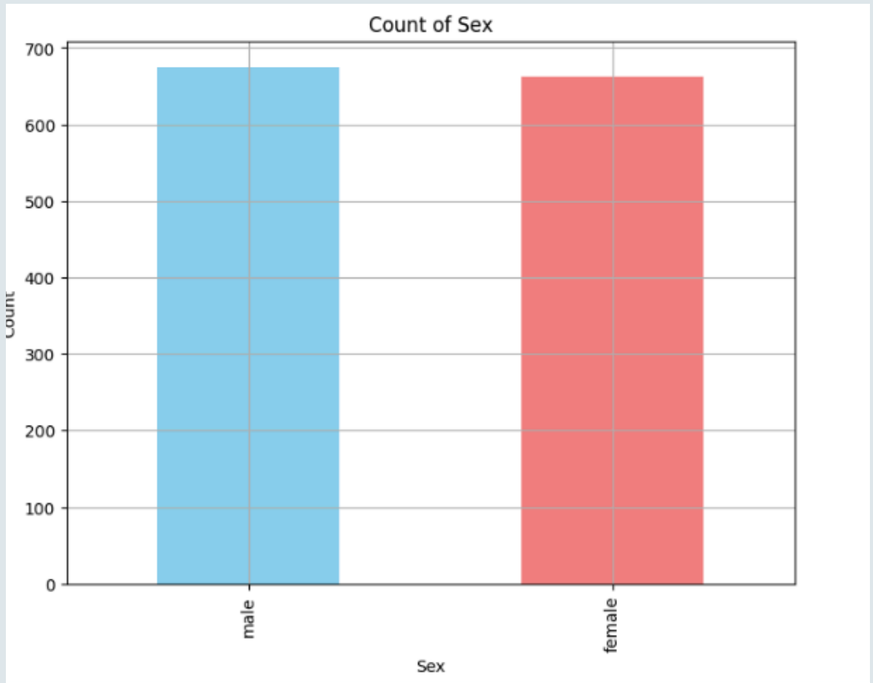
```
      age     sex     bmi  children smoker     region
0      19  female  27.900         0    yes  southwest
1      18    male  33.770         1     no  southeast
2      28    male  33.000         3     no  southeast
3      33    male  22.705         0     no  northwest
4      32    male  28.880         0     no  northwest
...   ...     ...     ...       ...    ...        ...
1333   50    male  30.970         3     no  northwest
1334   18  female  31.920         0     no  northeast
1335   18  female  36.850         0     no  southeast
1336   21  female  25.800         0     no  southwest
1337   61  female  29.070         0    yes  northwest

[1337 rows x 6 columns]
0       16884.92400
1        1725.55230
2        4449.46200
3       21984.47061
4        3866.85520
           ...
1333    10600.54830
1334     2205.98080
1335     1629.83350
1336     2007.94500
1337    29141.36030
Name: charges, Length: 1337, dtype: float64
```

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

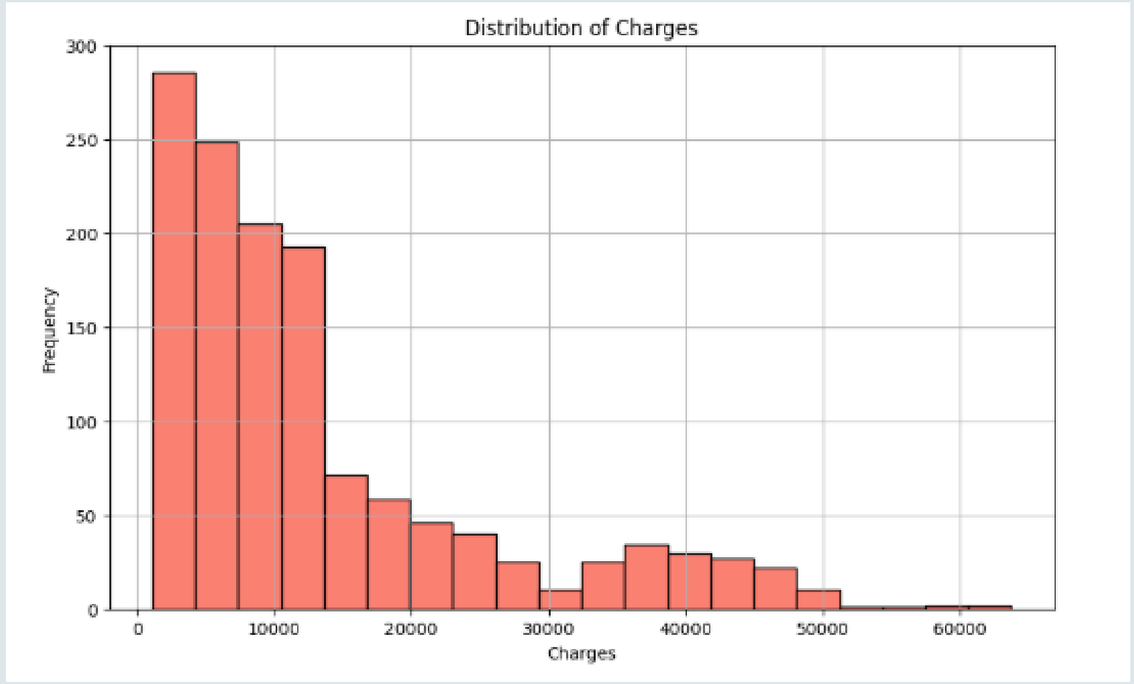
```
       age     bmi  children  sex_male  smoker_yes  region_northwest  \
0       19  27.900         0         0           1                 0
1       18  33.770         1         1           0                 0
2       28  33.000         3         1           0                 0
3       33  22.705         0         1           0                 1
4       32  28.880         0         1           0                 1
...    ...     ...       ...       ...         ...               ...
1333    50  30.970         3         1           0                 1
1334    18  31.920         0         0           0                 0
1335    18  36.850         0         0           0                 0
1336    21  25.800         0         0           0                 0
1337    61  29.070         0         0           1                 1

      region_southeast  region_southwest
0                    0                 1
1                    1                 0
2                    1                 0
3                    0                 0
4                    0                 0
...                ...               ...
1333                 0                 0
1334                 0                 0
1335                 1                 0
1336                 0                 1
1337                 0                 0

[1337 rows x 8 columns]
```

EDA

```
# Bar Plot for Sex
plt.figure(figsize=(8, 6))
data['sex'].value_counts().plot(kind='bar', color=['skyblue', 'lightcoral'])
plt.title('Count of Sex')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.grid(True)
plt.show()
```




```
# Histogram for Charges
plt.figure(figsize=(10, 6))
plt.hist(data['charges'], bins=20, color='salmon', edgecolor='black')
plt.title('Distribution of Charges')
plt.xlabel('Charges')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



Linear Regression

linear regression

```
[ ]  import pandas as pd
     import seaborn as sns
     import statsmodels.formula.api as smf
     from sklearn.linear_model import LinearRegression
     from sklearn import metrics
     from sklearn.model_selection import train_test_split
     import numpy as np

     # allow plots to appear directly in the notebook
     %matplotlib inline
```

```
[ ] 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)
```

```
[ ] #X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.20, train_size=0.80)
    lm2 = LinearRegression()
    lm2.fit(X_train1, y_train1)
    y_pred1 = lm2.predict(X_test1)
    print(np.sqrt(metrics.mean_squared_error(y_test1, y_pred1)))
    print((metrics.r2_score(y_test1, y_pred1)))
    print((metrics.mean_squared_error(y_test1, y_pred1)))
    print((metrics.mean_absolute_error(y_test1,y_pred1)))
```

```
5689.30829118911
0.7497814388540698
32368228.832193147
3924.6360380217848
```

```
[ ] #X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.25, train_size=0.75)
    lm2 = LinearRegression()
    lm2.fit(X_train2, y_train2)
    y_pred2 = lm2.predict(X_test2)
    print(np.sqrt(metrics.mean_squared_error(y_test2, y_pred2)))
    print((metrics.r2_score(y_test2, y_pred2)))
    print((metrics.mean_squared_error(y_test2, y_pred2)))
    print((metrics.mean_absolute_error(y_test2,y_pred2)))
```

```
5992.503495873213
0.7200784016998649
35910098.148052685
4151.7215200297605
```

```
#X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.30, train_size=0.70)
lm2 = LinearRegression()
lm2.fit(X_train3, y_train3)
y_pred3 = lm2.predict(X_test3)
print(np.sqrt(metrics.mean_squared_error(y_test3, y_pred3)))
print((metrics.r2_score(y_test3, y_pred3)))
print((metrics.mean_squared_error(y_test3, y_pred3)))
print((metrics.mean_absolute_error(y_test3,y_pred3)))
```

```
6043.804783305154
0.733326836658079
36527576.25870226
4207.799065841042
```

```
[ ] #X_train4, X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=0.40, train_size=0.60)
    lm2 = LinearRegression()
    lm2.fit(X_train4, y_train4)
    y_pred4 = lm2.predict(X_test4)
    print(np.sqrt(metrics.mean_squared_error(y_test4, y_pred4)))
    print((metrics.r2_score(y_test4, y_pred4)))
    print((metrics.mean_squared_error(y_test4, y_pred4)))
    print((metrics.mean_absolute_error(y_test4,y_pred4)))
```

```
6119.716442233048
0.7196282704835242
37450929.333337516
4274.286033572359
```

KNN

KNN

```
[ ] from sklearn.neighbors import KNeighborsRegressor
```

80-20

```
[ ] model=KNeighborsRegressor(n_neighbors=5)
    model.fit(X_train1,y_train1)
```

```
KNeighborsRegressor()
```

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

```
[16820.517086  18192.71901   10971.66693   10336.797548  18179.196618
  7182.362988   9037.28354   21986.61754   14312.35928   21926.88825
 18610.132964   6827.35397   15732.260012   8312.86098    1372.48868
 16637.80268    7331.625542  21151.78429   19167.73447   25937.297052
  4004.50979   29370.532788  18494.878844  14322.47749    7459.11708
 22671.025772  15867.571668  19609.90401    4940.15816    3823.70073
 24846.90293    3985.0733    10633.271286  25803.835716  12007.3807
  1561.134     31942.651644  19261.559494  14222.811394  15832.178256
 14240.17668    8291.637436  10355.2936    17902.479582  36689.978988
 12689.87445   32336.702692   7685.46873   11912.66588   11544.03559
 22747.741916  11633.36595   19818.911902  13898.827284  14108.608092
  6936.701148   7810.67289   11962.15698   11237.86892   33916.08512
 13534.861874  21308.474918  11393.717402  10578.2225     6427.785372
  7101.239332   2156.71866   21653.67231   13513.176664  15605.871344
 26177.87359    5929.00123    4934.41103    4167.00803   13000.478922
  4650.76106    9997.422312   6877.81562    6501.23893   18299.347248
 18274.134178  16558.12366   19623.184282  16619.632168  25804.07994
  6710.0803738  2775.06353    3171.43892   18822.322678  16387.936366
  5755.936754  12949.74305   16000.68619   15309.15557   10937.09363
 14278.12161    9766.20053   14581.99648    5042.35943   10495.71356
 18106.21812    5752.73892    6975.90214   14646.60893    4218.8003
 10710.477126  16950.269802  24713.328932  10106.7509     1687.57275
 14745.62035    6611.43847   12034.234918   8934.03378    7182.362988
 16824.57583   16756.68211   14950.1757     3952.04786    9459.23189
 28327.81532   12491.291998  25124.045864  15900.8316    10714.24287
 20068.935304  14371.02625   11995.21429   10833.60754   13390.4994
  3259.32124   12211.85262   12598.010172  10847.44178   15548.588846
  7372.140334  20862.72311    4087.79068   24304.27708   10336.034596
  5038.45901   14387.52593   10013.832312  10834.69038    7620.746626
 16744.98065    8217.60013   14390.92143    8935.52044   17659.44979
 21079.255988  13270.34132    1793.87728    2872.04059   25526.389972
  4441.25629   10672.46854    7379.43796    9968.37845   16522.75156
 22525.846804   1468.52017    1719.60885   14407.842862  12908.857306
 13254.19857    8469.99118    2204.13404    6854.73571   24152.910392
  8199.23485   14537.41461   16690.005556 ]
```

```
[ ] df=pd.DataFrame({'Predicted':y_pred1,'Actual':y_test1})
    print(df)
```

```
         Predicted       Actual
629   16820.517086  42983.45850
1087  18192.719010  11353.22760
283   10971.666930  11879.10405
790   10336.797548   5662.22500
594   18179.196618   5709.16440
...            ...          ...
1164   6854.735710   7153.55390
962   24152.910392  14474.67500
1158   8199.234850   2459.72010
1241  14537.414610  49577.66240
216   16690.005556  10355.64100

[268 rows x 2 columns]
```

```
[ ] from sklearn.metrics import r2_score
    r2_score(y_test1,y_pred1)
```

```
0.16403910584448667
```

```
from sklearn import metrics
metrics.mean_absolute_error(y_test1,y_pred1)
```

```
7452.4967916171645
```

SVM

Support Vector Machine

```
[ ] from sklearn.svm import SVR
```

80-20

```
[ ] model = SVR(kernel='rbf')
    model.fit(X_train1, y_train1)
```

```
SVR()
```

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

```
[9557.36283478 9623.37438268 9614.44584998 9530.91191586 9540.96051076
 9457.47775906 9449.81471916 9610.52989882 9617.95461902 9594.99472021
 9631.55493168 9516.48953317 9602.87109233 9556.90183299 9441.00932203
 9642.67591167 9490.8915501  9485.2060371  9624.30429591 9646.98682435
 9487.23023278 9637.26239626 9563.85196072 9548.76350184 9474.4928276
 9551.39095643 9546.42669573 9632.93485303 9496.23319828 9476.96033165
 9585.23060459 9481.64291506 9468.55776567 9589.57118653 9439.25031433
 9445.95335334 9481.06715618 9635.78961276 9511.40856751 9536.00137726
 9598.77461464 9443.92340724 9586.37287922 9582.55780875 9637.67808823
 9634.58492885 9595.07951433 9505.89551774 9584.81594366 9618.41263365
 9639.72670301 9613.28113717 9613.35306657 9501.47714703 9575.82243821
 9454.22477419 9450.77474553 9628.31783696 9496.41608895 9650.26398852
 9605.42552873 9619.08769011 9445.9204455  9468.60277389 9465.43394305
 9470.7373097  9449.13123413 9567.45438515 9598.66748635 9632.57322959
 9515.79041334 9447.51130949 9440.54868664 9442.45437821 9584.61907926
 9482.90938768 9440.97865694 9481.50896364 9472.53220043 9442.6841774
 9452.58321084 9507.77948979 9621.8676755  9577.39541026 9615.21398906
 9640.3134292  9634.50921891 9442.93959338 9453.58404602 9605.5826111
 9481.66488404 9614.56525966 9487.17030438 9522.20191096 9455.61261299
 9559.51566023 9440.62730292 9442.79949747 9609.51664705 9461.29176286
 9496.23594536 9566.46531159 9449.515595   9535.24571152 9647.2518449
 9443.21697585 9650.17052858 9601.53243202]
```

```
[ ] df = pd.DataFrame({'Predicted':y_pred1,'Actual':y_test1})
    print(df)
```

```
      Predicted       Actual
629   9557.362835  42983.45850
1087  9623.374383  11353.22760
283   9614.445850  11879.10405
790   9530.911915   5662.22500
594   9540.960511   5709.16440
...           ...          ...
1164  9535.245712   7153.55390
962   9647.251845  14474.67500
1158  9443.216976   2459.72010
1241  9650.170529  49577.66240
216   9601.532432  10355.64100

[268 rows x 2 columns]
```

```
[ ] from sklearn.metrics import r2_score
    r2_score(y_test1,y_pred1)
```

```
-0.037880557580482144
```

```
[ ] from sklearn import metrics
    metrics.mean_absolute_error(y_test1,y_pred1)
```

```
7409.859428577142
```

Decision tree regressor

DECISION TREE

```
[ ] import pandas as pd
    from sklearn.tree import DecisionTreeRegressor
    from sklearn.model_selection import train_test_split
    from sklearn import metrics
```

80-20

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

```
DecisionTreeRegressor()
```

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

```
[43896.3763  11743.9341  10825.2537   5649.715    5699.8375   3213.62205
  1532.4697  25517.11363 12222.8983  24667.419   13204.28565 11884.04858
  9863.4718   9715.841    1137.011   13457.9608   4500.33925 37607.5277
 33471.97189 15612.19335  4137.5227  13470.86    17929.30337  7726.854
  4922.9159  48885.13561  8410.04685 48517.56315  5002.7827   2483.736
  9549.5651   3736.4647   4949.7587  30284.64294  1621.8827   2438.0552
 36197.699   13451.122    5124.1887  14478.33015 24667.419    2103.08
 10702.6424  40720.55105 13470.86    12730.9996  10848.1343   5266.3656
  9264.797   11345.519   13143.33665 12096.6512   9850.432   24915.04626
 21232.18226  2395.17155  2850.68375 11842.62375  5926.846   14394.5579
  9724.53    24227.33724 16586.49771  5209.57885  3956.07145  4949.7587
  1880.487   41661.602   10197.7722  28923.13692 39047.285    4005.4225
```

```
  3277.161   26467.09737 63770.42801  5209.57885 26926.5144   7729.64575
 12269.68865  4005.4225  13405.3903   3490.5491   5246.047    8827.2099
 16884.924   33732.6867  26018.95052 39556.4945   1628.4709   9866.30485
  6986.697    5327.40025  1909.52745  4934.705   40904.1995   1728.897
  2020.5523   4402.233   27117.99378 10043.249   44260.7499  13143.33665
 12957.118    1744.465    2352.96845 10461.9794   4237.12655 10226.2842
  4074.4537   7986.47525  2020.5523  39556.4945   1621.8827   1628.4709
 10825.2537   2473.3341   6933.24225  8823.98575  2775.19215  6770.1925
 31620.00106  1877.9294  47496.49445  9863.4718 ]
```

```
[ ] print("R-squared:", metrics.r2_score(y_test1, y_pred1))
```

```
R-squared: 0.6346858489893212
```

```
[ ] print("Mean Squared Error:", metrics.mean_squared_error(y_test1, y_pred1))
```

```
Mean Squared Error: 47256973.988655426
```

```
[ ] print("Mean Absolute Error:", metrics.mean_absolute_error(y_test1, y_pred1))
```

```
Mean Absolute Error: 3225.587812649254
```

Random Forest Regressor

RANDOM FOREST

```
[ ] from sklearn.ensemble import RandomForestRegressor
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import classification_report, confusion_matrix
    from sklearn.tree import plot_tree

    from matplotlib import pyplot as plt
```

80-20

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

```
(1069, 8)
(1069,)
(268, 8)
(268,)
```

```
rf = RandomForestRegressor()
rf.fit(X_train1, y_train1)
```

```
RandomForestRegressor
RandomForestRegressor()
```

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

```
[47609.8972823  12420.1444007  13770.3127339   8939.0116013
  6667.336726    6410.4123499   2653.1529187  17064.4832888
 11930.403051   24090.5404887  14786.6453514   8807.2285616
 11882.7562533   9542.7891737   1140.607015   13958.4238374
  5342.0447745  41917.8111163  16746.9809348  20228.0005332
  4728.3231208  15865.9318877  13910.465246    8839.4475125
  7976.5098369  44552.2249421   8991.2383276  48085.1799809
  5046.576947    3660.952798   10114.2629025   4202.6061955
```

```
 1644.8299015  10512.6023285  10184.6392947   7678.8495179
 2297.44262089  5376.0367507  40357.7273325   1748.7698865
 3566.5597453   5645.8880857  13990.4913183  11596.8757597
45702.544574   13214.8747475  13220.489528    2789.48921752
 3120.6422092  17988.2060757   4309.5144795  11187.6256922
 6548.8763181   8096.7620208   3464.5083562  39989.5622315
 1845.5665335   1609.4367825  14131.6349277   4762.7182132
11883.9211921   8780.3784901   2721.1230978   6944.463928
24783.4965868   3129.16573339 47631.7350585  13050.3555403 ]
```

```
[ ] print("R-squared:", metrics.r2_score(y_test1, y_pred1))
```

```
R-squared: 0.8265979664603367
```

```
[ ] print("Mean Squared Error:", metrics.mean_squared_error(y_test1, y_pred1))
```

```
Mean Squared Error: 22431256.401902393
```

```
print("Mean Absolute Error:", metrics.mean_absolute_error(y_test1, y_pred1))
```

```
Mean Absolute Error: 2696.095002784179
```

XG Boost Regressor

XGBOOST

```
[ ] import numpy as np
    import pandas as pd
    import xgboost as xgb
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
```

80-20

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

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

```
[53555.18    11461.423   12328.625   11621.41     4761.934    7750.494
  1529.4352  20414.572   11197.441   25815.15    14904.92     8241.342
 10975.551   12085.234     783.871   21445.992    5929.791   47263.504
 14852.5     25863.543    4428.945   17889.02     9720.698    7515.8193
 11295.879   46785.555    9298.674   49988.33     3783.8862   1293.941
  8658.964    2485.7837   3588.8274  12714.674    2851.102    1347.1912
 38437.418   14930.253    9465.392    9512.608   24132.133    1301.1206
 11352.383   38335.387   13748.171   12944.448    6926.9644   4855.4585
  9496.143   10398.47    14612.465   13194.611   13377.695   16014.891
 13593.789    3873.0288   2928.6475  10825.764    4624.3604  19449.688
```

```
 17001.783   34284.746   12868.259   45361.18     1150.8846   9007.974
 14269.522    7715.562    2286.9023   7161.562   42406.285    1690.3274
  2005.7002   9996.726   14614.38     9520.275   44468.668   18835.94
 11878.636    2301.4807   3078.2236  27661.418    3302.828   10500.338
  5086.717    9126.196    3165.3435  42321.848    1258.3187    855.5152
 16049.87     2840.1963   9703.393    7843.708    1980.3663   7653.7427
 21099.135    3758.2148  46147.707   11940.217  ]
```

```
[ ] mse = mean_squared_error(y_test1, y_pred1)
    r2 = r2_score(y_test1, y_pred1)
    mae = mean_absolute_error(y_test1, y_pred1)


    print(f"Mean Squared Error: {mse}")
    print(f"R-squared: {r2}")
    print(f"Mean Absolute Error: {mae}")
```

```
Mean Squared Error: 26612354.110278934
R-squared: 0.7942765114303354
Mean Absolute Error: 3030.090976026156
```

ADA Boost Regressor

ADABOOST

```
[ ] import pandas as pd
    import seaborn as sns
    from sklearn.tree import DecisionTreeRegressor
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import mean_squared_error, r2_score
    import numpy as np
    import matplotlib.pyplot as plt
    from sklearn.ensemble import AdaBoostRegressor
```

80-20

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

```
AdaBoostRegressor(random_state=42)
```

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

```
[46699.55313864 14724.09342165 15686.0603305   6992.14362925
  6992.14362925  5404.47224727  5404.47224727 17458.23664369
 14724.09342165 26299.07696318 14724.09342165  9117.35326937
 14724.09342165 12860.44120335  5404.47224727 14724.09342165
  6992.14362925 39836.89793294 17458.23664369 17458.23664369
  6992.14362925 14724.09342165  8736.76553005  9117.35326937
```

```
 46699.55313864 14724.09342165 14724.09342165  5404.47224727
  5404.47224727 15686.0603305   8736.76553005 14724.09342165
  8736.76553005  9117.35326937  5404.47224727 46699.55313864
  5404.47224727  5404.47224727 15686.0603305   5404.47224727
  9117.35326937  8736.76553005  8736.76553005  8736.76553005
 17458.23664369  5404.47224727 46699.55313864 14724.09342165]
```

```
r2 = r2_score(y_test1, y_pred1)
print(f"R-squared: {r2:.2f}")

mse = mean_squared_error(y_test1, y_pred1)
print(f"Mean Squared Error: {mse:.2f}")

mae=mean_absolute_error(y_test1, y_pred1)
print(f"Mean Absolute Error: {mae:.2f}")
```

```
R-squared: 0.82
Mean Squared Error: 23615256.63
Mean Absolute Error: 3928.00
```

Neural Networks :

```
tf.random.set_seed(42)

# STEP1: Creating the model

model_nom2= tf.keras.Sequential([
                            tf.keras.layers.Dense(16),


                            tf.keras.layers.Dense(8),

                            tf.keras.layers.Dense(6),



                            tf.keras.layers.Dense(4),

                            tf.keras.layers.Dense(2),


                            tf.keras.layers.Dense(1)
])

# STEP2: Compiling the model

model_nom2.compile(loss= tf.keras.losses.mae,
             optimizer= tf.keras.optimizers.Adam(),  #SGD
             metrics= ["mae"])

# STEP3: Fit the model

history= model_nom2.fit(X_train2, y_train2, epochs= 500, verbose=1)
```

```
Epoch 1/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 4ms/step - loss: 13685.7686 - mae: 13685.7686
Epoch 2/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 13600.0674 - mae: 13600.0674
Epoch 3/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 13409.9844 - mae: 13409.9844
Epoch 4/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 12883.7832 - mae: 12883.7832
Epoch 5/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 11507.2715 - mae: 11507.2715
Epoch 6/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 8981.1768 - mae: 8981.1768
Epoch 7/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 7741.8447 - mae: 7741.8447
Epoch 8/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 7708.9766 - mae: 7708.9766
Epoch 9/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 7685.9336 - mae: 7685.9336
Epoch 10/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7668.1367 - mae: 7668.1367
Epoch 11/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 7647.6372 - mae: 7647.6372
Epoch 12/500
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7627.4692 - mae: 7627.4692
Epoch 13/500
```

```
[ ] model_nom2.evaluate(X_test2, y_test2)
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2678.4839 - mae: 2678.4839
[2932.37939453125, 2932.37939453125]
```

```
[ ] model_nom2.summary();
```

```
Model: "sequential_11"
```

Layer (type)	Output Shape	Param #
dense_66 (Dense)	(None, 16)	144
dense_67 (Dense)	(None, 8)	136
dense_68 (Dense)	(None, 6)	54
dense_69 (Dense)	(None, 4)	28
dense_70 (Dense)	(None, 2)	10
dense_71 (Dense)	(None, 1)	3

```
Total params: 1,127 (4.41 KB)
Trainable params: 375 (1.46 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 752 (2.94 KB)
```

```
pd.DataFrame(history.history).plot()
plt.ylabel("loss")
plt.xlabel("epochs")
```

```
Text(0.5, 0, 'epochs')
```