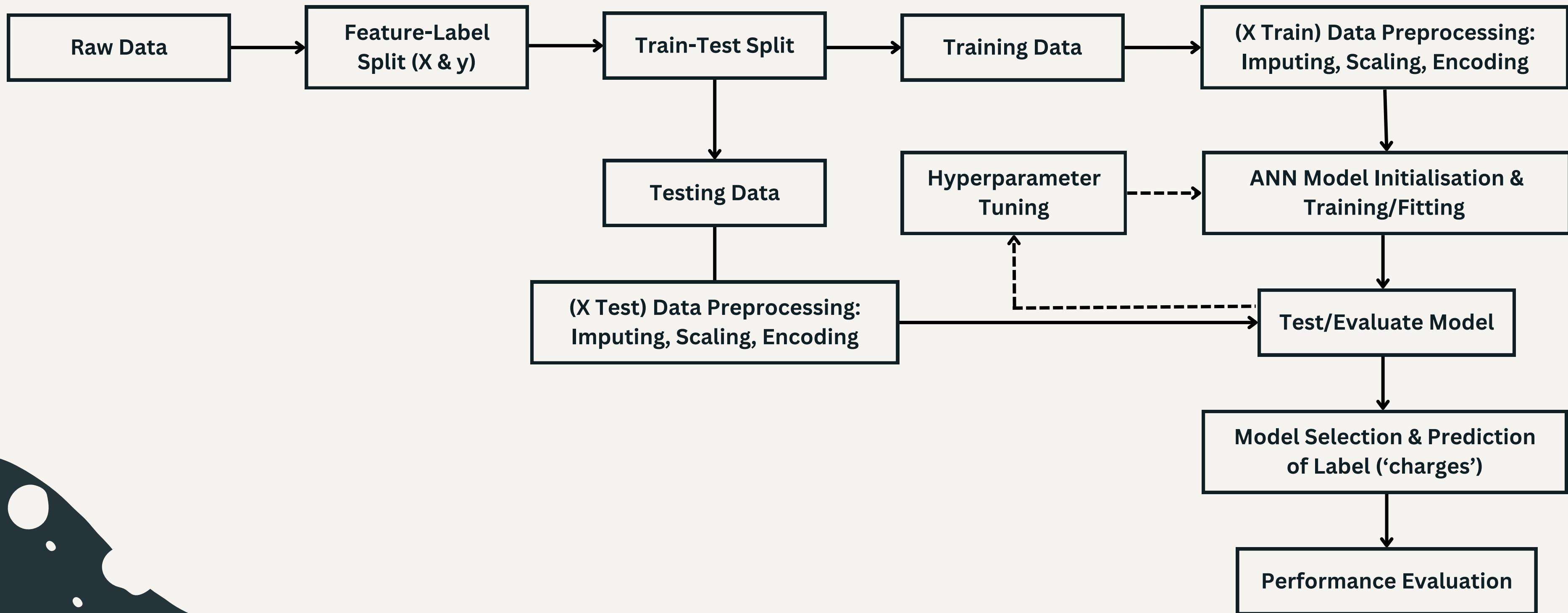




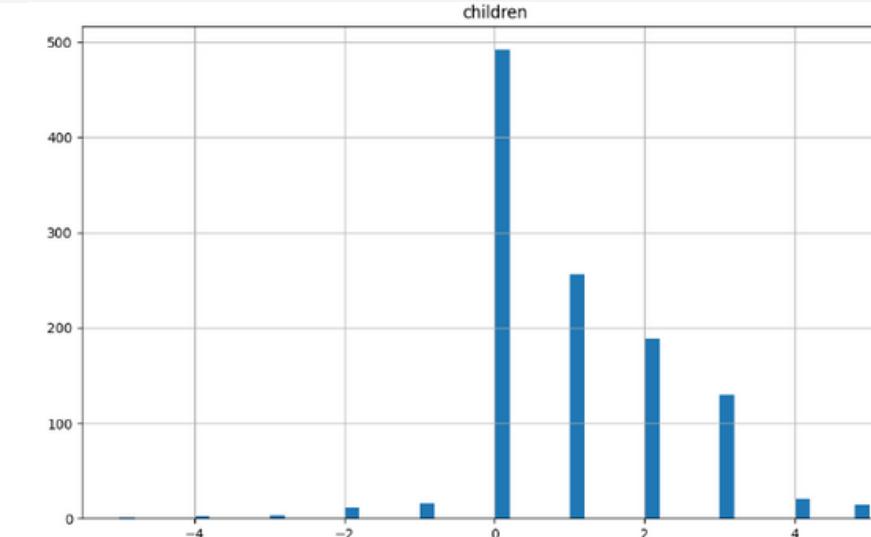
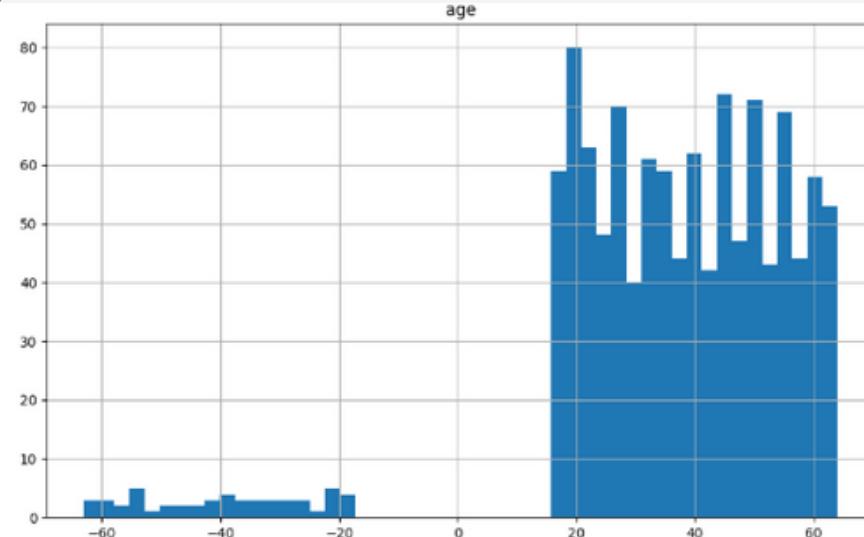
# COSC202: PROJECT

# WORKFLOW DIAGRAM

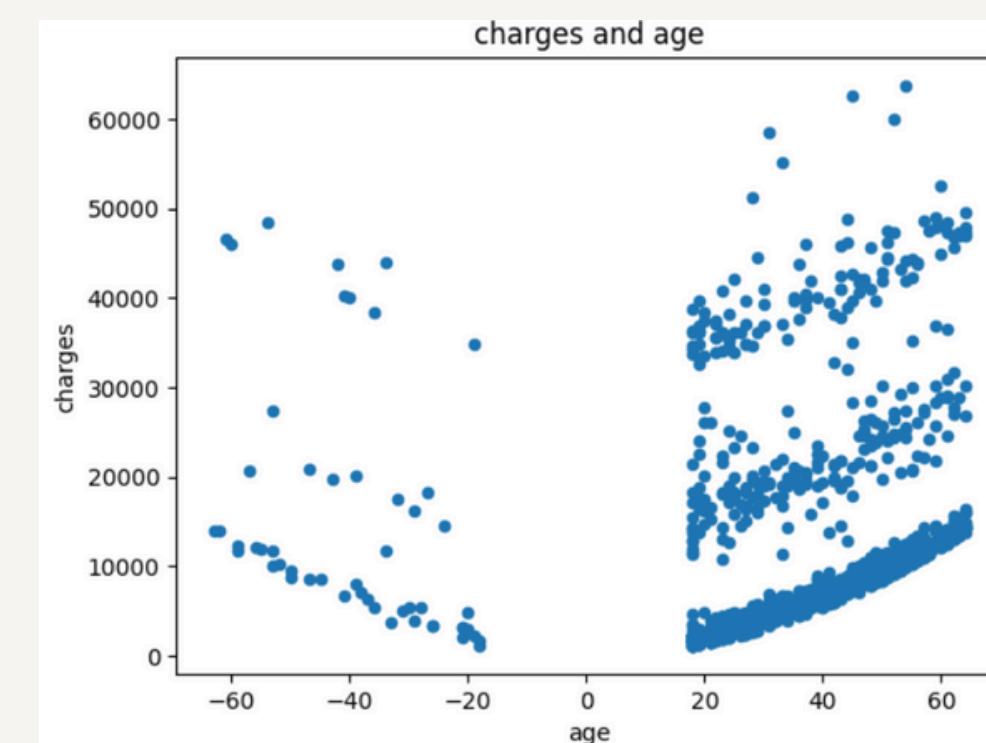


# DATASET VISUALIZATION

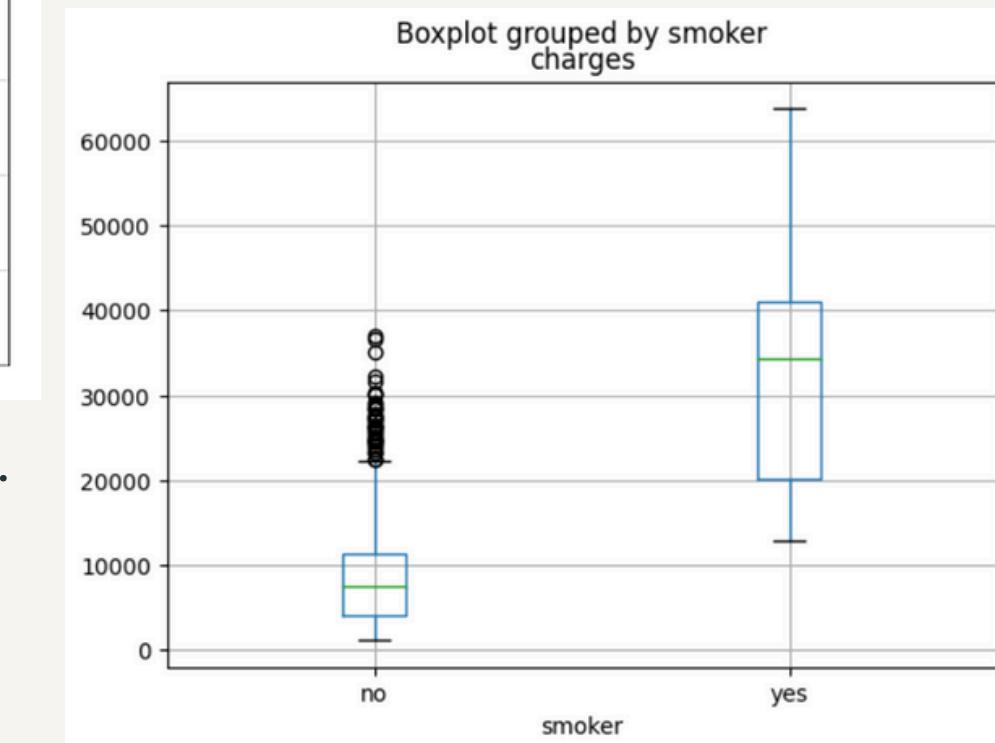
*By visualising the relationships between features, our key observations include:*



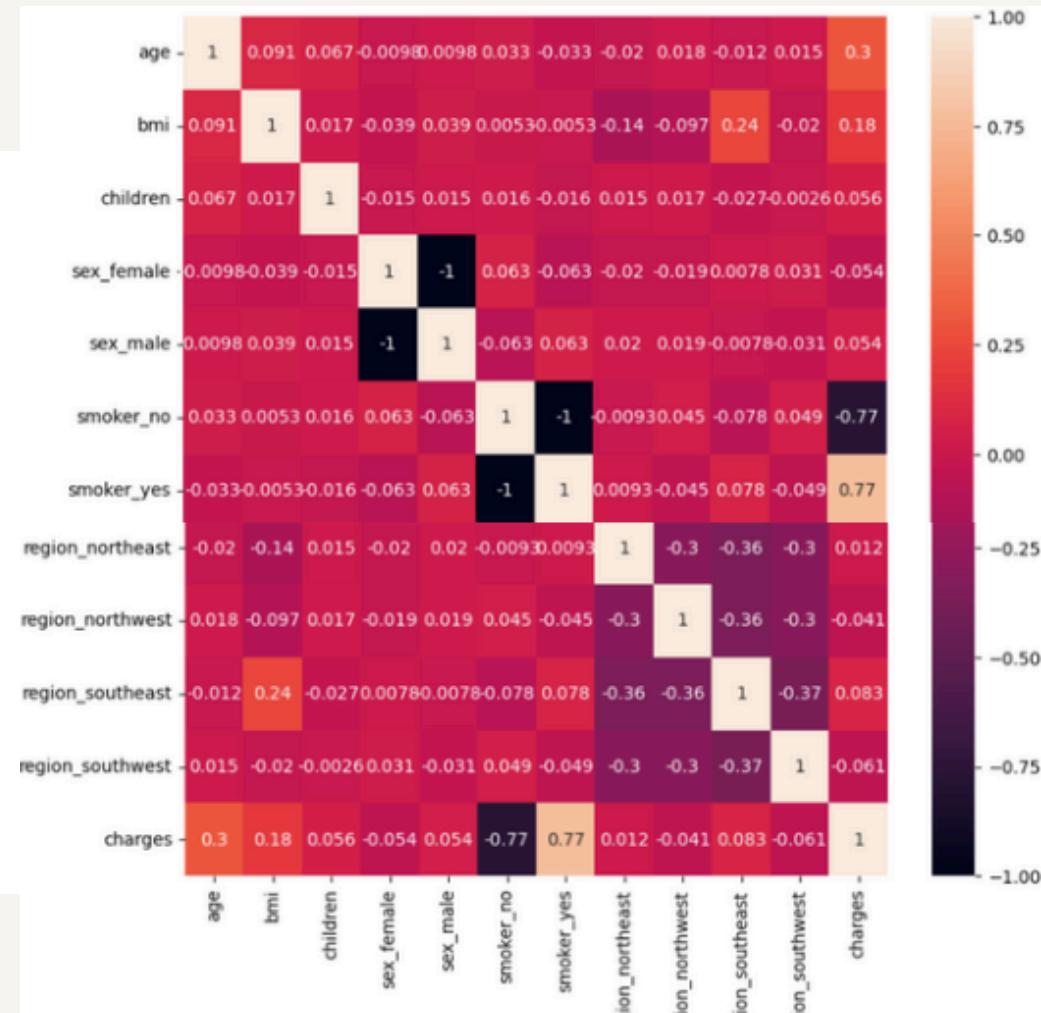
- The histograms showed **negative outliers** in ‘age’ and ‘children’.



- The **scatter plot** shows ‘age’ is **proportional** to ‘charges’, even for the negatives.



- Both the **box plot** & **heatmap** show a **strong relationship** between ‘smoking’ and ‘charges’.
- The **box plot** also shows ‘age’ and ‘bmi’ have **significant correlations** with ‘charges’.



# PREPROCESSING

# 1) Outlier & Typo Handling

- Took *absolute value* of ‘age’.
  - *Mode-imputed* negative ‘children’ values.
  - *Mode-imputed* repeated ‘sex’ typos.

# 2) Missing Data Imputation

- *Mode-imputed*  
missing data in ‘region’.
  - *Median-imputed*  
missing data in ‘bmi’.

# 3) Feature Scaling

- *MinMax scaled* the numerical columns:  
**‘age’**, **‘bmi’**, and  
**‘children’**.

# 4) Encoding

- One-hot encoded the categorical columns: ‘sex’, ‘smoker’, and ‘region’.

# HYPERPARAMETER TUNING

We experimented with tuning hyperparameters including the number of neurons, hidden layers, dropout rates, optimizer, and epochs.

	Model 1	Model 2	Model 3	Model 5 (Selected)
Number of Layers	<b>Input: 1 layer with 16 neurons</b>	<b>Input: 1 layer with 64 neurons</b>	<b>Input: 1 layer with 100 neuron</b>	<b>Input: 1 layer with 100 neuron</b>
	<b>Hidden: 1 layer with 64 neurons</b>	<b>Hidden: 2 layers, each with 64 and 32 neurons, respectively</b>	<b>Hidden: 3 layers with 128, 64, and 32 neurons, respectively</b>	<b>Hidden: 3 layers with 128, 64, and 32 neurons, respectively</b>
	<b>Output: 1 neuron</b>	<b>Output: 1 neuron</b>	<b>Output: 1 neuron</b>	<b>Output: 1 neuron</b>
Activation Function	ReLU	ReLU	ReLU	ReLU
Dropout Rate	<b>10% (0.1) after each layer</b>	<b>10% (0.1) after each layer</b>	<b>10% (0.1) after each layer</b>	<b>10% (0.1) after each layer</b>
Optimizer	Adam	Adam	RMSprop	RMSprop
Learning Rate	<b>Default (0.001)</b>	<b>Default (0.001)</b>	<b>Default (0.001)</b>	<b>0.0005</b>
Epochs	<b>500</b>	<b>500</b>	<b>500</b>	<b>150</b>
Batch Size	-	-	-	<b>16</b>

# SELECTED MODEL (MODEL 5)

*Chosen model architecture:*

```
model5 = Sequential([
    Dense(100, activation='relu', input_shape=(11,)), # Input layer
    Dropout(0.1), # Regularization
    Dense(128, activation='relu'), # Hidden layer 1
    Dropout(0.1), # Regularization
    Dense(64, activation='relu'), # Hidden layer 2
    Dropout(0.1), # Regularization
    Dense(32, activation='relu'), # Hidden layer 3
    Dropout(0.1), # Regularization
    Dense(1) # Single output for regression
])
```

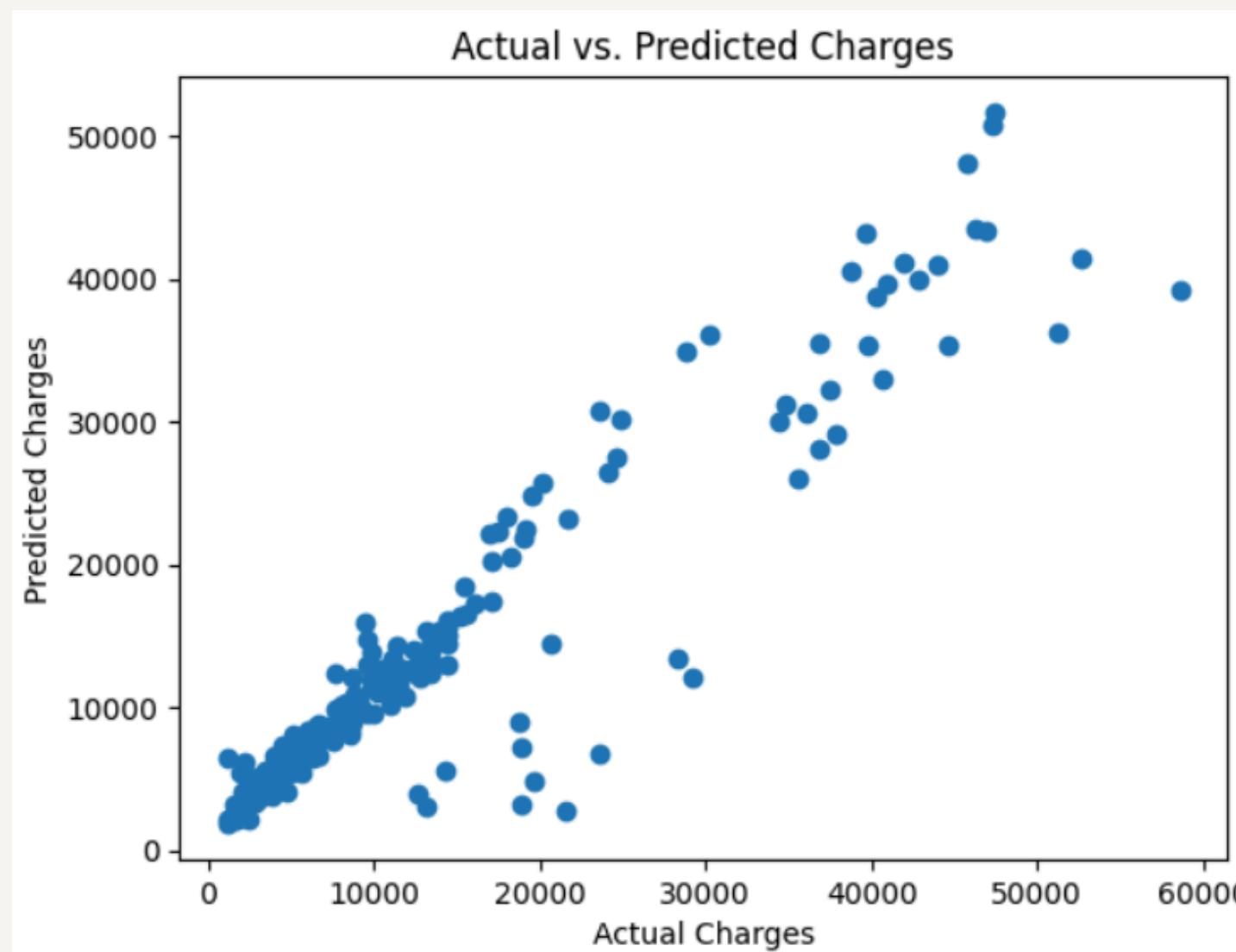
```
optimizer=RMSprop(learning_rate=0.0005)
model5.compile(
    optimizer = optimizer,
    loss='mean_squared_error',
    metrics=['mean_absolute_error']
)
history5 = model5.fit(
    X_train_transformed, y_train,
    validation_data=(X_test_transformed, y_test),
    epochs=150,
    batch_size=16
)
```

*Main differences from other models:*

- **RMSprop** optimizer with a **learning rate** of 0.0005
- **150 epochs**
- **Batch size = 16**

# MODEL PERFORMANCE

*The model has an **MAE** of **2585.68**, which is one of the **lowest** of our models. It also took the **least epochs** to get to this MAE, the others may have overfit.*



*Generally the model has **better predictions** for **lower charges**, this is due to there being **less data points with high charges** in the dataset.*

*However, the graph is **relatively linear** which means the is **performing well**.*

# THANK YOU