



# **EV CHARGING MANAGEMENT WITH DEEP LEARNING TECHNIQUES-BASED ELECTRICITY PRICE FORECASTING.**

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# Introduction

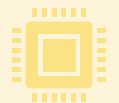
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The rapid adoption of electric vehicles (EVs) presents both opportunities and challenges for the modern energy landscape.



One of the critical aspects of optimizing EV adoption is the efficient management of EV charging, which necessitates careful consideration of factors such as electricity pricing dynamics and grid stability.



The cornerstone of this **presentation lies** in the seamless integration of artificial neural networks for electricity price forecasting and EV charging recommendation in response to forecasted price fluctuations.

# Problem Description

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The increasing adoption of electric vehicles (EVs) presents a growing challenge for electricity grid management due to the variable demand for electricity during charging periods.



Dynamic electricity pricing mechanisms, such as Time-of-Use (TOU) rates, offer cost-saving opportunities for EV owners but require accurate forecasting of electricity prices to optimize charging schedules.



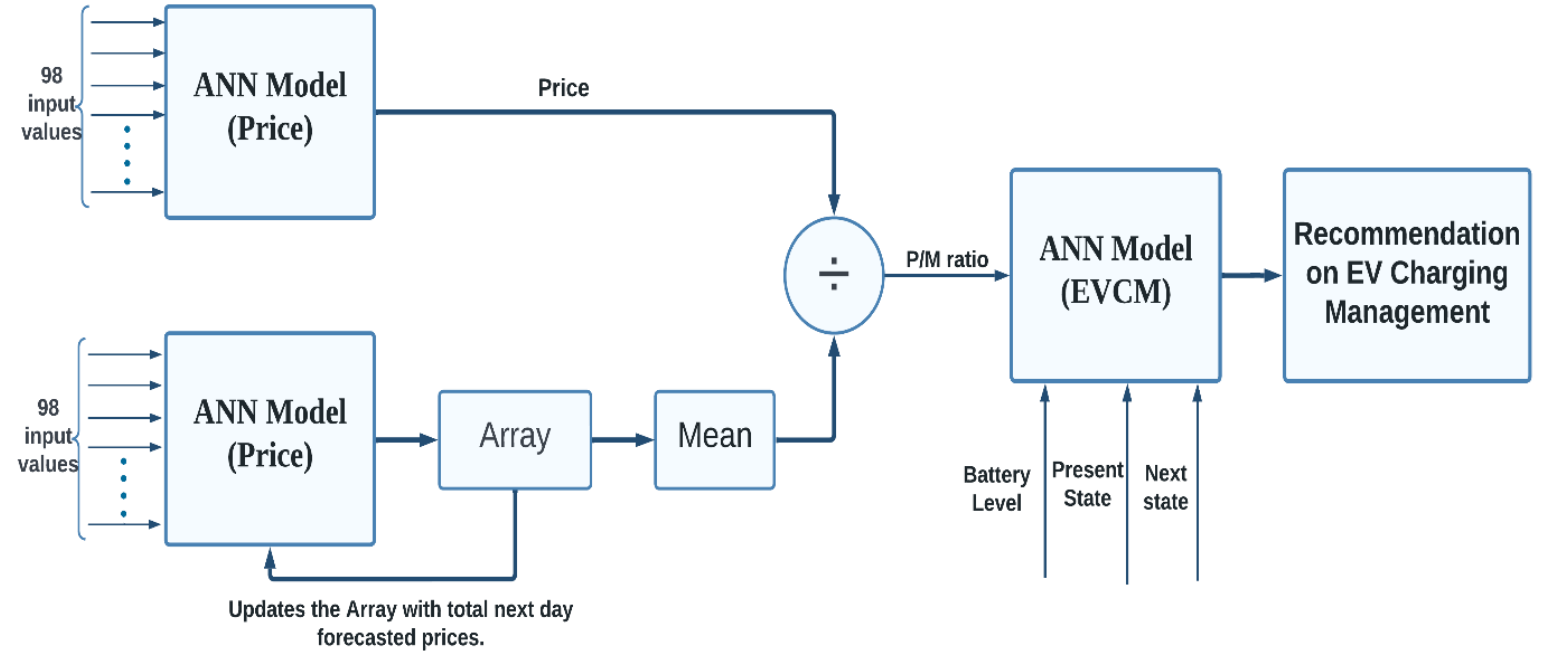
Existing forecasting methods often struggle with the complex patterns and dynamic nature of electricity prices, limiting their effectiveness in cost-efficient EV charging.

# OBJECTIVES

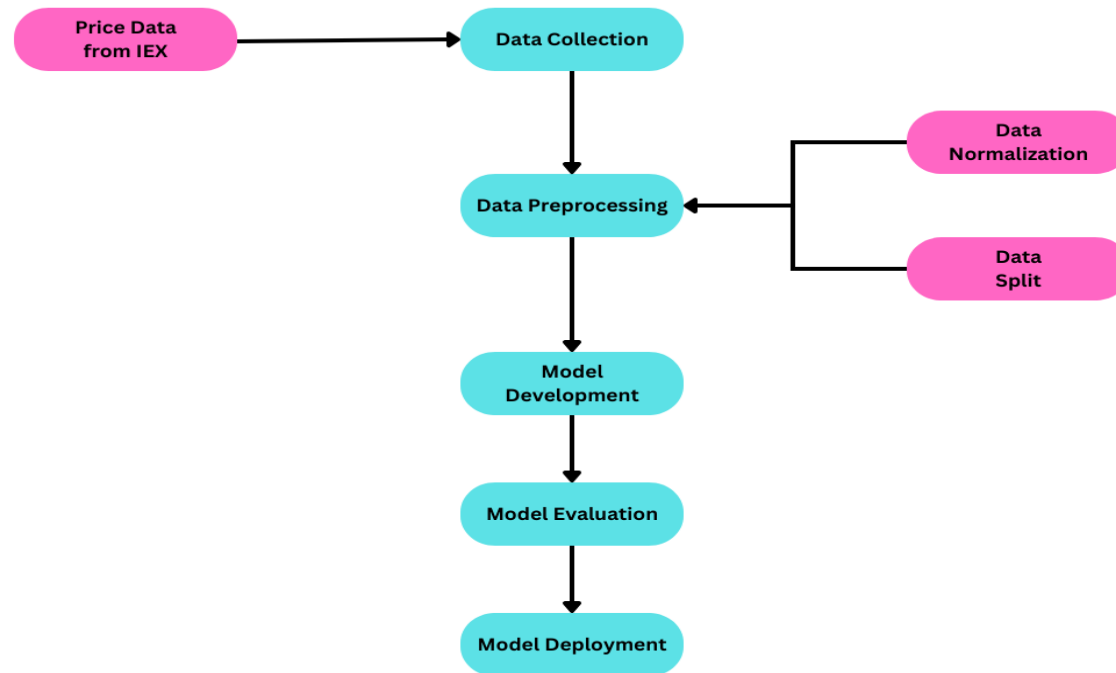


Develop	Develop a deep learning-based model for accurate short-term (15-minute) electricity price forecasting capable of handling the dynamic fluctuations in pricing data.
Integrate	Integrate the price forecasting model with another ANN model which is employed for EV charging management, optimizing charging schedules in response to forecasted electricity prices.
Evaluate	Evaluate the performance of the combined system on real-world datasets, demonstrating its effectiveness in reducing EV charging costs compared to traditional methods and accounting for potential unforeseen price spikes.

# BLOCK DIAGRAM

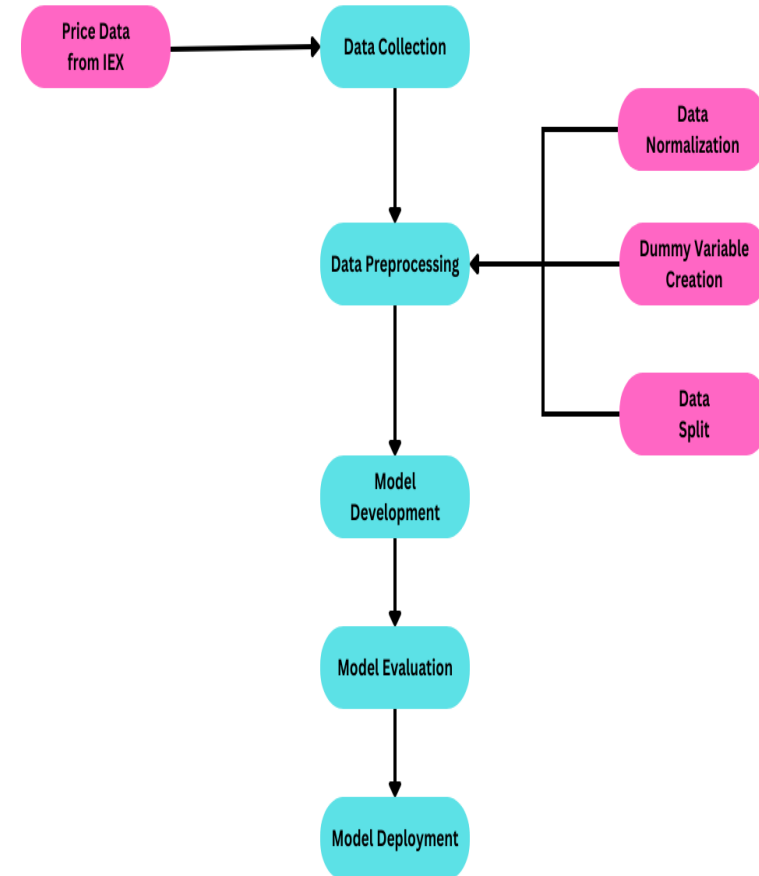


# ELECTRICITY PRICE FORECASTING



# EV CHARGING MANAGEMENT


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# DATA COLLECTION

The data is being collected from IEX(Indian Energy Exchange Limited). The data which is collected is of a 15 minute time range which is collected from 1<sup>st</sup> January 2022 to 30<sup>th</sup> January 2024.

	A	B	C	D
1				
2	Prices at IEX INR/MWh			
3	Date: 01-01-2022 To 31-01-2022			
4	Date   Hour   Time Block			MCP
5	01-01-2022	1	00:00 - 00:15	1999.11
6			00:15 - 00:30	1999.35
7			00:30 - 00:45	1999.50
8			00:45 - 01:00	1999.44
9		2	01:00 - 01:15	1999.24
10			01:15 - 01:30	1999.01
11			01:30 - 01:45	1899.81
12			01:45 - 02:00	1899.55
13		3	02:00 - 02:15	1899.07
14			02:15 - 02:30	1899.03
15			02:30 - 02:45	1899.06
16			02:45 - 03:00	1800.55
17		4	03:00 - 03:15	1899.51
18			03:15 - 03:30	1899.69
19			03:30 - 03:45	1899.87
20			03:45 - 04:00	1900.10
21		5	04:00 - 04:15	1899.91
22			04:15 - 04:30	1899.98
23			04:30 - 04:45	1999.06

# DATA PREPROCESSING

- **FEATURE SELECTION:**

- The features are the previous 24 hour Electricity prices which are divided into 96 i.e., for every 15-minute range, Season and Weekday/weekend.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
2	1999.11	1999.35	1999.5	1999.44	1999.24	1899.01	1899.81	1899.55	1899.07	1899.03	1899.06	1800.55	1899.51
3	1999.35	1999.5	1999.44	1999.24	1999.01	1899.81	1899.55	1899.07	1899.03	1899.06	1800.55	1899.51	1899.69
4	1999.5	1999.44	1999.24	1999.01	1899.81	1899.55	1899.07	1899.03	1899.06	1800.55	1899.51	1899.69	1899.87
5	1999.44	1999.24	1999.01	1899.81	1899.55	1899.07	1899.03	1899.06	1800.55	1899.51	1899.69	1899.87	1900.1
6	1999.24	1999.01	1899.81	1899.55	1899.07	1899.03	1899.06	1800.55	1899.51	1899.69	1899.87	1900.1	1899.91
7	1999.01	1899.81	1899.55	1899.07	1899.03	1899.06	1800.55	1899.51	1899.69	1899.87	1900.1	1899.91	1899.98
8	1899.81	1899.55	1899.07	1899.03	1899.06	1800.55	1899.51	1899.69	1899.87	1900.1	1899.91	1899.98	1999.06

# DATA NORMALIZATION & DATA SPLIT

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Data normalization, is the crucial step of transforming data into a uniform format. This process enhances consistency and facilitates seamless analysis and comparison, particularly when dealing with diverse datasets from various sources.



Data splitting is essential stage because, the model needs to be trained and tested. The training and testing width is choice of the person. 80% of the data for training and 20% of data is being used for testing.

# MODEL DEVELOPMENT

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The ANN model is trained on pre-processed load data where the data is being normalized and split as 80% for training and 20% for testing.



We have developed the model by tuning the Hyperparameters(like Hidden Layers, Neurons, Activation Function).



The best optimized values with less MSE(Mean Squared Error) are being selected for prediction.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y}_i)^2$$

Mean Squared Error (MSE) is a widely used evaluation metric for regression problems, including time series forecasting tasks like short-term electricity price forecasting. MSE measures the average squared difference between the predicted values and the actual values.

## MODEL EVALUATION

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# EV CHARGING MANAGEMENT SYSTEM

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The same data has been used for developing the EV Charging management ANN model with some other features included, they are; Battery Level, Present State and Next State.

The features are the p/m ratio (ratio of predicted price and mean of the total day prices predicted), Battery level, Present State and Next State.

State values are 0 (running) and 1 (parking)

	PM	BL	PS	NS	Rec
0	0.619441	0.626747	1	1	0
1	0.619392	0.679598	1	0	0
2	0.619388	0.561117	0	1	0
3	0.619341	0.140074	0	1	0
4	0.619321	0.958041	1	0	0

# DUMMY VARIABLE CREATION:

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As the target variable is a classification model, we need to convert the target variable into a categorical variable to develop the model in classification type.

	PM	BL	PS	NS	Rec_0	Rec_1	Rec_2
0	0.619441	0.626747	1	1	1	0	0
1	0.619392	0.679598	1	0	1	0	0
2	0.619388	0.561117	0	1	1	0	0
3	0.619341	0.140074	0	1	1	0	0
4	0.619321	0.958041	1	0	1	0	0
...	...	...	...	...	...	...	...
72957	0.565159	0.146952	1	0	1	0	0
72958	0.555188	0.588468	0	0	0	0	1
72959	0.547164	0.341833	1	0	1	0	0
72960	5.536234	0.588334	0	0	0	0	1
72961	0.132479	0.731396	0	0	0	0	1

# MODEL DEVELOPMENT& Evaluation

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$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$



The ANN model is being developed on tuning the hyperparameters like hidden layers, hidden neurons and activation functions



Optimal model with high accuracy is selected for real time deployment



Accuracy measures the proportion of correctly classified charging events out of total number of events evaluated by the model



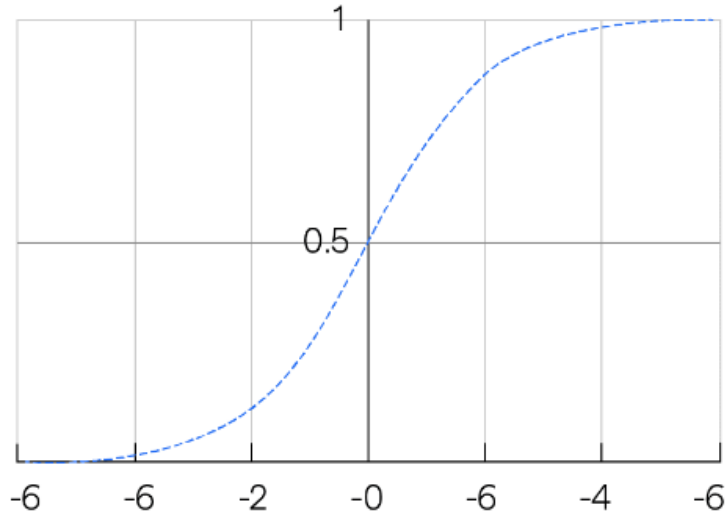
The model is developed by tuning different hyperparameters like Hidden Layers, Number of Neurons, Activation function, optimizers etc.,. All the models are developed in Google Colab notebook. A total of 69985 samples were used in the development of the model.

	F1	F2	F3	F4	F5	F6	F7	F8	F9
count	72960.000000	72960.000000	72960.000000	72960.000000	72960.000000	72960.000000	72960.000000	72960.000000	72960.000000
mean	5658.516518	5658.535922	5658.555008	5658.574088	5658.591926	5658.607709	5658.622941	5658.638316	5658.653549
std	3159.861901	3159.843776	3159.825878	3159.807987	3159.791003	3159.775601	3159.760638	3159.745076	3159.729633
min	998.400000	998.400000	998.400000	998.400000	998.400000	998.400000	998.400000	998.400000	998.400000
25%	3330.327500	3330.337500	3330.340000	3330.340000	3330.340000	3330.340000	3330.340000	3330.340000	3330.340000
50%	4400.970000	4400.970000	4400.970000	4400.970000	4400.970000	4400.970000	4400.970000	4400.970000	4400.970000
75%	7500.050000	7500.050000	7500.050000	7500.050000	7500.050000	7500.050000	7500.050000	7500.050000	7500.050000
max	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000

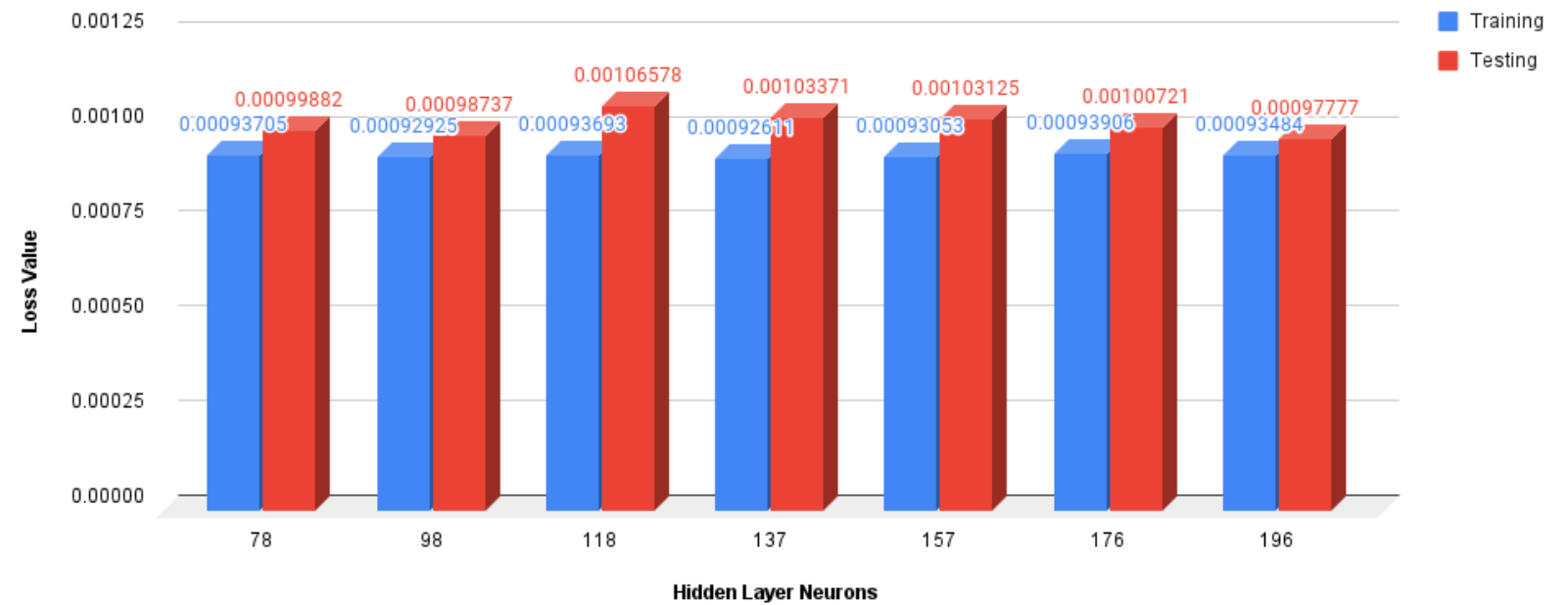
## ELECTRICITY PRICE FORECASTING:

# HYPERPARAMETERS TUNING (Sigmoid)

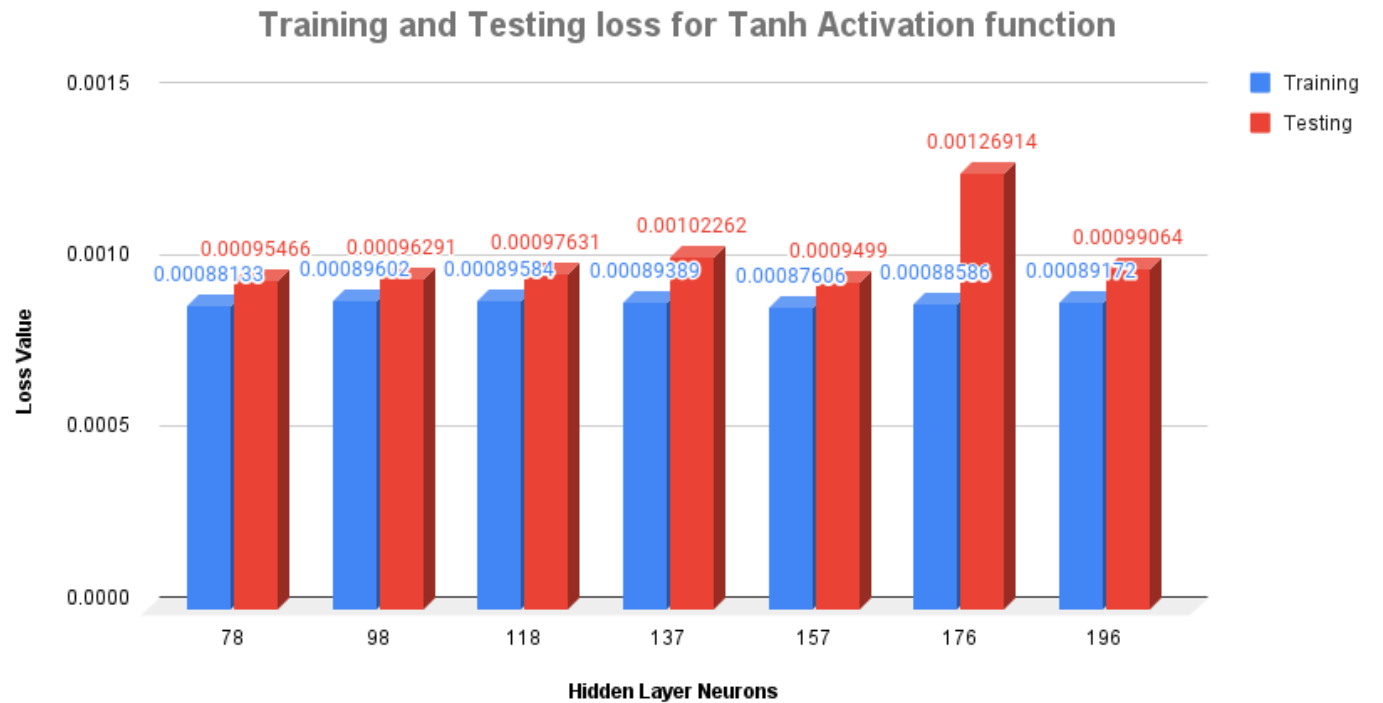
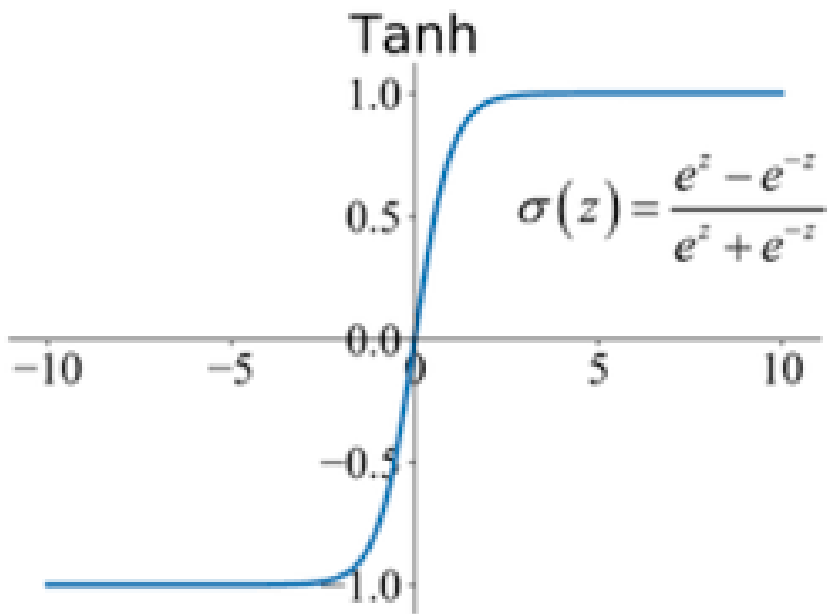
$$f(x) = \frac{1}{1 + e^{-fx}}$$



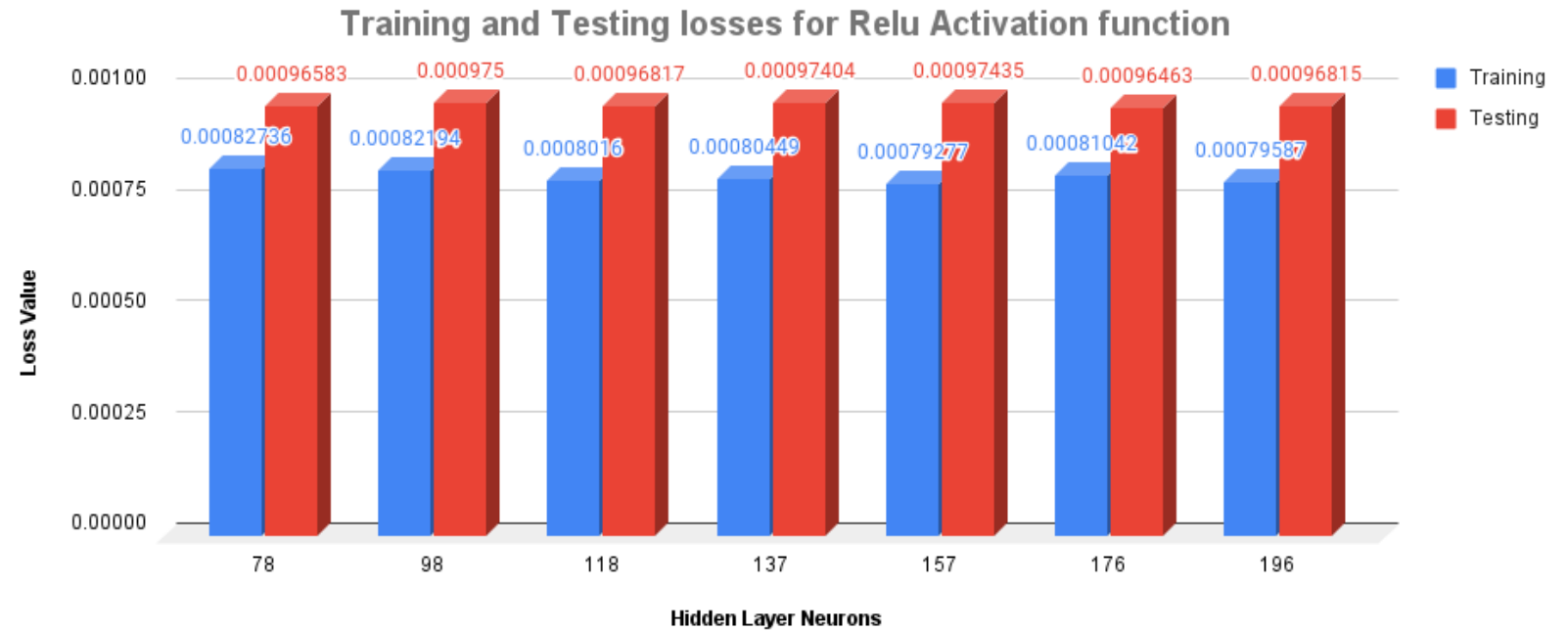
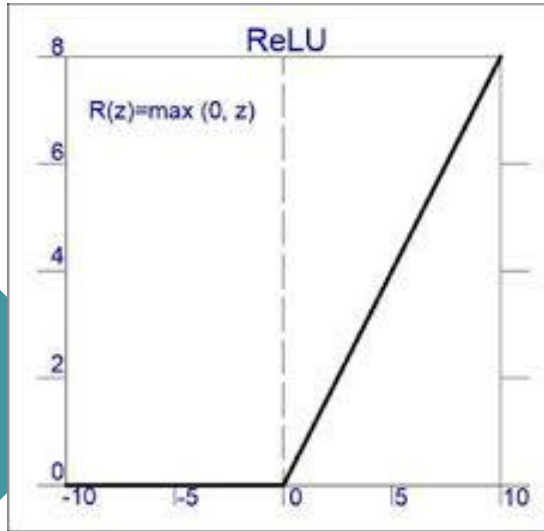
Training and Testing Losses for Sigmoid Activation Function



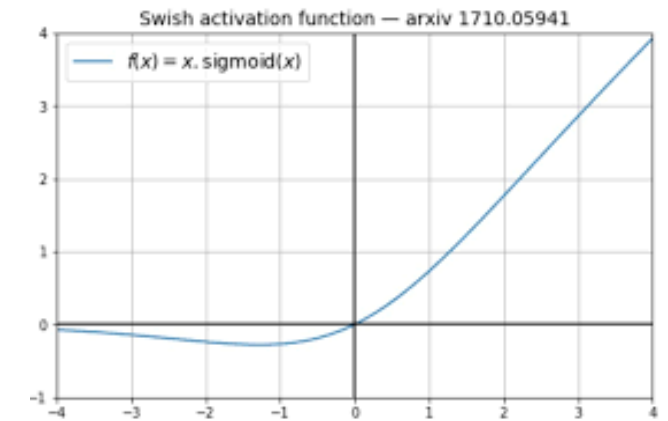
# HYPERPARAMETERS TUNING (Tanh)



# HYPERPARAMETERS TUNING (ReLu)

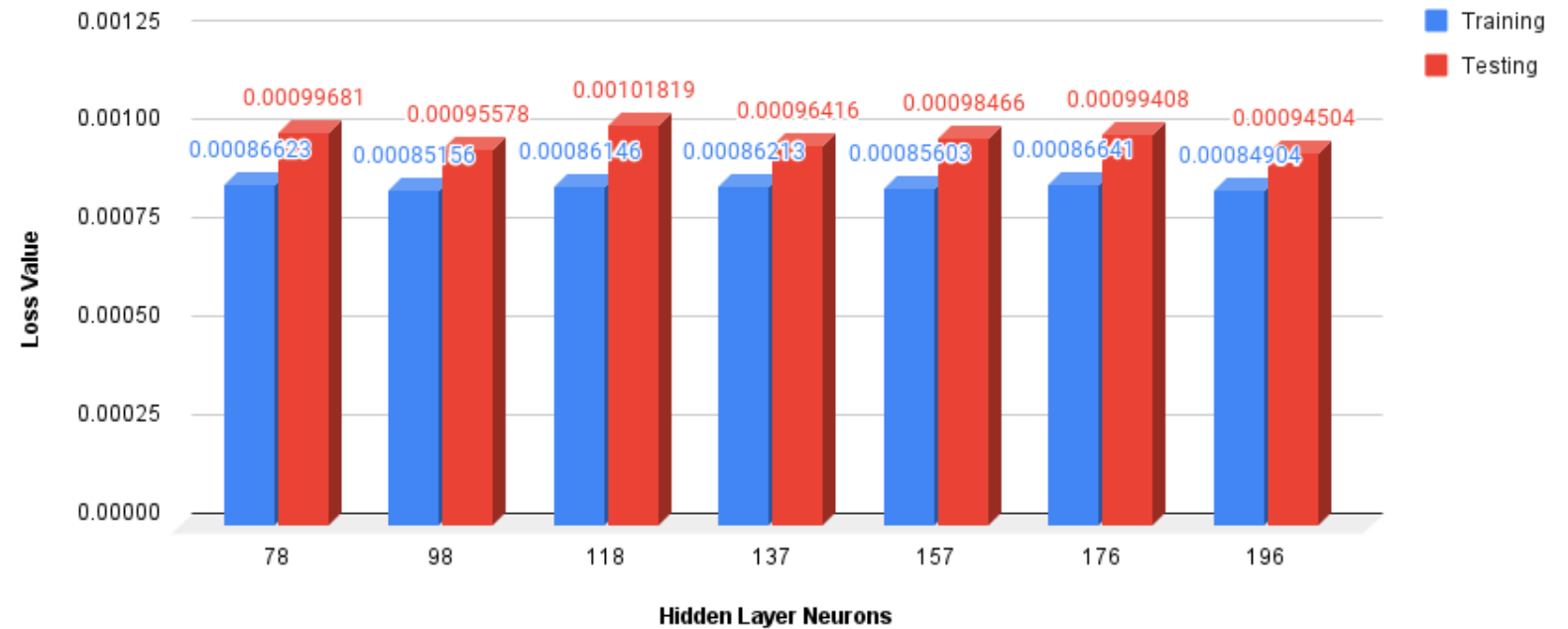


# HYPERPARAMETERS TUNING (Swish)

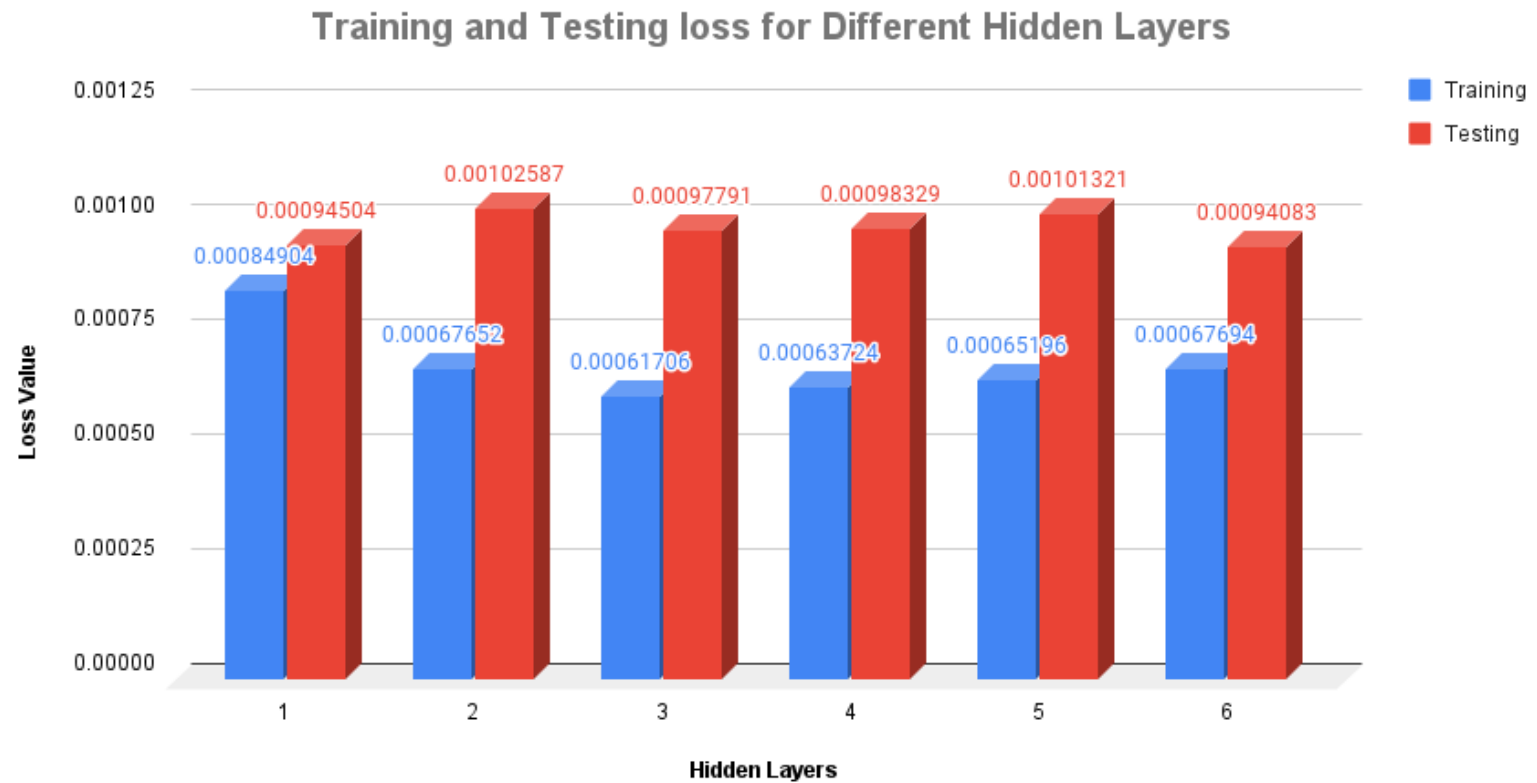


$$y = \frac{x}{1 + e^{-x}}$$

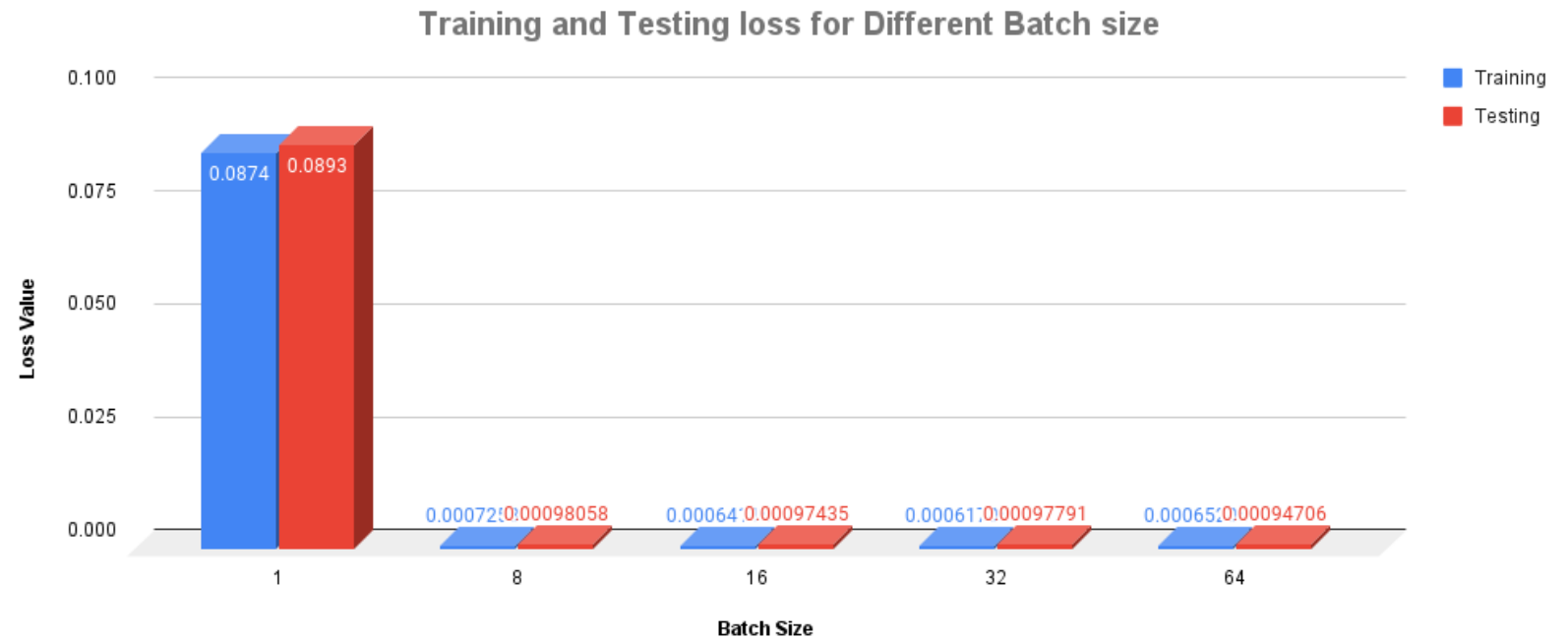
Training and Testing loss for Swish Activation function



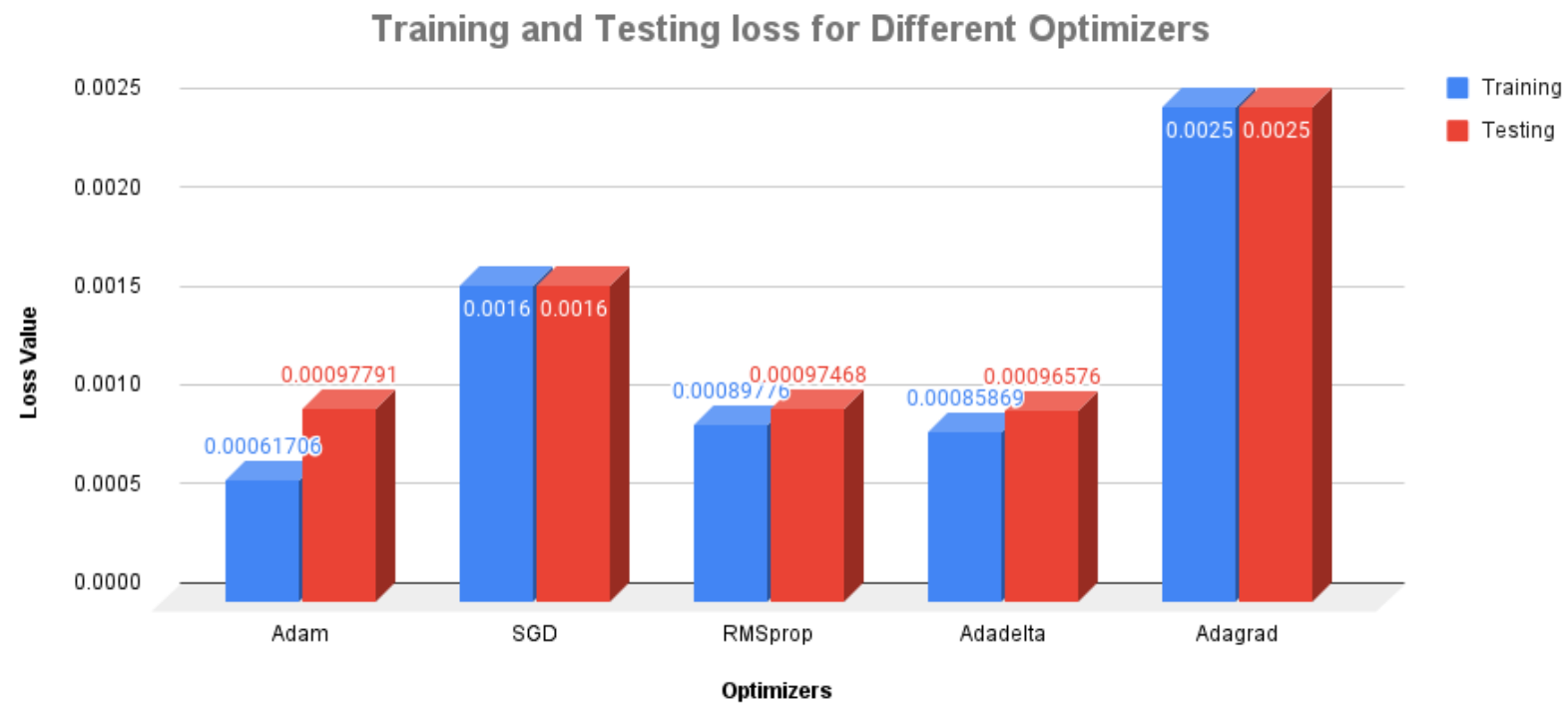
# Hyperparameter – Hidden Layers



# Hyperparameter – Batch Size

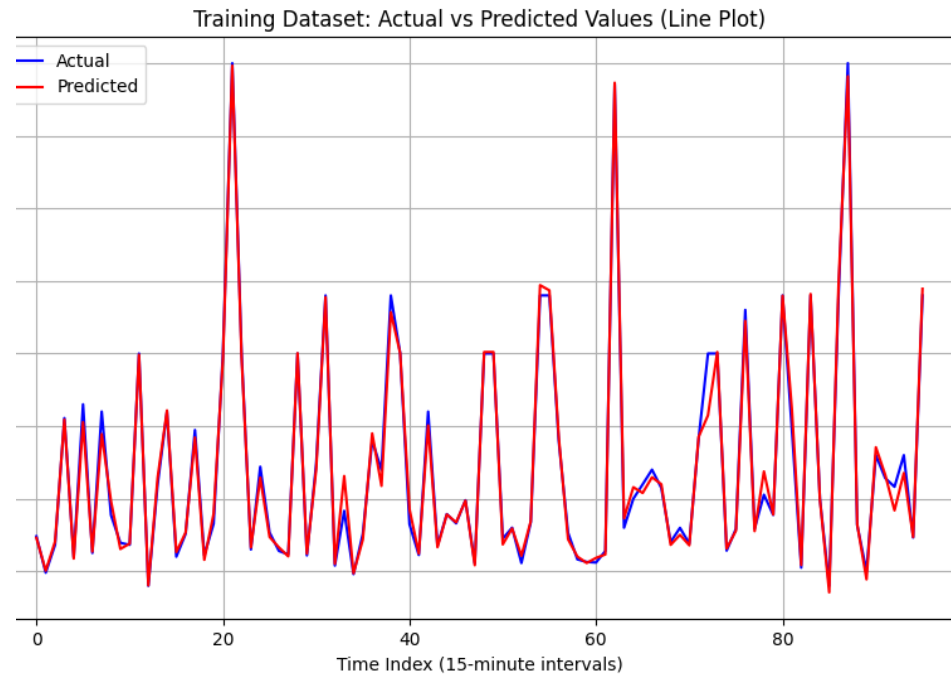
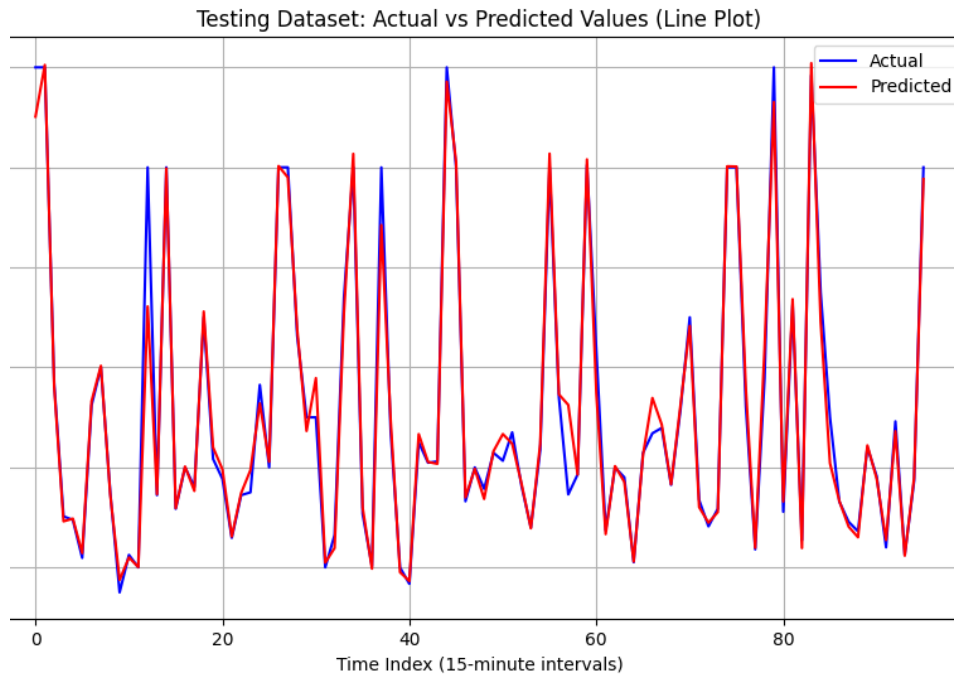


# Hyperparameter – Batch Size

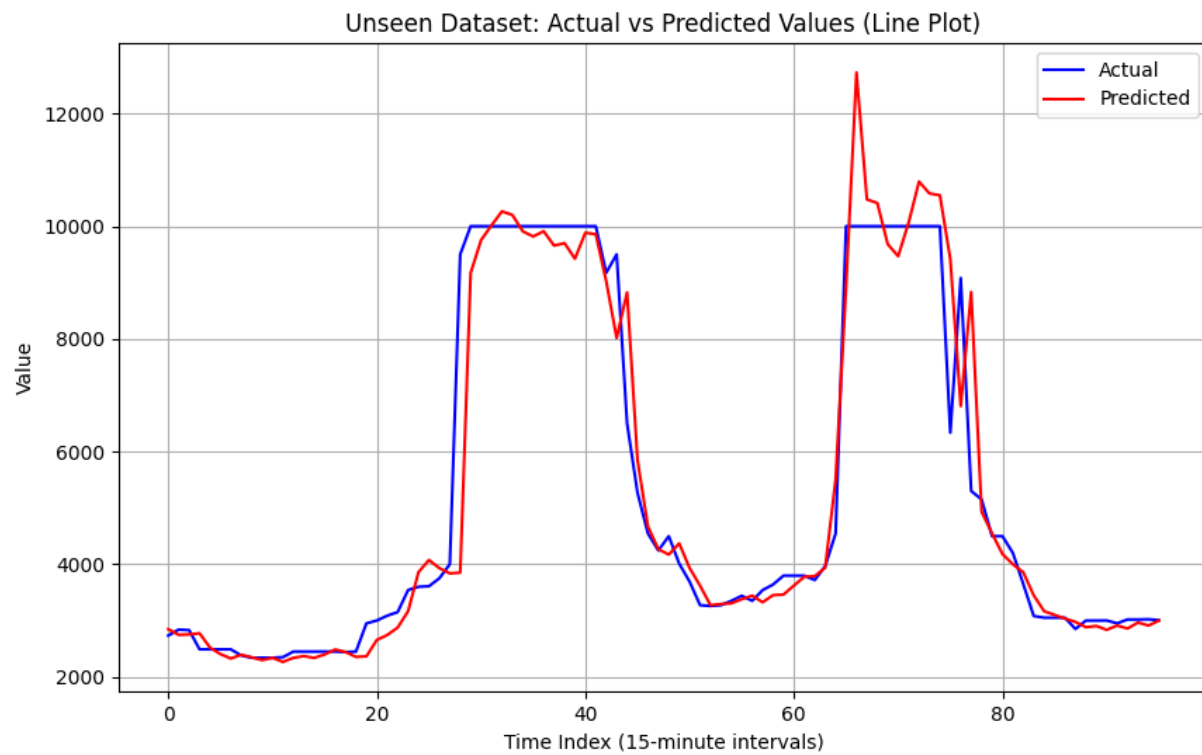




# PREDICTED VALUES BY ANN

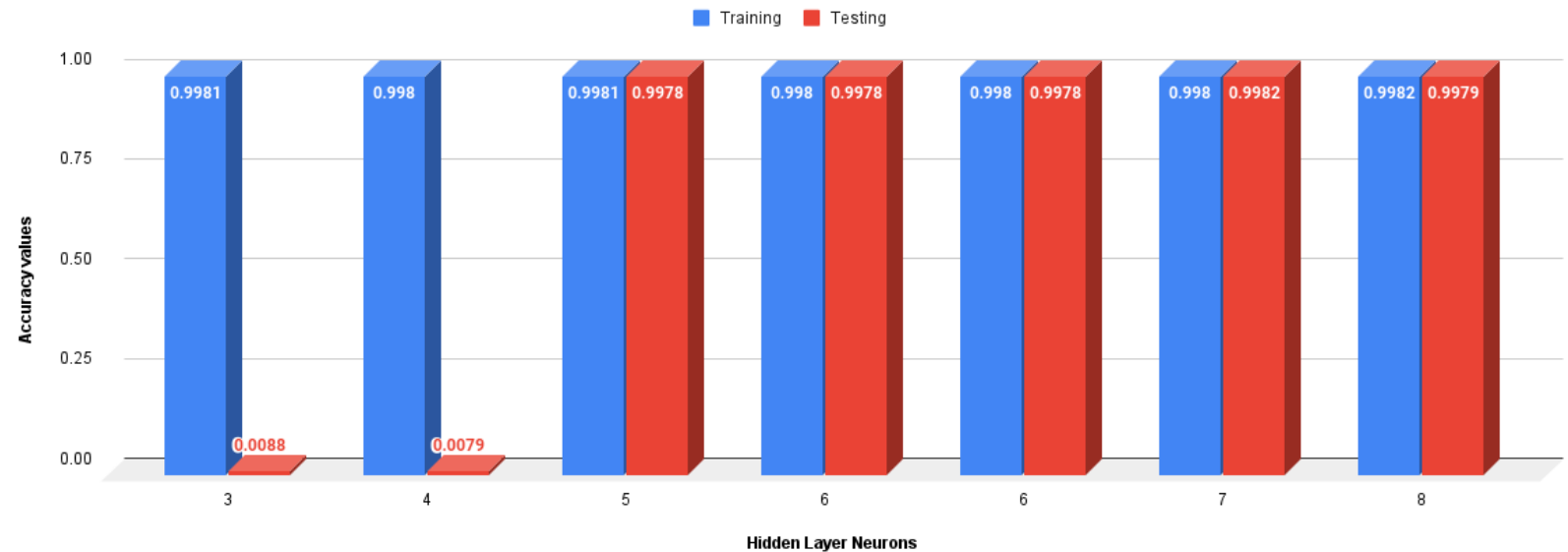


# Unseen Data



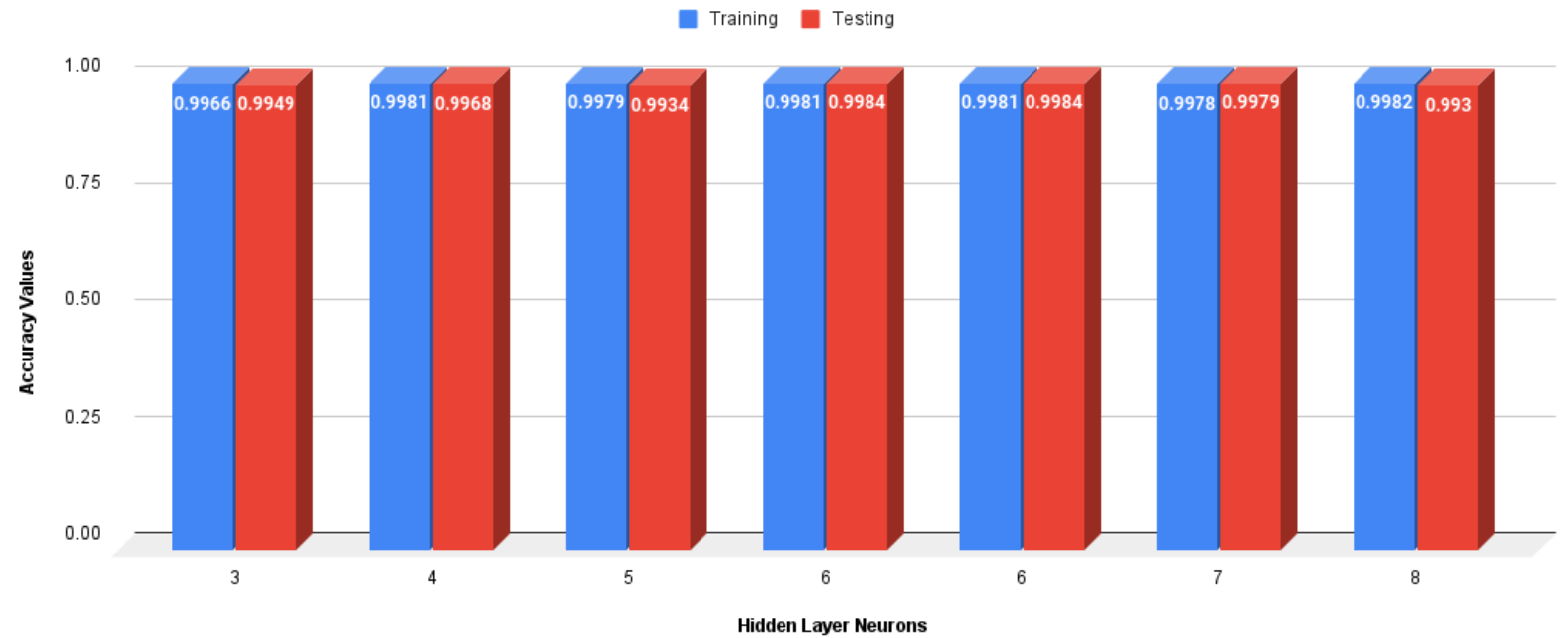
# EV CHARGING MANAGEMENT -RESULT ANALYSIS - sigmoid

Training and Testing Accuracy for Sigmoid Activation Function



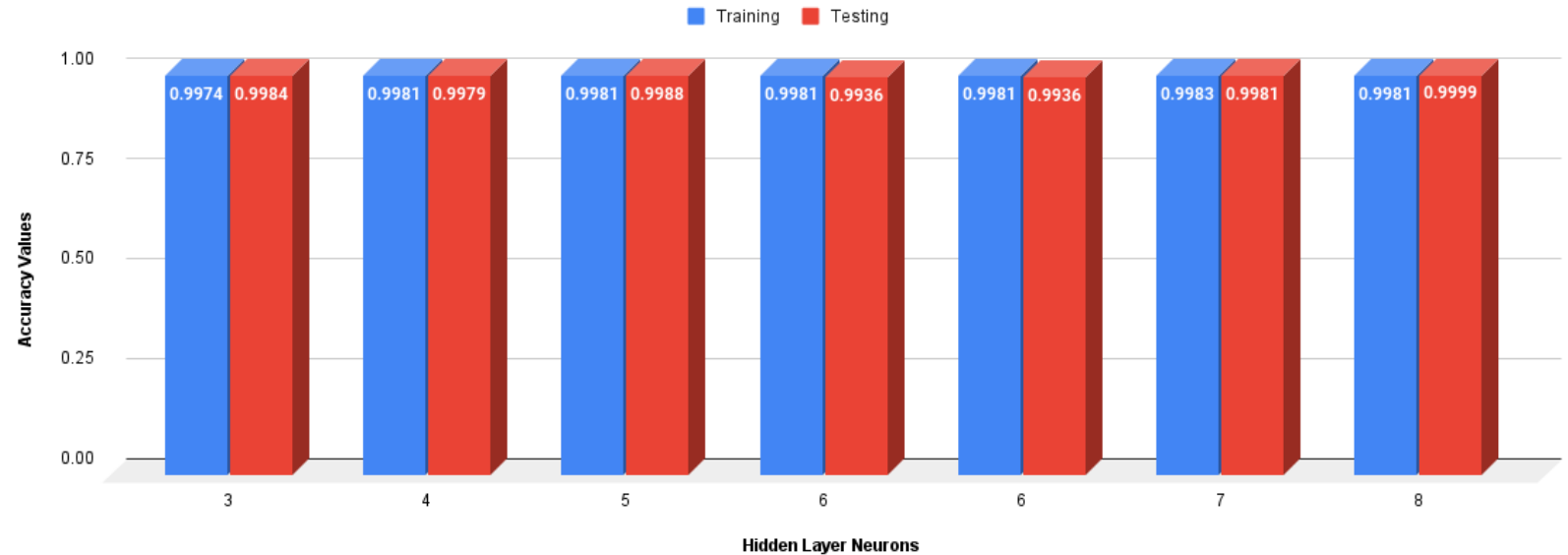
# EV CHARGING MANAGEMENT -RESULT ANALYSIS - Tanh

Training and Testing Accuracy for Tanh Activation Function



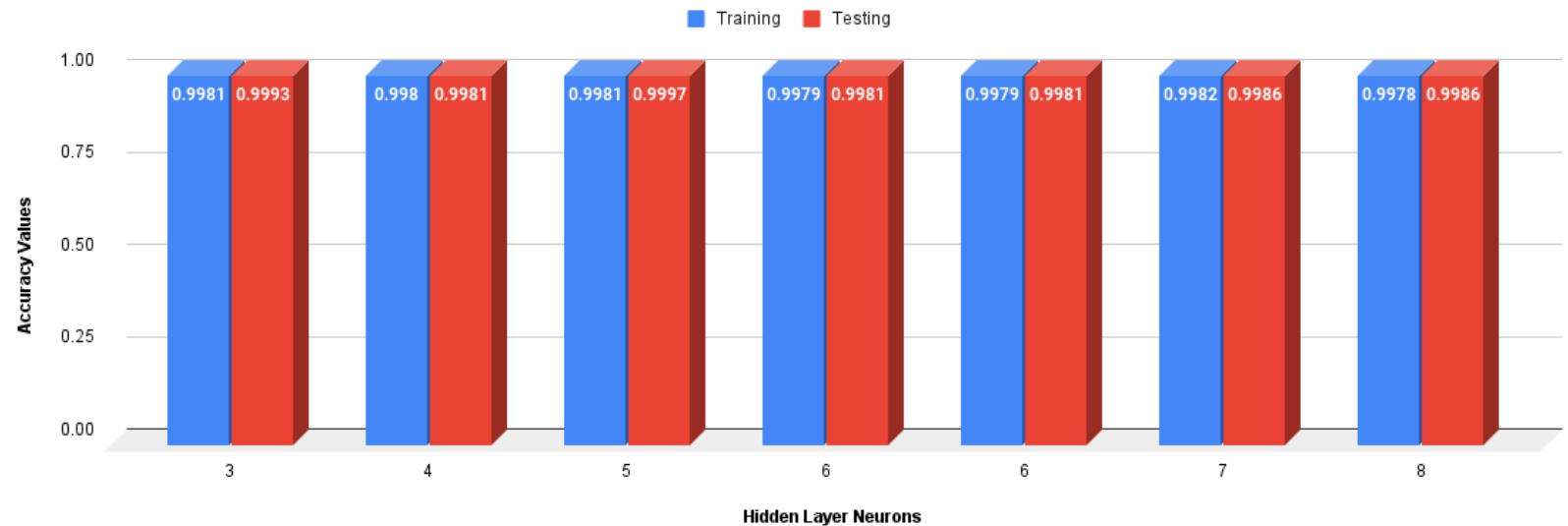
# EV CHARGING MANAGEMENT -RESULT ANALYSIS - ReLu

Training and Testing Accuracy for Relu Activation Function



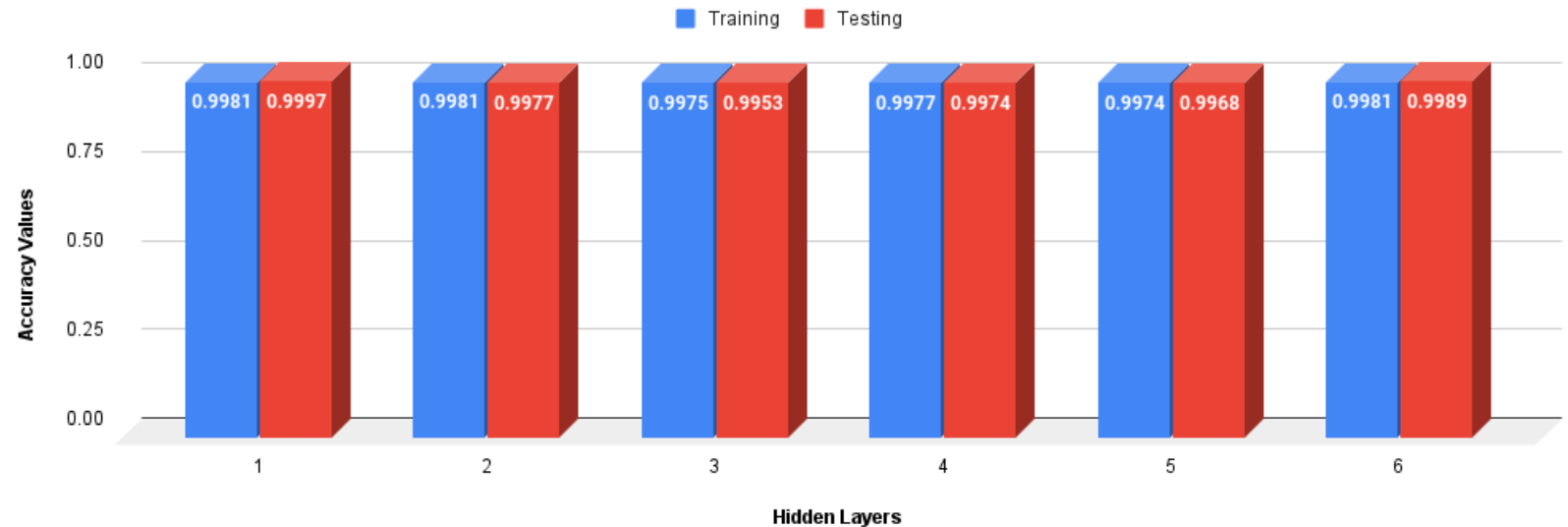
# EV CHARGING MANAGEMENT -RESULT ANALYSIS - SWISH

Training and Testing Accuracy for Swish Activation Function



# Hyperparameter – Hidden Layers

Training and Testing Accuracy for Different Hidden Layers



# Hyperparameter – Batch Size

Training and Testing Accuracy for Different Batch Sizes





# Hyperparameter – Optimizer

Training and Testing Accuracy for Different Optimizers



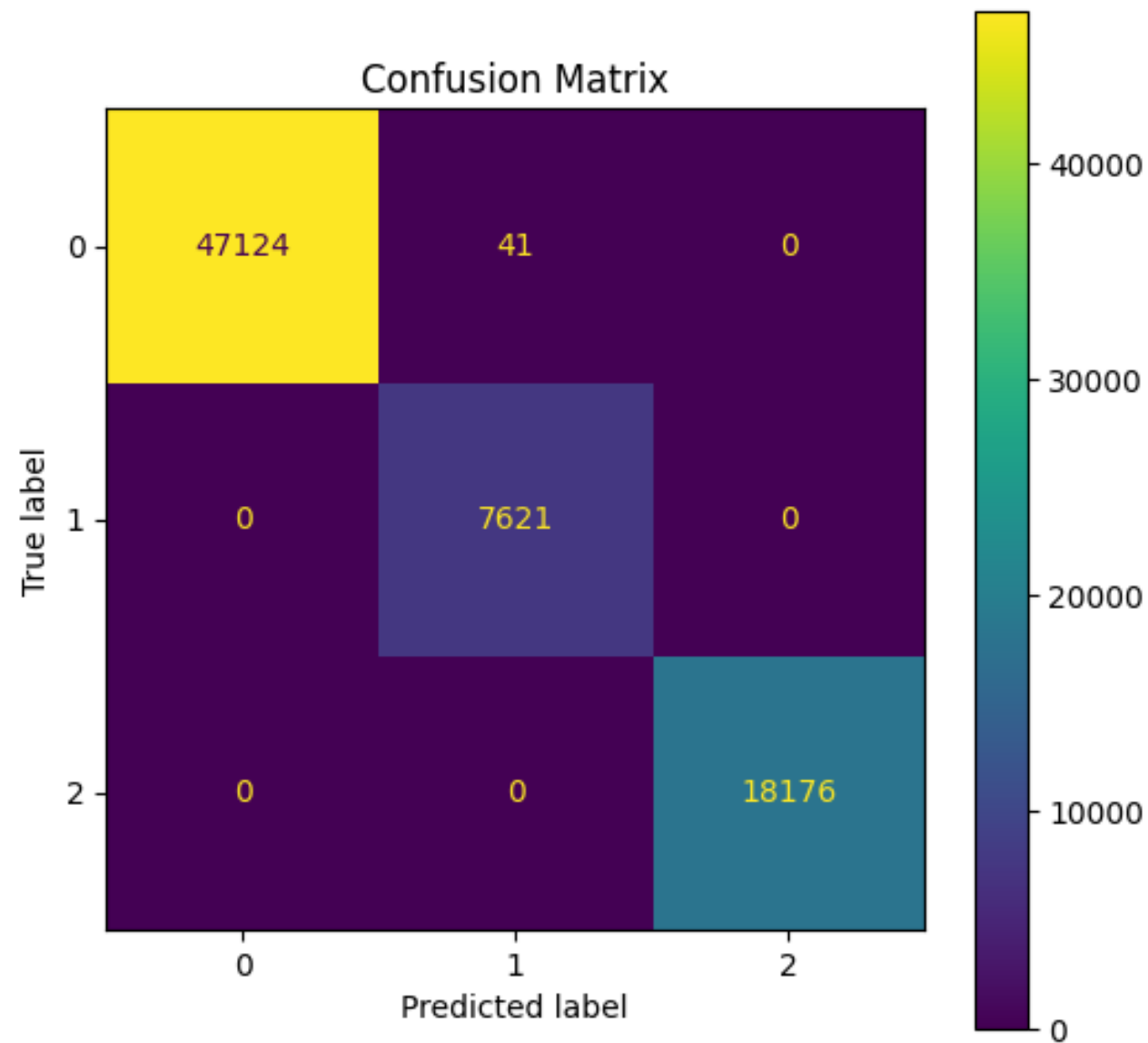
# CONFUSION MATRIX



0: G2V

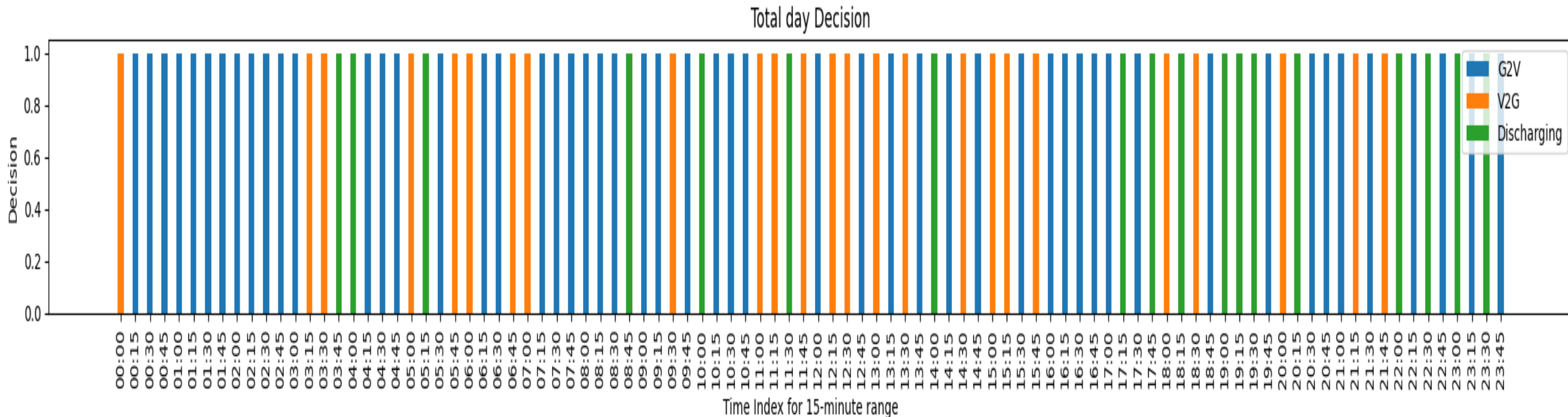
1: V2G

2: Discharge



# MODEL DEPLOYMENT

- Once the model evaluation is done and the model is performing at good accuracy then the model can be used for real world applications for prediction of the price. It is essential for setting up the processes for continuous improvement, allowing for model updates, retraining, and performance enhancement.
- The following figure shows the total one-day decisions.



# ANN MODEL SUPERIORITY

- The ANN model outperforms other machine learning models, presenting significantly lower MSE values on both training and testing data which is on left table. And the right table illustrates the high accuracy. The consistent performance of two ANN models showcases their robustness and superior generalization making them the favorable choice for Decision making on EV charging Management.

Model	Training Loss	Testing Loss
ANN	0.00061706	0.00097791
Linear regression	0.00097871	0.00098608
Random Forest	0.00019034	0.00101795
Decision Tree	0.00552187	0.00189322
SVR	0.00258344	0.00281071

Model	Training Accuracy	Testing accuracy
ANN	99.87%	99.97%
Linear SVC	84.58%	84.85%

# CONCLUSION

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In conclusion, our project on "EV Charging Management with Deep learning techniques-based Electricity Price Forecasting" has successfully given the EV charging recommendation on considering the Electricity price given by the first ANN model, the Battery levels, Present states and Next states by the user preferences. The two ANN models have been developed on the best loss and accuracy values which has satisfied the objectives of the project.



This project can be further extended by using new features which have a good dependency with the target variable. The electricity price forecasting ANN model can also be extended by using Convolutional Neural Networks, Recurrent Neural Networks. And, the EVCM model can be extended with Reinforcement Learning.



**THANK YOU**

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