MEDICAL INSURANCE PREMIUM

Group 12 | Bhavan's Vivekananda College

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Abstract

- The project focuses on developing a model that accurately predicts medical insurance premiums, enabling better financial planning and efficient cost management for healthcare providers and insurers.
- The study explores machine learning algorithms such as Linear Regression, Decision Tree, Random Forest, K-Nearest Neighbours, Support Vector Machines, Bagging, and Boosting to predict insurance premiums based on demographic and health-related factors.

Objective

- To identify the most suitable machine learning model for predicting medical insurance premiums to aid in cost-effective and personalized insurance policy pricing.

CONTENT

- Introduction
- Literature Review
- Data Preprocessing
- Exploratory Data Analysis
- Data Modeling & Evaluation
- Summary
- Appendix

Introduction

- **Topic Overview:** Medical insurance premiums are influenced by multiple factors, including age, BMI, smoking status, and geographic region.
- **Objective:** This project aims to use regression techniques to predict medical insurance premiums based on key factors.
- **Dataset:** Utilized a publicly available dataset containing variables such as age, sex, BMI, number of children, smoking status, and region to predict premium costs.
- **Significance:** Accurate premium predictions help insurers set fair prices, aid consumers in financial planning, and assist policymakers in understanding healthcare cost determinants.

LITERATURE REVIEW

Literature Review -1

1. K. Bhatia
2. S. S. Gill
3. N. Kamboj
4. M. Kumar
5. R. K. Bhatia

- This paper represents a machine learning-based health insurance prediction system. Recently, many attempts have been made to solve this problem, as after Covid-19 pandemic, health insurance has become one of the most prominent areas of research.
- We have used the USA's medical cost personal dataset from kaggle, having 1338 entries. Features in the dataset that are used for the prediction of insurance cost include: Age, Gender, BMI, Smoking Habit, number of children etc.
- We used linear regression and also determined the relation between price and these features. We trained the system using a 70-30 split and achieved an accuracy of 81.3%.

DATA PREPROCESSING

DATA

Dataset: Our Dataset Consists1338 rows and 7 columns

Source : https://drive.google.com/file/d/1CZBa0RBm88cfdQzSyLVkn6n9Peuo3fsm/view?usp=drivesdk

	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

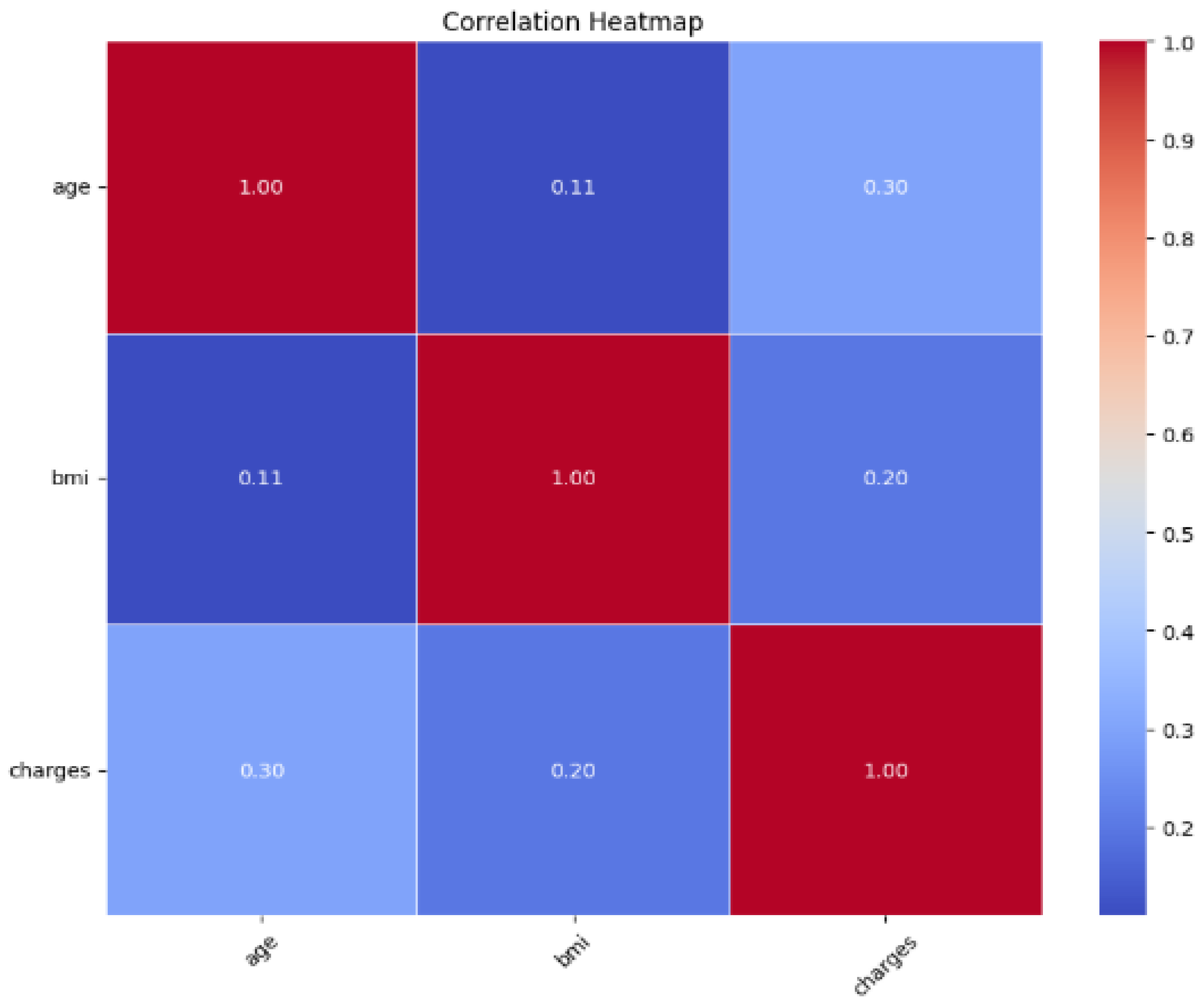
DATA CLEANING

- Checked for null /NaN values : We replaced the Nan values with mean and mode of the column based on the attribute type.
- Garbage values : We replaced the garbage values of the column based on the domain knowledge of the dataset.
- Dummification: enabled and dummified the categorical variables

CATEGORICAL VARIABLES	CONTINUOUS VARIABLES
SEX	BMI
SMOKER	CHARGES
REGION	

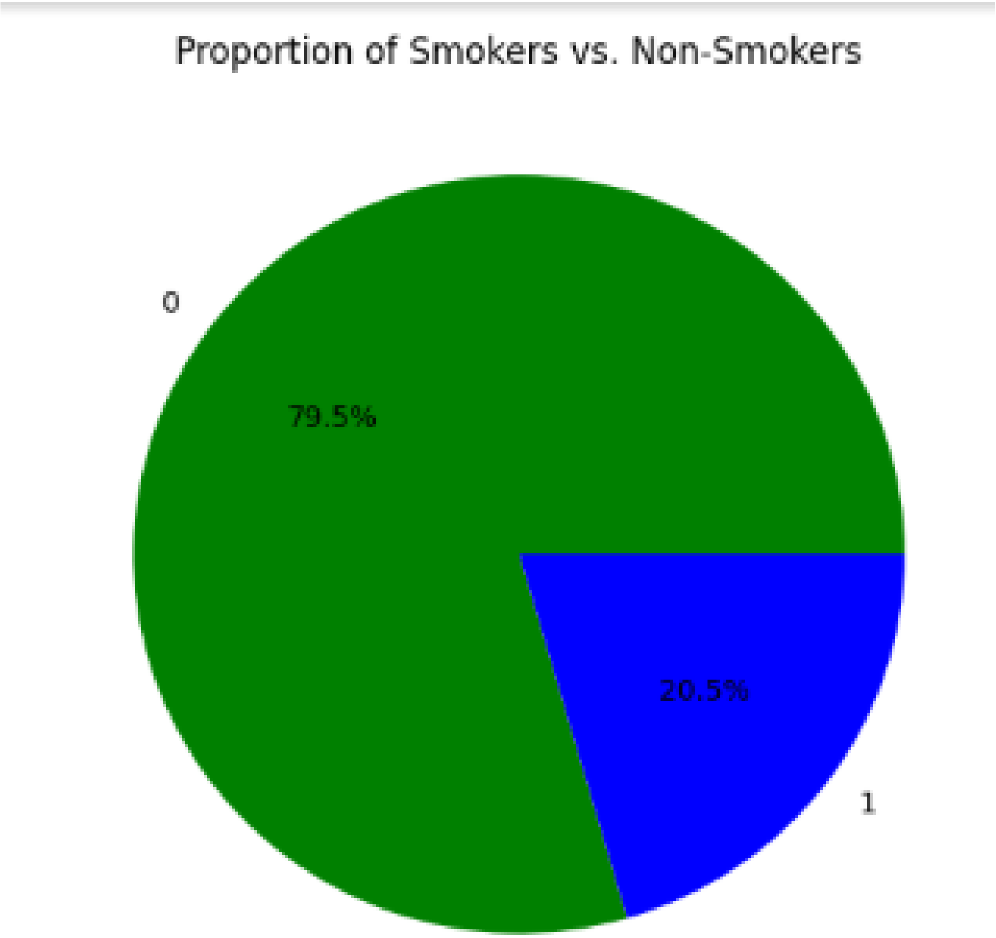
EXPLORATORY DATA ANALYSIS

CORRELATION MATRIX



- The Most Positively Correlated Variables Are Age and Charges
- The Next Most Positively Correlated Variables Are Bmi and Charges

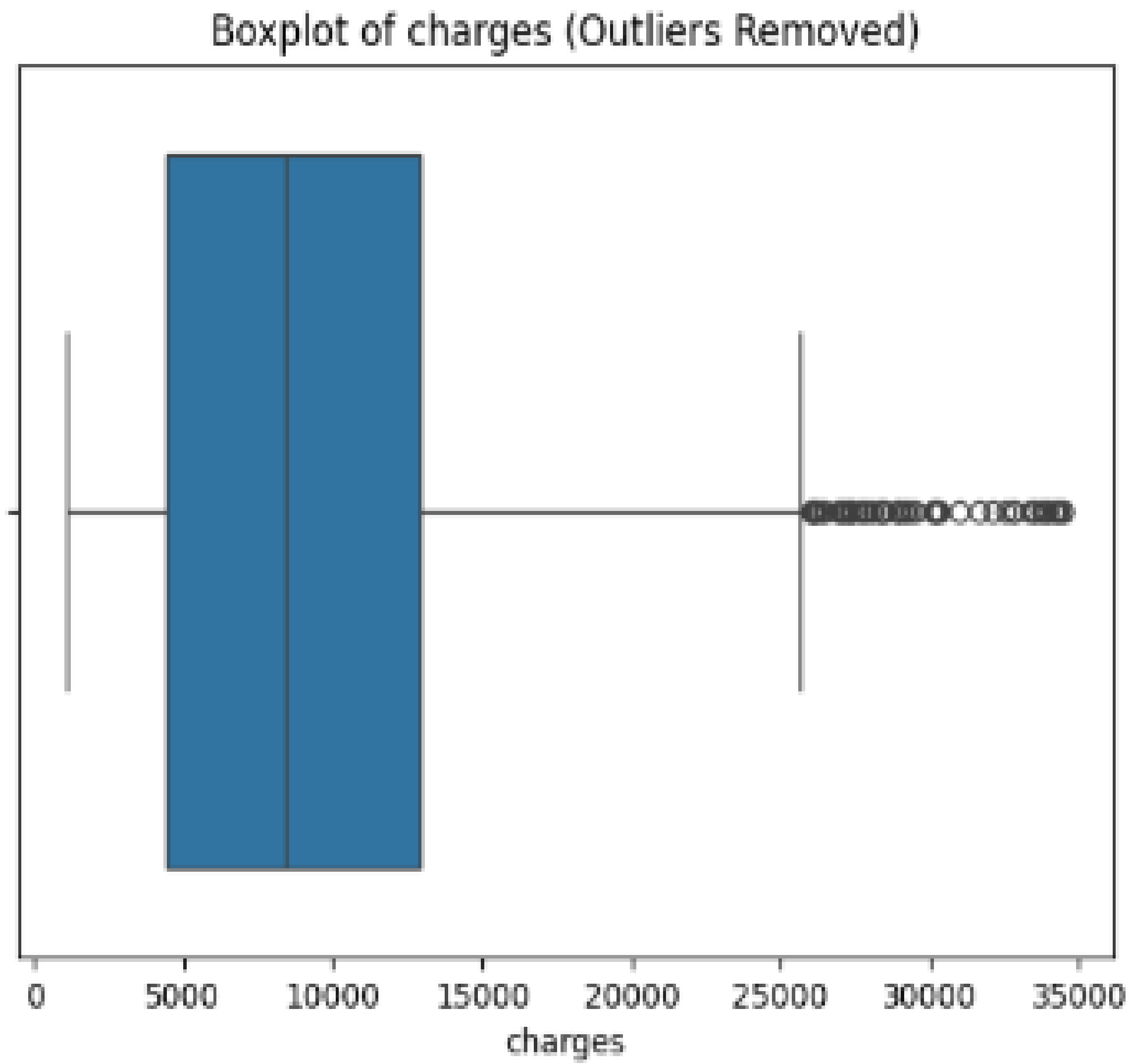
PIE CHART



- THE PORTION OF SMOKERS IS LESS THAN NON SMOKERS

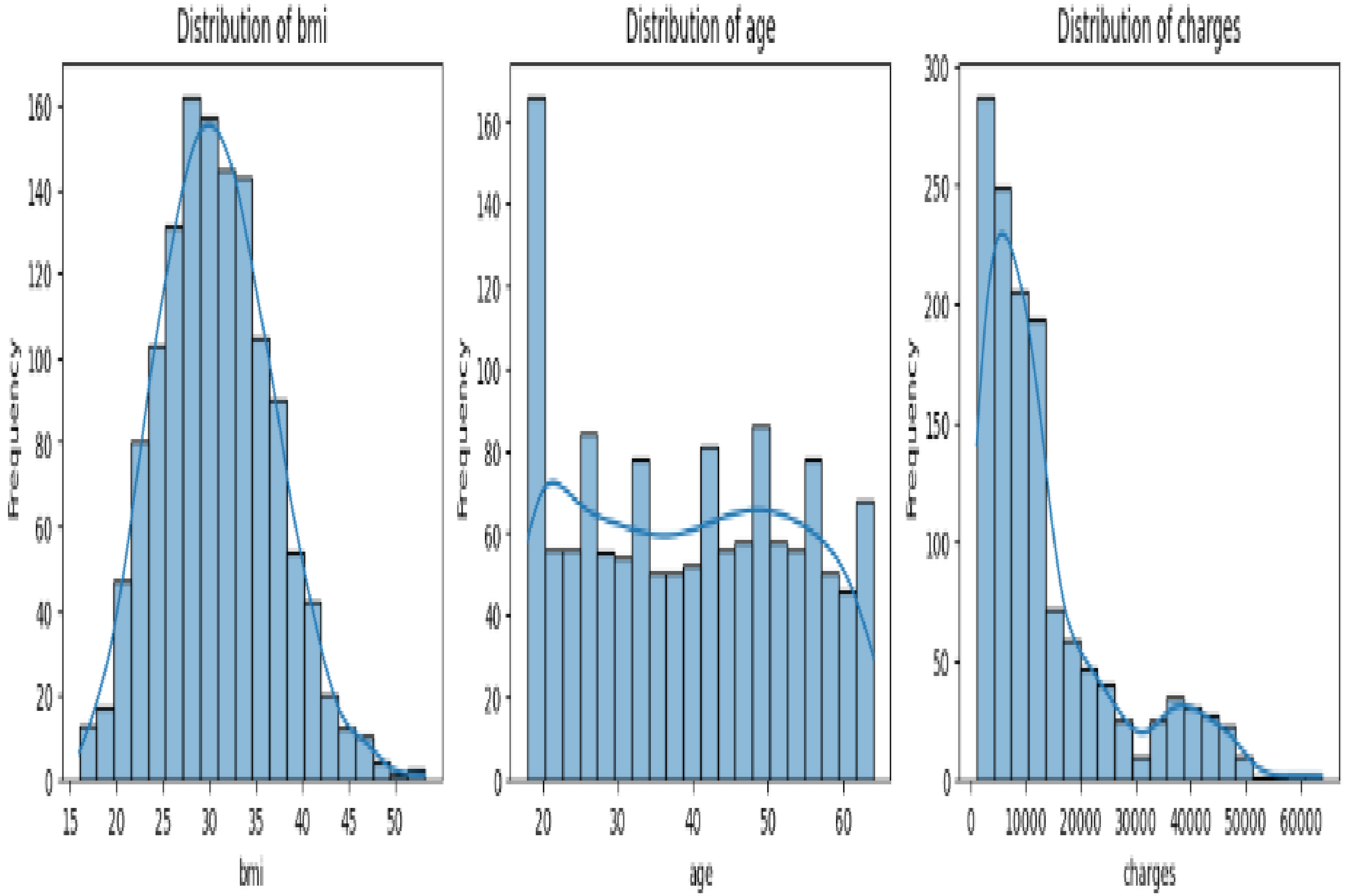
- SMOKERS-20.5%
- NON-SMOKERS-79.5%

BOX PLOT



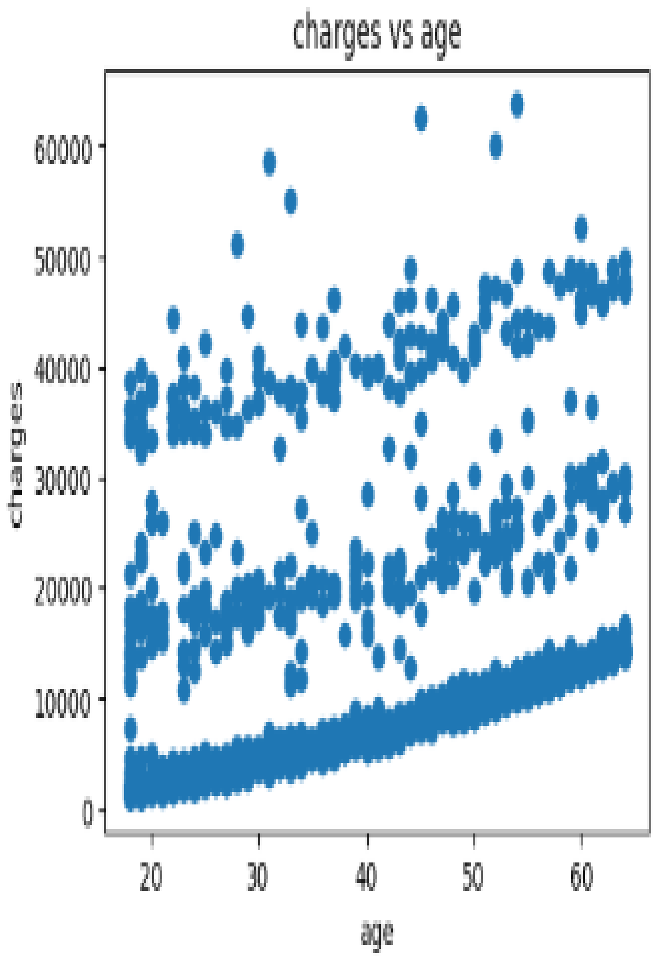
- The majority of data lies between approximately **0 and 25,000**.
- A significant number of outliers are present beyond the **25,000 mark**, with some values approaching **35,000**.
- The median (central line) is roughly in the middle of the box, suggesting a moderately symmetric distribution for non-outlier data.

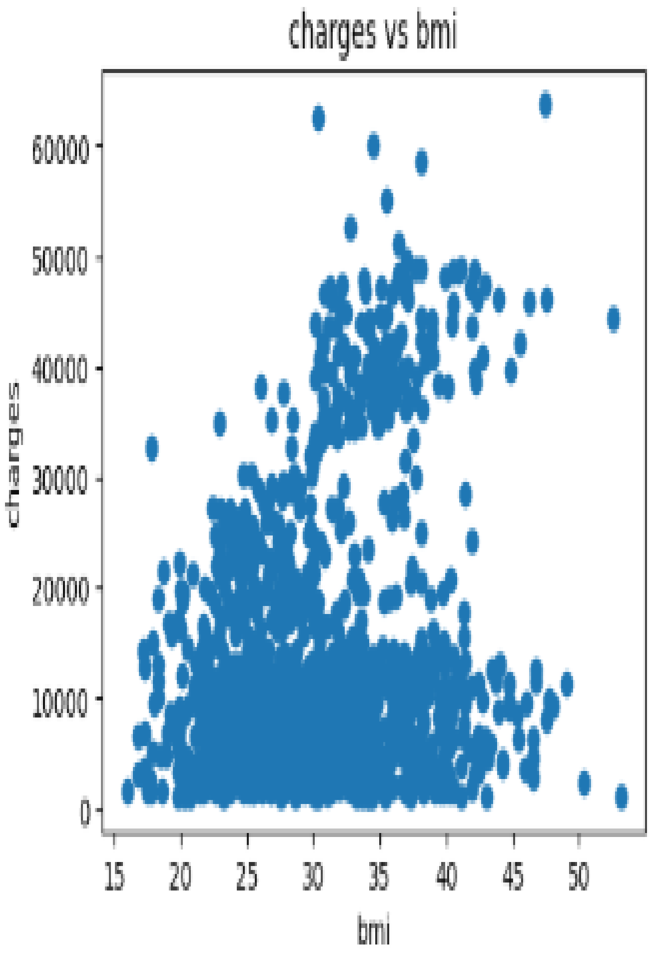
HISTOGRAM



- **Distribution of BMI** (left plot):
- The data is approximately **bell-shaped**, resembling a normal distribution.
- The majority of BMI values range between **20 and 40**, peaking around **30–35**.
- **Distribution of Age** (middle plot):
- The distribution is **relatively uniform**, with some peaks, especially at the lower ages (~20s).
- Ages are spread across **20 to 65** without a dominant concentration.
- **Distribution of Charges** (right plot):
- The data is **right-skewed** (positively skewed), with most charges concentrated under **15,000**.
- A few higher values extend beyond **50,000**, suggesting the presence of outliers.

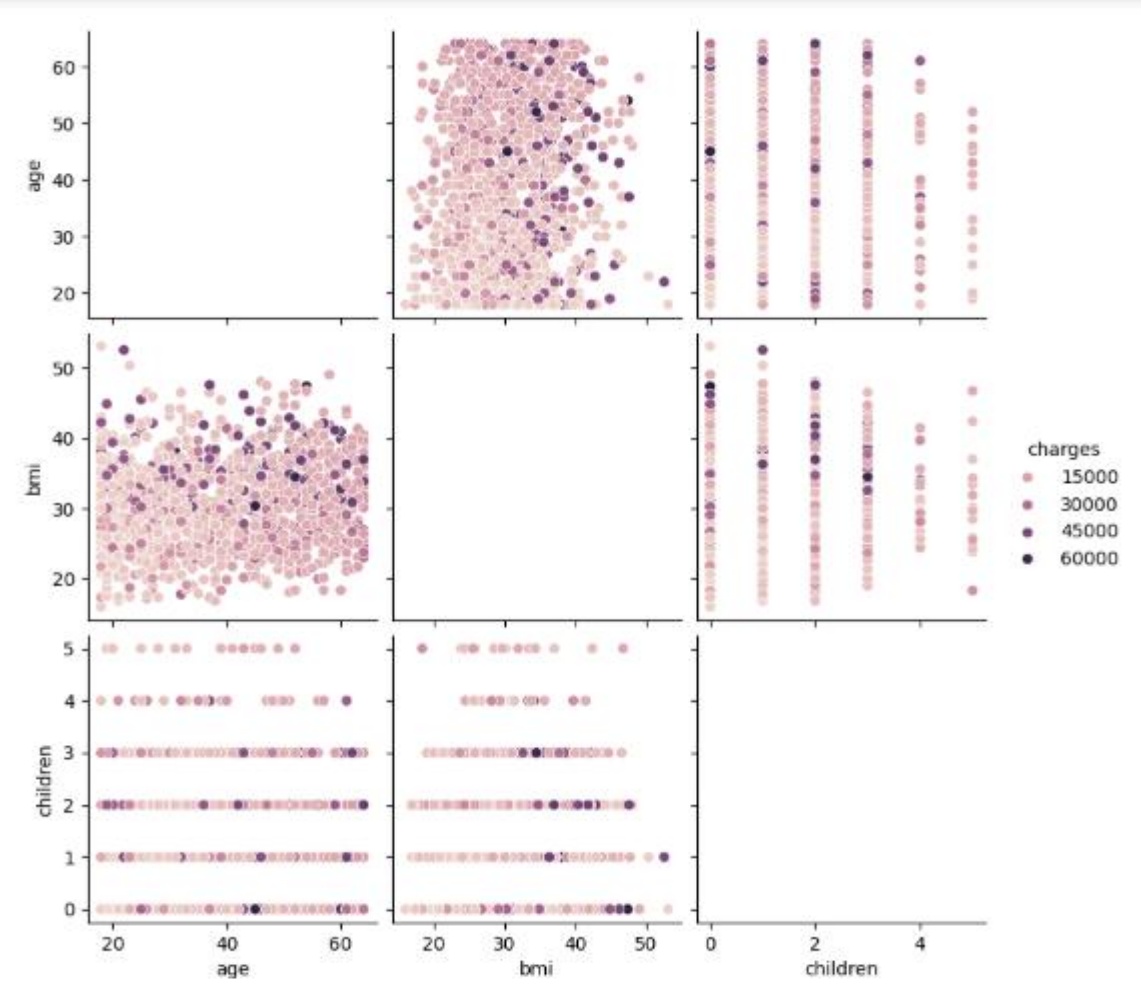
SCATTER PLOT





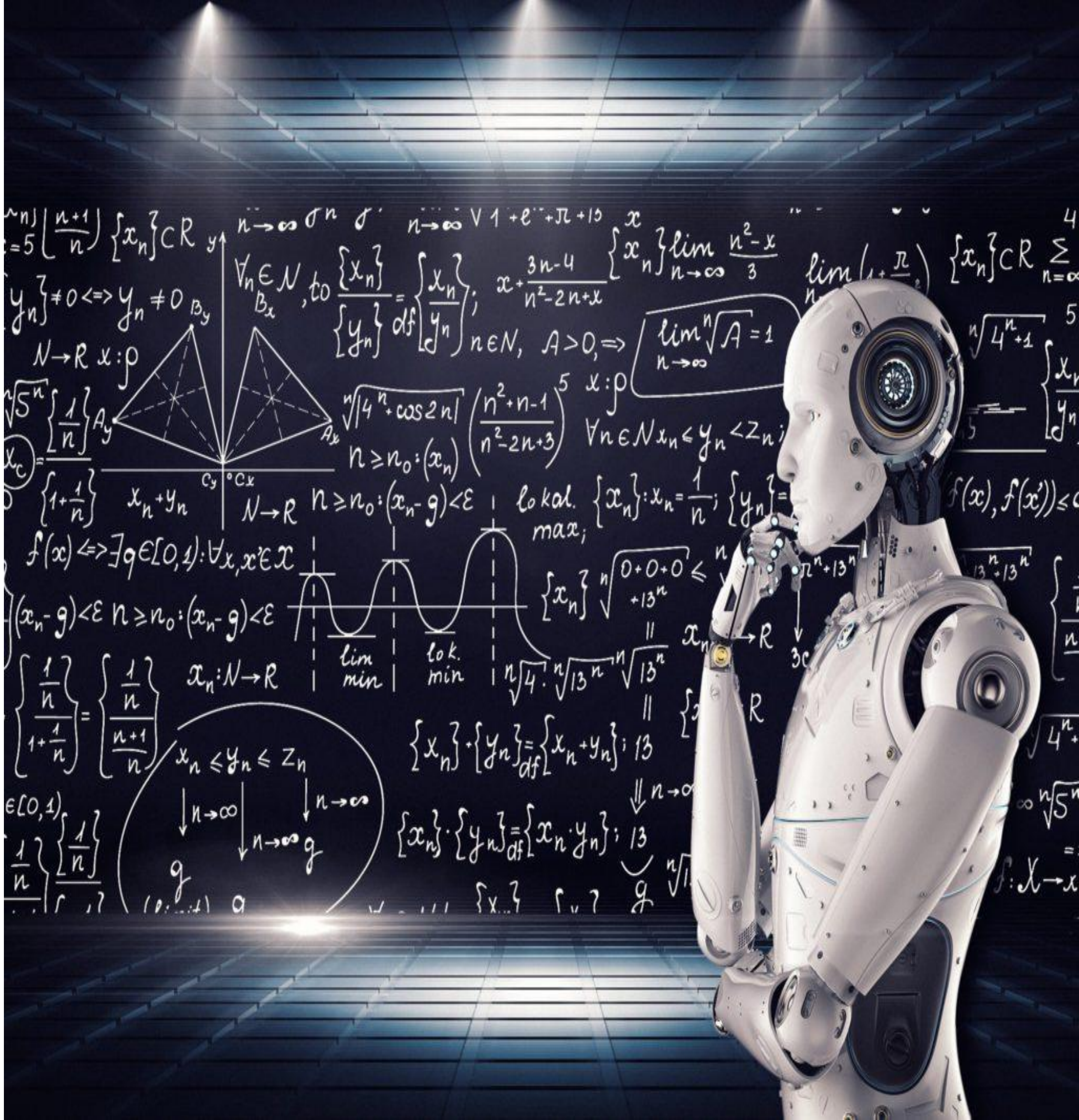
•**Charges vs Age** (left plot):
•There is a **positive trend** where charges generally increase with age.
•Distinct clusters suggest groups with higher charges, possibly influenced by other factors like health conditions or insurance tiers.
•A lower band of points indicates a baseline level of charges that increases steadily with age.
•**Charges vs BMI** (right plot):
•The relationship between charges and BMI shows **scattered data** without a strong linear trend.
•Higher charges appear concentrated for **BMI values between 30 and 40**, suggesting that elevated BMI may influence higher costs.
•Many individuals with low charges exist across the entire BMI range.

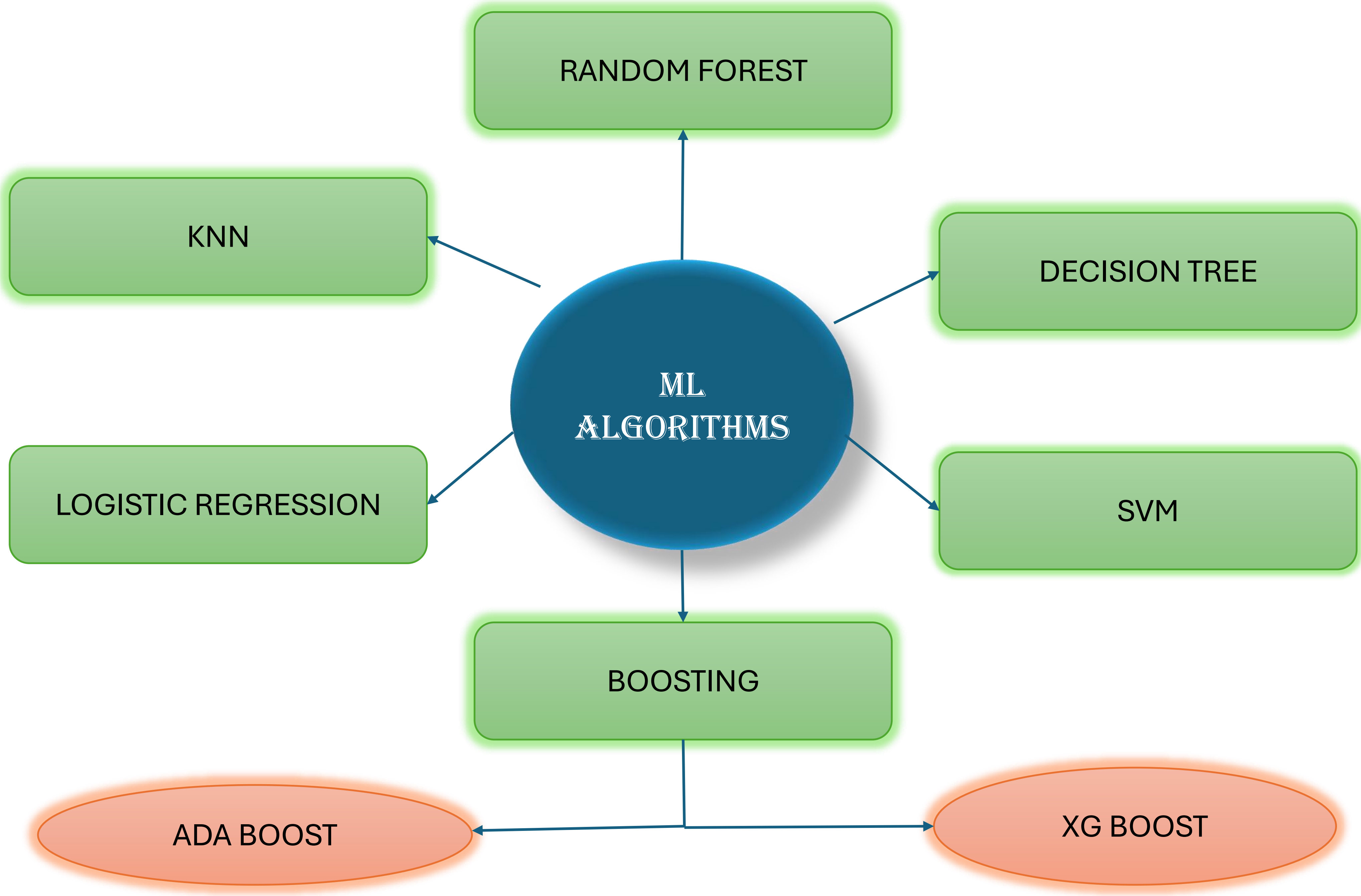
PAIR PLOT



- Age vs BMI: Data is widely spread with no clear pattern between age andBMI.
- Age vs Children: Data shows that people of various ages have different numbers of children, with most individuals having 0–3 children.
- BMI vs Children: BMI values are consistent across different numbers of children.
- Charges: Larger and darker dots represent higher charges. These appear more scattered, but higher charges seem to cluster for higher BMI and age.

MACHINE LEARNING ALGORITHMS




RANDOM FOREST
KNN
DECISION TREE
ML ALGORITHMS
LOGISTIC REGRESSION
SVM
BOOSTING
ADA BOOST
XG BOOST

60:40 TRAIN TEST SPLIT

ALGORITHMS	MODEL 1
LINEAR REGRESSION	11431.265806495396
KNN	11729.448347067131
SVM	13125.787740041129
DECISION TREE	16179.484384739933
RANDOM FOREST	13122.963924673244
XG BOOST	13968.427863698407
ADA BOOST	11811.288756729913

70:30 TRAIN TEST SPLIT

ALGORITHMS	MODEL 1
LINEAR REGRESSION	11182.436478201516
KNN	11036.302509526595
SVM	12216.363130385913
DECISION TREE	16179.484384739933
RANDOM FOREST	12491.832175681928
XG BOOST	13099.292006046864
ADA BOOST	11040.990002151222

75:25 TRAIN TEST SPLIT

ALGORITHMS	MODEL 1
LINEAR REGRESSION	10847.593384283526
KNN	11261.344306644703
SVM	12724.896113492025
DECISION TREE	15996.586496155332
RANDOM FOREST	12789.831896644697
XG BOOST	13901.025024984147
ADA BOOS	11565.838526413283

80:20 TRAIN TEST SPLIT

ALGORITHMS	MODEL 1
LINEAR REGRESSION	11425.44386403564
KNN	11540.148271602695
SVM	13033.447076242333
DECISION TREE	16429.20930806319
RANDOM FOREST	13225.56472929329
XG BOOST	13713.484479004674
ADA BOOST	11655.560366092102

ALGORITHMS COMPARISION

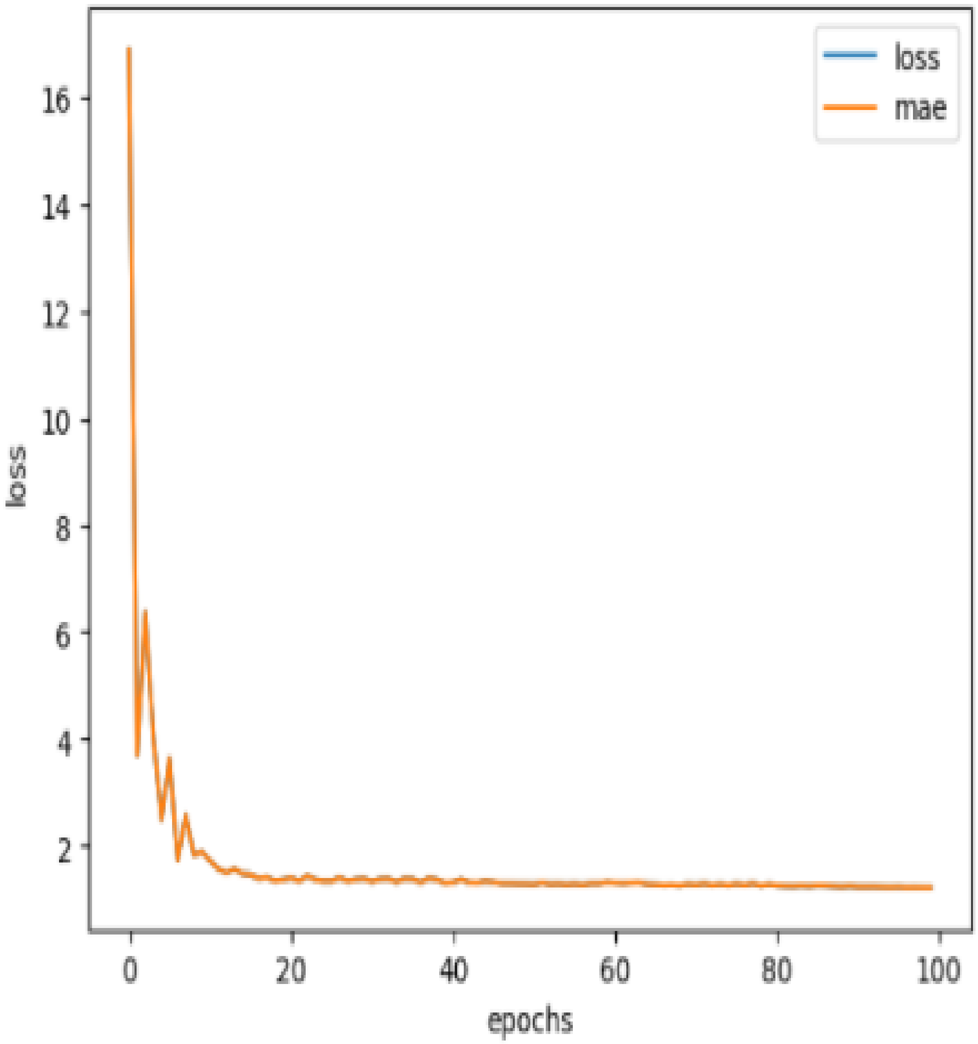
ALGORITHMS	MODEL 1
LOGISTIC REGRESSION	11425.44386403564
KNN	11540.148271602695
SVM	13033.447076242333
DECISION TREE	16429.20930806319
RANDOM FOREST	13225.56472929329
XG BOOST	13713.484479004674
ADA BOOST	11655.560366092102

NEURAL NETWORK

Train test	Architecture	Optimizer	Epochs	Mae
60-40	34-32-30-26	Adam	100	1.5688951015472412
70-30	34-32-30-26	Adam	100	1.2450635433197021
75-25	34-32-30-26	Adam	100	2.426121234893799
80-20	34-32-30-26	Adam	100	1.582599401473999

NEURAL NETWORK PLOT

Text(0.5, 0, 'epochs')



Train-test split	80-20
Architecture	34-32-30-26
Optimizer	Adams
Epochs	100

SUMMARY

- The main aim of this research is to predict the charges of the medical insurance based on the BMI and Gender.
- Based on the table, the algorithm with the lowest score (which typically indicates better performance for metrics like error or loss) is **Logistic Regression**, with a score of **11425.44**. This suggests that Logistic Regression is the best-performing algorithm in this scenario.

WORK DISTRIBUTION

TEAM MEMBER	WORK DONE
A RAHUL	COLLECTED REQUIRED INFORMATION AND DATA
AKASH	DATA PRE PROCESSING
Y SRUTHI	EXPLORATORY DATA ANALYSIS
SHAN KOUSHIK	IMPLMENTATION OF ML ALGORITHMS

Thank You

SHAN KOUSHIK
A RAHUL
Y SRUTHI
V AKASH

Collab Notebook Link

LOADING THE DATASET

```
data= pd.read_excel('Insurance1.xlsx',names = ["age","sex","bmi","children","smoker","region","charges"], header=None)
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   object 
 4   smoker    1338 non-null   object 
 5   region    1338 non-null   object 
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(1), object(4)
memory usage: 73.3+ KB
```

Replacing the Vairables

```
df= df.replace(to_replace='yes', value='1')
df= df.replace(to_replace='no', value='0')
df
```

	age	sex	bmi	children	smoker	region	charges
0	19	0	27.900	0	1	southwest	16884.92400
1	18	1	33.770	1	0	southeast	1725.55230
2	28	1	33.000	3	0	southeast	4449.46200
3	33	1	22.705	0	0	northwest	21984.47061
4	32	1	28.880	0	0	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	1	30.970	3	0	northwest	10600.54830
1334	18	0	31.920	0	0	northeast	2205.98080
1335	18	0	36.850	0	0	southeast	1629.83350
1336	21	0	25.800	0	0	southwest	2007.94500
1337	61	0	29.070	0	1	northwest	29141.36030

1338 rows × 7 columns

DROPING THE TARGET VAIRABLES

```
X=df.drop(['charges'],axis=1)
print(X)
y = df['charges']
print(y)
```

```
      age  sex     bmi  children  smoker     region
0      19    0  27.900         0       1  southwest
1      18    1  33.770         1       0  southeast
2      28    1  33.000         3       0  southeast
3      33    1  22.705         0       0  northwest
4      32    1  28.880         0       0  northwest
...   ...  ...     ...       ...     ...        ...
1333   50    1  30.970         3       0  northwest
1334   18    0  31.920         0       0  northeast
1335   18    0  36.850         0       0  southeast
1336   21    0  25.800         0       0  southwest
1337   61    0  29.070         0       1  northwest

[1338 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: 1338, dtype: float64
```

LINEAR REGRESSION

```python
from sklearn import metrics
X = data[['age', 'bmi']]
y = data.charges
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
lm2 = LinearRegression()
lm2.fit(X_train, y_train)
y_pred = lm2.predict(X_test)
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
10847.593384283526
```

```python
test_sizes = [0.20]

# Loop over different test sizes
for test_size in test_sizes:
    X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=test_size, random_state=1)

    # Train and fit the model
    lm2 = LinearRegression()
    lm2.fit(X_train1, y_train1)
    y_pred = lm2.predict(X_test1)

    # Calculate the Root Mean Squared Error (RMSE)
    rmse = np.sqrt(metrics.mean_squared_error(y_test1, y_pred))
    print(f" for Test size {test_size * 100}% RMSE: {rmse}")
```

```
 for Test size 20.0% RMSE: 11431.265806495396
```

```
test_sizes = [0.30]

# Loop over different test sizes
for test_size in test_sizes:
    X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=test_size, random_state=1)

    # Train and fit the model
    lm2 = LinearRegression()
    lm2.fit(X_train3, y_train3)
    y_pred = lm2.predict(X_test3)

    # Calculate the Root Mean Squared Error (RMSE)
    rmse = np.sqrt(metrics.mean_squared_error(y_test3, y_pred))
    print(f" for Test size {test_size * 100}% RMSE: {rmse}")
```

```
for Test size 30.0% RMSE: 11182.436478201516
```

```
test_sizes = [0.40]

# Loop over different test sizes
for test_size in test_sizes:
    X_train4, X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=test_size, random_state=1)

    # Train and fit the model
    lm2 = LinearRegression()
    lm2.fit(X_train4, y_train4)
    y_pred = lm2.predict(X_test4)
```

KNN

```
[ ] #knn
from sklearn.neighbors import KNeighborsRegressor
model=KNeighborsRegressor(n_neighbors=25)
model.fit(X_train1, y_train1)
```

```
KNeighborsRegressor
KNeighborsRegressor(n_neighbors=25)
```

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

```
16073.5700056 ,  6348.9743044 , 22857.6255396 , 15080.1226792 ,
10722.2342716 , 20278.9248068 , 15184.2099496 , 21683.7448564 ,
 8720.0872444 , 15470.41036   , 10224.110586  ,  9292.5937892 ,
11638.26348   , 16956.290602  , 24481.1012072 , 17945.9389416 ,
 5064.7335008 , 11078.91848   ,  9622.10569836, 11514.7706336 ,
 9007.9871828 , 25457.1968124 ,  4856.8487148 , 11756.582768  ,
15284.8238696 , 26054.9786516 ,  7749.489838  ,  7147.27076   ,
21807.9889884 , 15644.3422528 , 13546.9324108 , 13005.453128  ,
 5273.4814348 ,  6249.4965072 , 18703.6134092 , 11367.2384544 ,
 9427.15934476, 16615.1606348 , 22127.0971132 , 12147.9669216 ,
 5102.712322  ,  8535.8044756 , 14277.114974  , 17125.7769888 ,
 5745.0147488 , 17989.0402408 , 17415.6802224 , 10085.0134236 ,
 9619.186014  , 14122.2885772 , 13094.5477408 , 16384.71948   ,
17030.3138888 ,  9679.58257   ,  7881.514732  , 15558.2373244 ,
22355.8506024 , 15568.9653328 ,  6000.4769472 , 16093.896042  ,
17281.9492908 , 19186.3510904 , 20785.8332268 ,  8803.3746076 ,
15528.9044252 ,  5870.6278188 ,  8818.7633284 ,  9784.3601392 ,
18910.710548  ,  7749.489838  ,  5296.9582268 , 15126.9496672 ,
```

```python
#Evalution metrix
from sklearn.metrics import r2_score
r2_score(y_test1,y_pred1)
```

```
0.07838043241371 55
```

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

```
9154.393822653283
```

```python
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test1,y_pred1)
```

```
137579958.52651587
```

```python
mse = mean_squared_error(y_test1, y_pred1)
rmse = np.sqrt(mse)
rmse
```

```
11729.448347067131
```

```python
from sklearn.metrics import mean_absolute_percentage_error
mape = mean_absolute_percentage_error(y_test1, y_pred1)
print(mape)
mape = mape * 100
```

```
from sklearn import metrics
metrics.mean_absolute_error(y_test4,y_pred4)
```

```
9034.187735966567
```

```
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test4,y_pred4)
```

```
133175022.13057467
```

```
mse = mean_squared_error(y_test4, y_pred4)
rmse = np.sqrt(mse)
rmse
```

```
11540.148271602695
```

```
from sklearn.metrics import mean_absolute_percentage_error
mape = mean_absolute_percentage_error(y_test4, y_pred4)
print(mape)
mape = mape * 100
mape
```

```
1.1683706233560116
```

SVM

```
#svm
from sklearn.svm import SVR
model = SVR(kernel='linear')
model.fit(X_train1, y_train1)
```

```
SVR
SVR(kernel='linear')
```

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

```
array([ 1905.20936523, 12088.60091979, 10451.71193829,  9919.22456837,
        2519.31095978,  5120.29709905,  9913.94364795, 11838.92012159,
        4101.05032919,  6772.36872676, 12932.72988712, 11195.56342814,
        7271.43027085,  8093.53539962,  1644.45663729,  9690.45741524,
        5725.12707764,  6229.85961014, 12593.42346798, 13415.40857583,
       10741.56973897,  4824.97834657,  9170.51223131, 10246.76893749,
        1670.35115048,  7829.75214349,  8370.7309934 ,  9671.67414148,
        5663.9464144 ,  4906.53256074, 11795.68258568,  5966.70646383,
       11072.77474611,  1926.87314103,  9716.56196503, 11062.51295757,
        4847.4822688 ,  2498.90740362, 12310.88694332,  8886.62547132,
        4326.57691753, 12338.85181735, 10239.387651  , 12589.94286134,
        5185.04838462, 12908.33563542,  2173.88347379,  4334.49829815,
       10565.43175864, 12105.13380132, 13157.83640223, 11564.93508739,
        3313.24117791,  8915.40048655,  1686.88403201,  5328.66069603,
        8339.52555457, 12869.29883165,  3042.46670327,  1592.96766323,
        4578.74814978, 13146.04434698,  3016.87224239,  3019.09262938,
       12858.16689145,  9677.85521879,  9966.87287304, 12133.96882701,
```

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

```
-0.15411016623814744
```

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

```
6638.806276256675
```

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

```
172286303.79661402
```

```
mse = mean_squared_error(y_test1, y_pred1)
rmse = np.sqrt(mse)
rmse
```

```
13125.787740041129
```

```
[ ] from sklearn.metrics import mean_absolute_percentage_error
    mape = mean_absolute_percentage_error(y_test1, y_pred1)
    print(mape)
    mape = mape * 100
    mape
```

DECISSION TREE

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

```
-0.5953894661491503
```

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

```
9840.463405257462
```

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

```
238160759.93405038
```

```
mse = mean_squared_error(y_test1, y_pred1)
rmse = np.sqrt(mse)
rmse
```

```
15432.45800039807
```

```
[ ] from sklearn.metrics import mean_absolute_percentage_error
    mape = mean_absolute_percentage_error(y_test1, y_pred1)
    print(mape)
    mape = mape * 100
    mape
```

```
[ ] #evalution metrix
    from sklearn.metrics import r2_score
    r2_score(y_test4,y_pred4)
```

```
-0.8778575040057566
```

```
[ ] from sklearn import metrics
    metrics.mean_absolute_error(y_test4,y_pred4)
```

```
10601.602630725745
```

```
[ ] from sklearn.metrics import mean_squared_error
    mean_squared_error(y_test4,y_pred4)
```

```
269918918.4881502
```

```
mse = mean_squared_error(y_test4, y_pred4)
rmse = np.sqrt(mse)
rmse
```

```
16429.20930806319
```

```
[ ] from sklearn.metrics import mean_absolute_percentage_error
    mape = mean_absolute_percentage_error(y_test4, y_pred4)
    print(mape)
    mape = mape * 100
    mape
```

RANDOM FOREST

```
[ ] #random forest
    from sklearn.ensemble import RandomForestRegressor
    from sklearn.tree import plot_tree
    rf=RandomForestRegressor()
    rf.fit(X_train1,y_train1)
```

```
RandomForestRegressor
RandomForestRegressor()
```

```
y_pred1=rf.predict(X_test1)
y_pred1
```

```
        18831.5991559 ,  2906.145957  , 15403.7342934 , 15869.037168  ,
         6071.69111817, 13899.2869611 , 17827.9928102 , 27452.9548311 ,
        11540.3286458 , 13739.5136059 , 12121.320012  , 11945.438202  ,
        10078.070628  , 12998.9869255 , 28122.1670988 , 19408.4177548 ,
         8839.6924825 ,  9282.9755485 , 12779.7482906 ,  6183.7768159 ,
         8127.3467855 , 33268.1579711 ,  3353.5000062 , 27821.725882  ,
        36772.4968488 , 30523.2474944 , 13873.67089863, 12146.98637113,
        34187.265596  , 11966.820441  ,  9240.4917561 , 11584.7064055 ,
         5325.516317  ,  7405.4222255 , 19331.601352  , 11340.7966155 ,
        14153.03985119, 21238.342086  , 16294.2820805 , 15214.6667204 ,
         8069.9575783 , 15222.6637165 , 13416.1151212 , 16944.4850301 ,
         7701.2199195 , 15508.9844468 , 20840.0487416 ,  8194.18276367,
        29646.296648  ,  8259.1937961 , 12020.2596226 , 20636.4459017 ,
        18628.3051758 ,  8033.0073406 , 17591.2261975 , 14089.4268326 ,
        38271.3875094 , 11859.145185  ,  3243.5791585 , 14547.3252038 ,
        16149.7764742 , 20278.377667  , 18310.009187  ,  7059.2926134 ,
        12772.699334  ,  4170.0304498 , 10945.7706676 , 25013.8575045 ,
```

```
[ ] #evalution metrix
    print("RMSE",np.sqrt(metrics.mean_squared_error(y_test4,y_pred4)))
    print("R2 score:",metrics.r2_score(y_test4,y_pred4))

    RMSE 13225.56472929329
    R2 score: -0.21690803770405154
```

```
[ ] from sklearn import metrics
    metrics.mean_absolute_error(y_test4,y_pred4)

    9722.17949024921
```

```
    from sklearn.metrics import mean_squared_error
    mean_squared_error(y_test4,y_pred4)

    174915562.4087267
```

```
[ ] from sklearn.metrics import mean_absolute_percentage_error
    mape = mean_absolute_percentage_error(y_test4, y_pred4)
    print(mape)
    mape = mape * 100
    mape

    1.3045008883519413
    130.45008883519412
```

XG BOOST

```
[ ] #XGboost
    import xgboost as xgb
    model1 = xgb.XGBRegressor()
    model2 = xgb.XGBRegressor(n_estimators=100, max_depth=8, learning_rate=0.1, subsample=0.5)

    train_model1 = model1.fit(X_train1, y_train1)
    train_model2 = model2.fit(X_train1, y_train1)
```

```
[ ] pred1 = train_model1.predict(X_test1)
    pred2 = train_model2.predict(X_test1)
```

```
[ ] #evalution metrix
    print("RMSE1:",np.sqrt(metrics.mean_squared_error(y_test1, pred1)))
    print("RMSE2:",np.sqrt(metrics.mean_squared_error(y_test1, pred2)))
    print("R2 score1:",metrics.r2_score(y_test1,pred1))
    print("R2 score2:",metrics.r2_score(y_test1,pred2))
```

```
RMSE1: 14355.489943493878
RMSE2: 13968.427863698407
R2 score1: -0.38048773140260383
R2 score2: -0.30704810411377537
```

```
mae1=metrics.mean_absolute_error(y_test1,pred1)
mae2=metrics.mean_absolute_error(y_test1,pred2)
print("MAE1:",mae1)
print("MAE2:",mae2)
```

```
MAE1: 10111.485606117854
```

```
#evalution metrix
print("RMSE:",np.sqrt(metrics.mean_squared_error(y_test4, pred1)))
print("RMSE:",np.sqrt(metrics.mean_squared_error(y_test4, pred2)))
print("R2 score:",metrics.r2_score(y_test4,pred1))
print("R2 score:",metrics.r2_score(y_test4,pred2))
```

```
RMSE: 14464.566003670305
RMSE: 13713.484479004674
R2 score: -0.4555935549630441
R2 score: -0.3083530389136093
```

```
mae1=metrics.mean_absolute_error(y_test4,pred1)
mae2=metrics.mean_absolute_error(y_test4,pred2)
print("MAE1:",mae1)
print("MAE2:",mae2)
```

```
MAE1: 10253.346605412888
MAE2: 9907.443675122599
```

```
from sklearn.metrics import mean_squared_error
mse1=mean_squared_error(y_test4,pred1)
mse2=mean_squared_error(y_test4,pred2)
print("MSE1:",mse1)
print("MSE2:",mse2)
```

```
MSE1: 209223669.67453474
MSE2: 188059656.5559021
```

ADA BOOST

```
[ ] #ADAboost
    from sklearn.ensemble import AdaBoostRegressor
    from sklearn.tree import DecisionTreeRegressor
    # Replace 'base_estimator' with 'estimator'
    base_estimator = DecisionTreeRegressor(max_depth=3, random_state=0)
    adaboost = AdaBoostRegressor(estimator=base_estimator, # Changed argument name here
                                 n_estimators=3,random_state=0)
```

```
[ ] adaboost.fit(X_train1, y_train1)
```

```
▸ AdaBoostRegressor
▸ estimator: DecisionTreeRegressor
    ▸ DecisionTreeRegressor
```

```
y_pred1 = adaboost.predict(X_test1)
y_pred1
```

```
array([16463.52109117, 24067.46585327, 19149.97186129, 19149.97186129,
        7837.68691867, 16463.52109117, 19149.97186129, 16059.58574176,
        9359.48958517,  9359.48958517, 16210.85696644, 19149.97186129,
       16463.52109117, 15807.66626925, 13869.39064146, 16059.58574176,
        9359.48958517,  9359.48958517, 24067.46585327, 24067.46585327,
       17629.42631379, 16463.52109117, 15807.66626925, 15807.66626925,
        6750.59661578, 15807.66626925, 15807.66626925, 17629.42631379,
       16463.52109117,  9359.48958517, 24067.46585327,  9359.48958517,
```

```
#evalution metrix
print("RMSE:",np.sqrt(metrics.mean_squared_error(y_test4,y_pred4)))
print("R2 score:",metrics.r2_score(y_test4,y_pred4))
```

```
RMSE: 11655.560366092102
R2 score: 0.05486112912254548
```

```
metrics.mean_absolute_error(y_test4,y_pred4)
```

```
9539.25543417836
```

```
mean_squared_error(y_test4,y_pred4)
```

```
135852087.44761705
```

```
mape = mean_absolute_percentage_error(y_test4, y_pred4)
print(mape)
mape = mape * 100
mape
```

```
1.3917498934940569
139.17498934940568
```

ANN

```
#ann
import tensorflow as tf
import pandas as pd
import matplotlib.pyplot as plt
```

```
[544] # Convert 'Approved' column to numeric (if it's not already)
y = pd.to_numeric(y, errors='coerce')

# Convert all columns in X to numeric
for column in X.columns:
    X[column] = pd.to_numeric(X[column], errors='coerce')
```

```
<ipython-input-544-a855d705886e>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X[column] = pd.to_numeric(X[column], errors='coerce')
```

```
[545] from sklearn.model_selection import train_test_split
X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.40, random_state=42)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.30, random_state=42)
X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.25, random_state=42)
X_train4 ,X_test4, y_train4, y_test4 = train_test_split(X, y, test_size=0.20, random_state=42)
```

60-40

```
model.evaluate(X_test1, y_test1)
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.0000e+00 - loss: -399050964992.0000 - precision: 1.0000 - recall: 1.0000
[-391140868096.0, 0.0, 1.0, 1.0]
```

```
model.summary();
```

Model: "sequential_13"

Layer (type)	Output Shape	Param #
dense_52 (Dense)	(None, 30)	90
dense_53 (Dense)	(None, 20)	620
dense_54 (Dense)	(None, 10)	210
dense_55 (Dense)	(None, 1)	11

Total params: 2,795 (10.92 KB)
Trainable params: 931 (3.64 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 1,864 (7.29 KB)

[552]
```
pd.DataFrame(history.history).plot()
plt.ylabel("loss")
plt.xlabel("epochs")
```

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

70-30

```
[558] model.evaluate(X_test2, y_test2)
```

```
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.0000e+00 - loss: -945034952704.0000 - precision: 1.0000 - recall: 1.0000
[-911839592448.0, 0.0, 1.0, 1.0]
```

```
[559] model.summary();
```

Model: "sequential_17"

Layer (type)	Output Shape	Param #
dense_68 (Dense)	(None, 30)	90
dense_69 (Dense)	(None, 20)	620
dense_70 (Dense)	(None, 10)	210
dense_71 (Dense)	(None, 1)	11

Total params: 2,795 (10.92 KB)
Trainable params: 931 (3.64 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 1,864 (7.29 KB)

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

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

75-25

```
[564] model.evaluate(X_test3, y_test3)
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.0000e+00 - loss: -618509041664.0000 - precision: 1.0000 - recall: 1.0000
[-603104608256.0, 0.0, 1.0, 1.0]
```

```
model.summary();
```

Model: "sequential_19"

Layer (type)	Output Shape	Param #
dense_76 (Dense)	(None, 30)	90
dense_77 (Dense)	(None, 20)	620
dense_78 (Dense)	(None, 10)	210
dense_79 (Dense)	(None, 1)	11

Total params: 2,795 (10.92 KB)
Trainable params: 931 (3.64 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 1,864 (7.29 KB)

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

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

80-20

```
[569] model.evaluate(X_test4, y_test4)
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.0000e+00 - loss: -1266557779968.0000 - precision: 1.0000 - recall: 1.0000
[-1209574752256.0, 0.0, 1.0, 1.0]
```

```
model.summary();
```

Model: "sequential_20"

Layer (type)	Output Shape	Param #
dense_80 (Dense)	(None, 30)	90
dense_81 (Dense)	(None, 20)	620
dense_82 (Dense)	(None, 10)	210
dense_83 (Dense)	(None, 1)	11

Total params: 2,795 (10.92 KB)
Trainable params: 931 (3.64 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 1,864 (7.29 KB)

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

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