EDFA Gain Modelling with Machine Learning

Step 1.Data Collection and Preprocessing

```
import pandas as pd

# File paths for each dataset
datasets = {
    'train': 'train_file.csv',
    'test_random': 'test_random.csv',
    'test_goalpost': 'test_goalpost.csv',
}

# Dictionary to store memory usage of each dataset
memory_usage_dict = {}

# First, calculate the memory usage of each dataset and total memory
usage
total_memory = 0
for name, path in datasets.items():
    # Load the dataset
    df = pd.read_csv(path)

    # Calculate memory usage in MB
    memory_mb = df.memory_usage(deep=True).sum() / (1024**2)

    # Store memory usage
    memory_usage_dict[name] = memory_mb

    # Update total memory usage
    total_memory += memory_mb

    # Delete the dataframe to free up memory
    del df

# Header for the output table
print(f"{'Dataset Name':<15} | {'Shape (Rows, Columns)':<25} |
{'Memory (MB)':<15} | {'% of Total':<15}")
print("-" * 80)

# Now print the shape, memory usage, and percentage for each dataset
for name, path in datasets.items():
    # Reload the dataset to get its shape
    df = pd.read_csv(path)

    # Get memory usage from the dictionary
    memory_mb = memory_usage_dict[name]

    # Calculate percentage of total memory
    memory_percentage = (memory_mb / total_memory) * 100
```

```
    # Print the dataset name, shape, memory usage, and percentage
    print(f"{name:<15} | {df.shape}                    | {memory_mb:.2f} MB
| {memory_percentage:.2f}%")

    # Delete the dataframe to free up memory
    del df

# Line for separation
print("-" * 80)

# Print total memory usage
print(f"Total Memory Usage: {total_memory:.2f} MB")
```

```
Dataset Name    | Shape (Rows, Columns)     | Memory (MB)     | % of
Total
----------------------------------------------------------------------
----------
train           | (128688, 384)               | 377.02 MB       |
86.01%
test_random     | (10560, 384)               | 30.94 MB       | 7.06%
test_goalpost   | (10368, 384)               | 30.38 MB       | 6.93%
----------------------------------------------------------------------
----------
Total Memory Usage: 438.33 MB
```

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.gaussian_process import GaussianProcessRegressor
from sklearn.gaussian_process.kernels import RBF, ConstantKernel as C
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LeakyReLU
from tensorflow.keras.optimizers import RMSprop
import matplotlib.pyplot as plt
import warnings
import pickle
import gc
warnings.filterwarnings("ignore")

# Path to the datasets folder
# folder_path = 'path_to_your_datasets/'  # Replace with your actual
path
folder_path = "D:\\class\\Modules\\ICE-4001 Individual Project\\
EDFA_Gain_Model"

# List of datasets
db_values = [15, 18, 21, 24, 27]
```

```
datasets = {
    'train': [f'train_file_{db}dB.csv' for db in db_values],
    'test_random': [f'test_random_{db}dB.csv' for db in db_values],
    'test_goalpost': [f'test_goalpost_{db}dB.csv' for db in
db_values],
}

# Function to convert dB to linear scale
def db_to_linear(db_value):
    return 10 ** (db_value / 10)

# Function to preprocess data
def preprocess_data(df):
    channels_data = []
    for i in range(95):
        channel_index = f'{i:02d}'
        input_power =
df[f'EDFA_input_spectra_{channel_index}'].apply(db_to_linear)
        power_index =
df[f'DUT_WSS_activated_channel_index_{channel_index}']
        output_power =
df[f'EDFA_output_spectra_{channel_index}'].apply(db_to_linear)
        gain =
df[f'calculated_gain_spectra_{channel_index}'].apply(db_to_linear)

        channel_data = {
            'effective_input_power': input_power * power_index,
            'power_index': power_index,
            'output_power': output_power,
            'gain': gain  # This is the actual gain from the dataset
        }
        channels_data.append(pd.DataFrame(channel_data))

    # Concatenate all channels data into a single DataFrame
    all_channels_df = pd.concat(channels_data, axis=1, keys=range(95))

    # Flatten the multi-index columns
    all_channels_df.columns = [f'{outer}_{inner}' for outer, inner in
all_channels_df.columns]

    return all_channels_df

# Function to prepare data for training and testing
def prepare_data(train_df, test_random_df, test_goalpost_df,
fixed_gain_db):
    train_data = preprocess_data(train_df)
    test_random_data = preprocess_data(test_random_df)
    test_goalpost_data = preprocess_data(test_goalpost_df)

    X_train = train_data.filter(regex='effective_input_power|gain')
```

```
    y_train = train_data.filter(regex='output_power')

    X_test_random =
test_random_data.filter(regex='effective_input_power|gain')
    y_test_random = test_random_data.filter(regex='output_power')

    X_test_goalpost =
test_goalpost_data.filter(regex='effective_input_power|gain')
    y_test_goalpost = test_goalpost_data.filter(regex='output_power')

    return X_train, y_train, X_test_random, y_test_random,
X_test_goalpost, y_test_goalpost
```

Step 2. Deep Neural Network (DNN) Model and Model Evaluation

```
# Lists to store results
mae_train_list_dnn = []
mse_train_list_dnn = []
mae_random_list_dnn = []
mse_random_list_dnn = []
mae_goalpost_list_dnn = []
mse_goalpost_list_dnn = []

# Dictionaries to store actual and predicted gains
actual_gains_dnn = {}
dnn_predicted_gains = {}



# Iterate over each dB gain
for db in db_values:
    # Load datasets
    train_df = pd.read_csv(datasets['train'][db_values.index(db)])
    train_df = train_df.sample(frac=1).reset_index(drop=True)

    test_random_df = pd.read_csv(datasets['test_random']
[db_values.index(db)])
    test_random_df =
test_random_df.sample(frac=1).reset_index(drop=True)

    test_goalpost_df = pd.read_csv(datasets['test_goalpost']
[db_values.index(db)])
    test_goalpost_df =
test_goalpost_df.sample(frac=1).reset_index(drop=True)

    # Prepare data
    X_train, y_train, X_test_random, y_test_random, X_test_goalpost,
y_test_goalpost = prepare_data(train_df, test_random_df,
test_goalpost_df, db)

    # Apply MinMaxScaler to the features
```

```
    scaler = MinMaxScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_random_scaled = scaler.transform(X_test_random)
    X_test_goalpost_scaled = scaler.transform(X_test_goalpost)

    # Define and train the DNN model
    dnn_model = Sequential()
    dnn_model.add(Dense(521, input_dim=X_train_scaled.shape[1]))
    dnn_model.add(LeakyReLU(alpha=0.1))
    dnn_model.add(Dense(256))
    dnn_model.add(LeakyReLU(alpha=0.1))
    dnn_model.add(Dense(128))
    dnn_model.add(LeakyReLU(alpha=0.1))
    dnn_model.add(Dense(95, activation='linear'))

    dnn_model.compile(optimizer=RMSprop(learning_rate=0.001),
loss='mse')
    dnn_model.fit(X_train_scaled, y_train, epochs=100, batch_size=32,
validation_split=0.2, verbose=0)

    # Evaluate the models on train dataset
    y_pred_train_dnn = dnn_model.predict(X_train_scaled)
    mae_train = mean_absolute_error(y_train, y_pred_train_dnn)
    mse_train = mean_squared_error(y_train, y_pred_train_dnn)
    mae_train_list_dnn.append(mae_train)
    mse_train_list_dnn.append(mse_train)

    # Evaluate the models on test_random dataset
    y_pred_random_dnn = dnn_model.predict(X_test_random_scaled)
    mae_random = mean_absolute_error(y_test_random, y_pred_random_dnn)
    mse_random = mean_squared_error(y_test_random, y_pred_random_dnn)
    mae_random_list_dnn.append(mae_random)
    mse_random_list_dnn.append(mse_random)

    # Evaluate the models on test_goalpost dataset
    y_pred_goalpost_dnn = dnn_model.predict(X_test_goalpost_scaled)
    mae_goalpost = mean_absolute_error(y_test_goalpost,
y_pred_goalpost_dnn)
    mse_goalpost = mean_squared_error(y_test_goalpost,
y_pred_goalpost_dnn)
    mae_goalpost_list_dnn.append(mae_goalpost)
    mse_goalpost_list_dnn.append(mse_goalpost)

    # Store actual and predicted gains
    actual_gains_dnn[db] = y_test_goalpost.values.flatten()
    dnn_predicted_gains[db] = y_pred_goalpost_dnn.flatten()

    print(f'dB: {db}')
    print(f'    MAE on train dataset: {round(mae_train,4)}')
    print(f'    MSE on train dataset: {round(mse_train,4)}')
```

```
    print(f'    MAE on test_random dataset: {round(mae_random,4)}')
    print(f'    MSE on test_random dataset: {round(mse_random,4)}')
    print(f'    MAE on test_goalpost dataset:
{round(mae_goalpost,4)}')
    print(f'    MSE on test_goalpost dataset:
{round(mse_goalpost,4)}')
    # Delete variables to free up memory
    # Saving the variables to a file
    with open('dnn_results.pkl', 'wb') as f:
        pickle.dump({
            'mae_train_list_dnn': mae_train_list_dnn,
            'mse_train_list_dnn': mse_train_list_dnn,
            'mae_random_list_dnn': mae_random_list_dnn,
            'mse_random_list_dnn': mse_random_list_dnn,
            'mae_goalpost_list_dnn': mae_goalpost_list_dnn,
            'mse_goalpost_list_dnn': mse_goalpost_list_dnn,
            'actual_gains_dnn': actual_gains_dnn,
            'dnn_predicted_gains': dnn_predicted_gains,
            'scaler': scaler # Save the scaler for later use
        }, f)
    # Delete variables to free up memory

    del train_df, test_random_df, test_goalpost_df, X_train, y_train,
X_test_random, y_test_random, X_test_goalpost, y_test_goalpost,
X_train_scaled, X_test_random_scaled, X_test_goalpost_scaled,
dnn_model, y_pred_train_dnn, y_pred_random_dnn, y_pred_goalpost_dnn
    gc.collect()
```

```
1341/1341 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step
110/110 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
108/108 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
dB: 15
    MAE on train dataset: 0.0151
    MSE on train dataset: 0.0005
    MAE on test_random dataset: 0.0188
    MSE on test_random dataset: 0.0009
    MAE on test_goalpost dataset: 0.015
    MSE on test_goalpost dataset: 0.0005
1341/1341 ━━━━━━━━━━━━━━━━━━━━ 8s 6ms/step
110/110 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
108/108 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
dB: 18
    MAE on train dataset: 0.0247
    MSE on train dataset: 0.0014
    MAE on test_random dataset: 0.0609
    MSE on test_random dataset: 0.0102
    MAE on test_goalpost dataset: 0.0478
    MSE on test_goalpost dataset: 0.006
1341/1341 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step
110/110 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

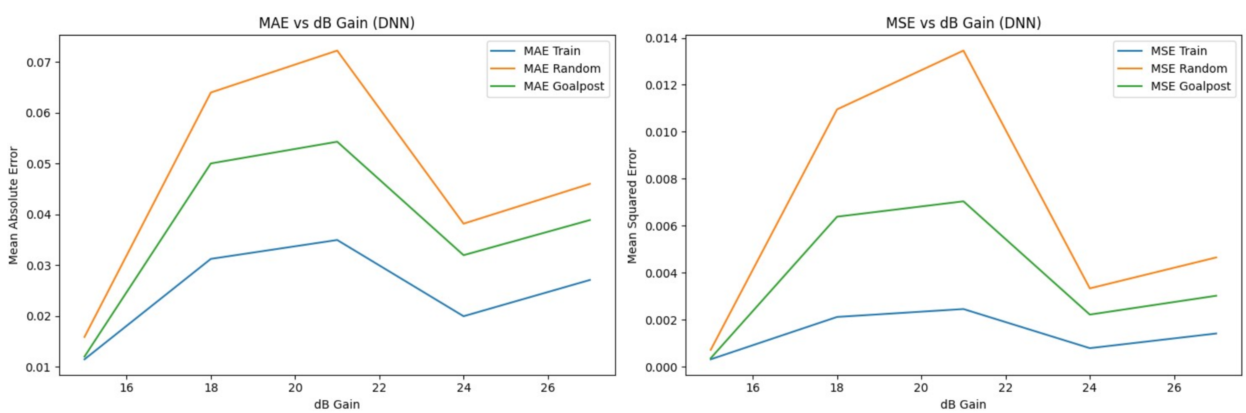
```
108/108 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
dB: 21
    MAE on train dataset: 0.0258
    MSE on train dataset: 0.0014
    MAE on test_random dataset: 0.0671
    MSE on test_random dataset: 0.0126
    MAE on test_goalpost dataset: 0.0479
    MSE on test_goalpost dataset: 0.0056
671/671 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step
55/55 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
dB: 24
    MAE on train dataset: 0.0346
    MSE on train dataset: 0.0024
    MAE on test_random dataset: 0.0453
    MSE on test_random dataset: 0.0043
    MAE on test_goalpost dataset: 0.0377
    MSE on test_goalpost dataset: 0.0029
671/671 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
55/55 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
54/54 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
dB: 27
    MAE on train dataset: 0.0398
    MSE on train dataset: 0.0033
    MAE on test_random dataset: 0.0513
    MSE on test_random dataset: 0.0056
    MAE on test_goalpost dataset: 0.0457
    MSE on test_goalpost dataset: 0.0041
```

dB Gain	Dataset	MAE	MSE
15	Training	0.0151	0.0005
	Test Random	0.0188	0.0009
	Test Goalpost	0.0150	0.0005
18	Training	0.0247	0.0014
	Test Random	0.0609	0.0102
	Test Goalpost	0.0478	0.0060
21	Training	0.0258	0.0014
	Test Random	0.0671	0.0126
	Test Goalpost	0.0479	0.0056
24	Training	0.0346	0.0024
	Test Random	0.0453	0.0043
	Test Goalpost	0.0377	0.0029
27	Training	0.0398	0.0033
	Test Random	0.0513	0.0056

dB Gain	Dataset	MAE	MSE
	Test Goalpost	0.0457	0.0041

Step 3. Model Evaluation

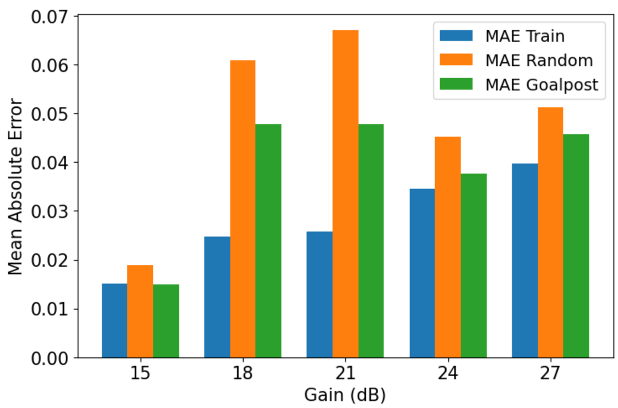
```
# Plot the results as line plots
plt.figure(figsize=(15, 5))

# MAE plot
plt.subplot(1, 2, 1)
plt.plot(db_values, mae_train_list_dnn, label='MAE Train')
plt.plot(db_values, mae_random_list_dnn, label='MAE Random')
plt.plot(db_values, mae_goalpost_list_dnn, label='MAE Goalpost')
plt.xlabel('dB Gain')
plt.ylabel('Mean Absolute Error')
plt.title('MAE vs dB Gain (DNN)')
plt.legend()

# MSE plot
plt.subplot(1, 2, 2)
plt.plot(db_values, mse_train_list_dnn, label='MSE Train')
plt.plot(db_values, mse_random_list_dnn, label='MSE Random')
plt.plot(db_values, mse_goalpost_list_dnn, label='MSE Goalpost')
plt.xlabel('dB Gain')
plt.ylabel('Mean Squared Error')
plt.title('MSE vs dB Gain (DNN)')
plt.legend()

plt.tight_layout()
plt.show()
```

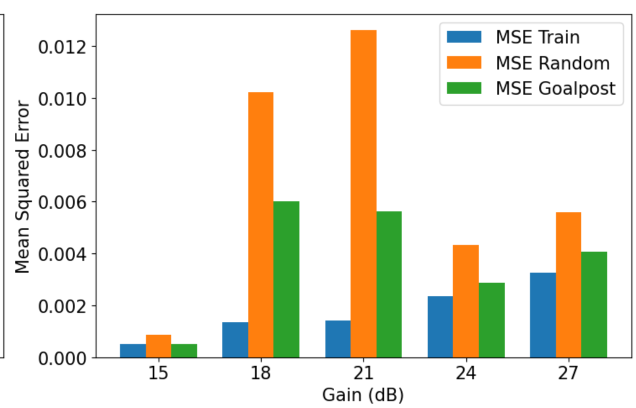



```
import pandas as pd
import numpy as np
import pickle
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
```

```
db_values = [15, 18, 21, 24, 27]

# Load the saved variables including the scaler
with open('dnn_results.pkl', 'rb') as f:
    results = pickle.load(f)

# Extract the saved data
mae_train_list_dnn = results['mae_train_list_dnn']
mse_train_list_dnn = results['mse_train_list_dnn']
mae_random_list_dnn = results['mae_random_list_dnn']
mse_random_list_dnn = results['mse_random_list_dnn']
mae_goalpost_list_dnn = results['mae_goalpost_list_dnn']
mse_goalpost_list_dnn = results['mse_goalpost_list_dnn']
actual_gains_dnn = results['actual_gains_dnn']
dnn_predicted_gains = results['dnn_predicted_gains']
scaler = results['scaler']  # Load the saved scaler

# Plot the results as bar plots
import matplotlib.pyplot as plt
plt.figure(figsize=(15, 5))

# MAE plot
plt.subplot(1, 2, 1)
bar_width = 0.25
index = np.arange(len(db_values))

plt.bar(index, mae_train_list_dnn, bar_width, label='MAE Train')  #
Red
plt.bar(index + bar_width, mae_random_list_dnn, bar_width, label='MAE
Random')  # Dark Gray
plt.bar(index + 2 * bar_width, mae_goalpost_list_dnn, bar_width,
label='MAE Goalpost')  # Light Gray

plt.xlabel('Gain (dB)', fontsize=18)
plt.ylabel('Mean Absolute Error', fontsize=18)
plt.xticks(index + bar_width, db_values)
plt.legend(fontsize=14)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18)

# MSE plot
plt.subplot(1, 2, 2)

plt.bar(index, mse_train_list_dnn, bar_width, label='MSE Train')  #
Red
plt.bar(index + bar_width, mse_random_list_dnn, bar_width, label='MSE
Random')  # Dark Gray
plt.bar(index + 2 * bar_width, mse_goalpost_list_dnn, bar_width,
label='MSE Goalpost')  # Light Gray
```

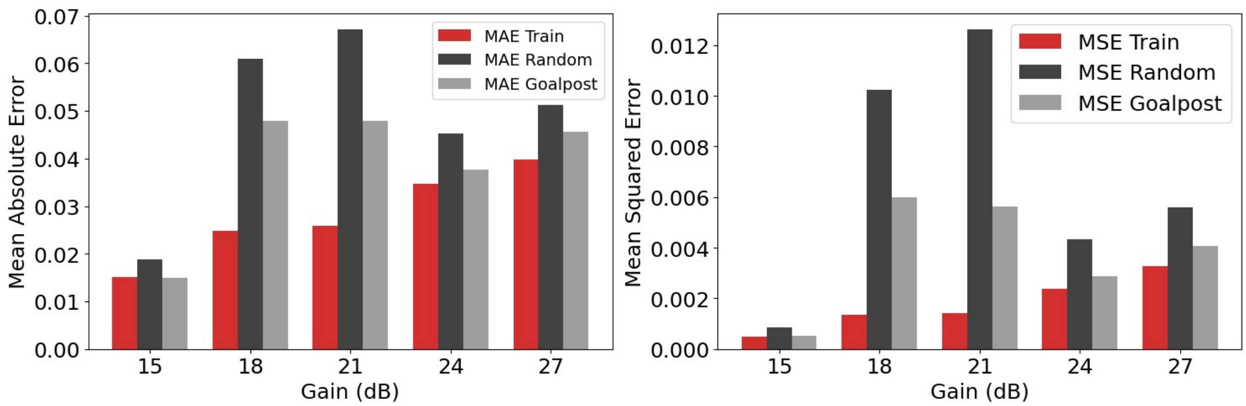
```
plt.xlabel('Gain (dB)', fontsize=18)
plt.ylabel('Mean Squared Error', fontsize=18)
plt.xticks(index + bar_width, db_values)
plt.legend(fontsize=18)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18)

plt.tight_layout()
plt.show()
```





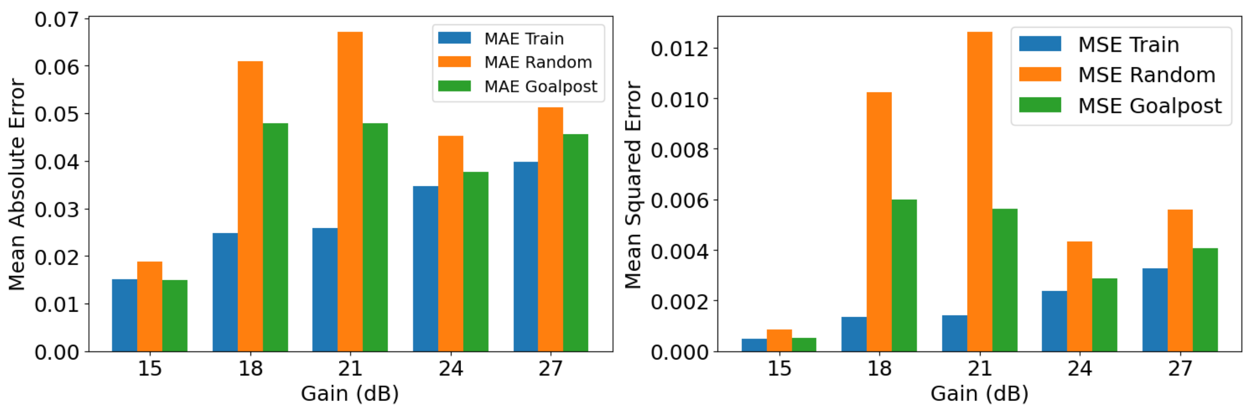

```
import pandas as pd
import numpy as np
import pickle
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt

db_values = [15, 18, 21, 24, 27]

# Load the saved variables including the scaler
with open('dnn_results.pkl', 'rb') as f:
    results = pickle.load(f)

# Extract the saved data
mae_train_list_dnn = results['mae_train_list_dnn']
mse_train_list_dnn = results['mse_train_list_dnn']
mae_random_list_dnn = results['mae_random_list_dnn']
mse_random_list_dnn = results['mse_random_list_dnn']
mae_goalpost_list_dnn = results['mae_goalpost_list_dnn']
mse_goalpost_list_dnn = results['mse_goalpost_list_dnn']
actual_gains_dnn = results['actual_gains_dnn']
dnn_predicted_gains = results['dnn_predicted_gains']
scaler = results['scaler']  # Load the saved scaler

# Plot the results as bar plots
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(15, 5))

# MAE plot
plt.subplot(1, 2, 1)
bar_width = 0.25
index = np.arange(len(db_values))

plt.bar(index, mae_train_list_dnn, bar_width, color='#D32F2F',
label='MAE Train')  # Red
plt.bar(index + bar_width, mae_random_list_dnn, bar_width,
color='#424242', label='MAE Random')  # Dark Gray
plt.bar(index + 2 * bar_width, mae_goalpost_list_dnn, bar_width,
color='#9E9E9E', label='MAE Goalpost')  # Light Gray

plt.xlabel('Gain (dB)', fontsize=18)
plt.ylabel('Mean Absolute Error', fontsize=18)
plt.xticks(index + bar_width, db_values)
plt.legend(fontsize=14)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18)

# MSE plot
plt.subplot(1, 2, 2)

plt.bar(index, mse_train_list_dnn, bar_width, color='#D32F2F',
label='MSE Train')  # Red
plt.bar(index + bar_width, mse_random_list_dnn, bar_width,
color='#424242', label='MSE Random')  # Dark Gray
plt.bar(index + 2 * bar_width, mse_goalpost_list_dnn, bar_width,
color='#9E9E9E', label='MSE Goalpost')  # Light Gray

plt.xlabel('Gain (dB)', fontsize=18)
plt.ylabel('Mean Squared Error', fontsize=18)
plt.xticks(index + bar_width, db_values)
plt.legend(fontsize=18)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18)

plt.tight_layout()
plt.show()
```



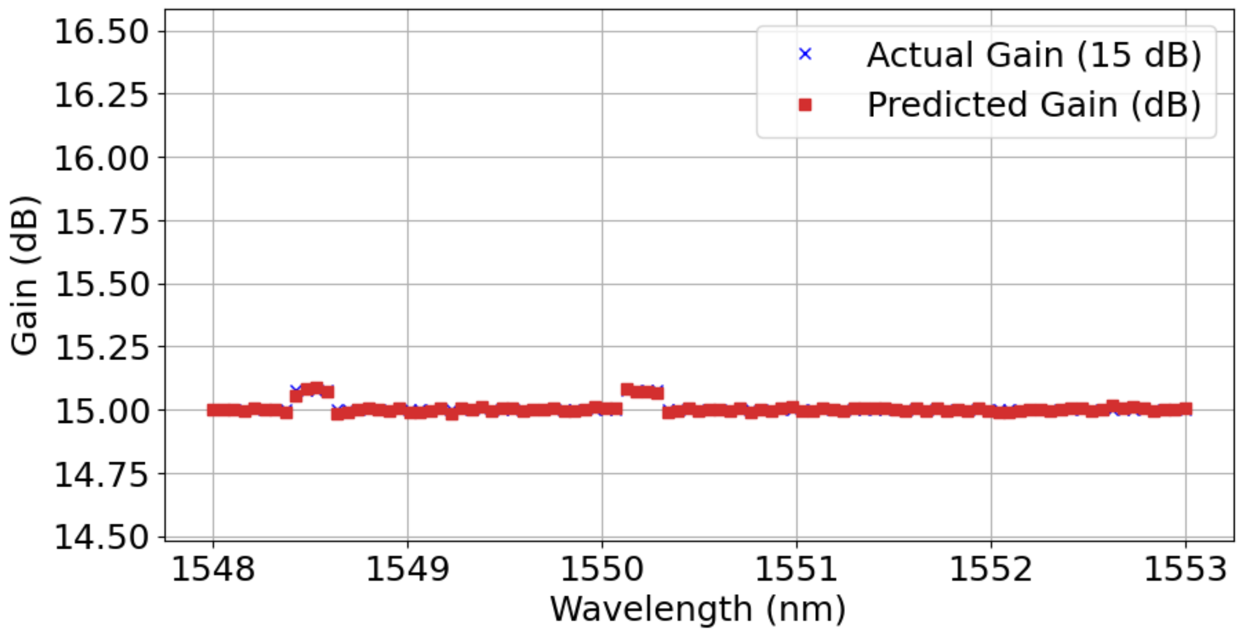

```
# Plot the results as bar plots
import matplotlib.pyplot as plt
import numpy as np
plt.figure(figsize=(15, 5))

# MAE plot
plt.subplot(1, 2, 1)
bar_width = 0.25
index = np.arange(len(db_values))

plt.bar(index, mae_train_list_dnn, bar_width, label='MAE Train')
plt.bar(index + bar_width, mae_random_list_dnn, bar_width, label='MAE
Random')
plt.bar(index + 2 * bar_width, mae_goalpost_list_dnn, bar_width,
label='MAE Goalpost')

plt.xlabel('Gain (dB)', fontsize=18)
plt.ylabel('Mean Absolute Error', fontsize=18)
plt.xticks(index + bar_width, db_values)

plt.legend(fontsize=14)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18)

# MSE plot
plt.subplot(1, 2, 2)

plt.bar(index, mse_train_list_dnn, bar_width, label='MSE Train')
plt.bar(index + bar_width, mse_random_list_dnn, bar_width, label='MSE
Random')
plt.bar(index + 2 * bar_width, mse_goalpost_list_dnn, bar_width,
label='MSE Goalpost')

plt.xlabel('Gain (dB)', fontsize=18)
plt.ylabel('Mean Squared Error', fontsize=18)
plt.xticks(index + bar_width, db_values)
```

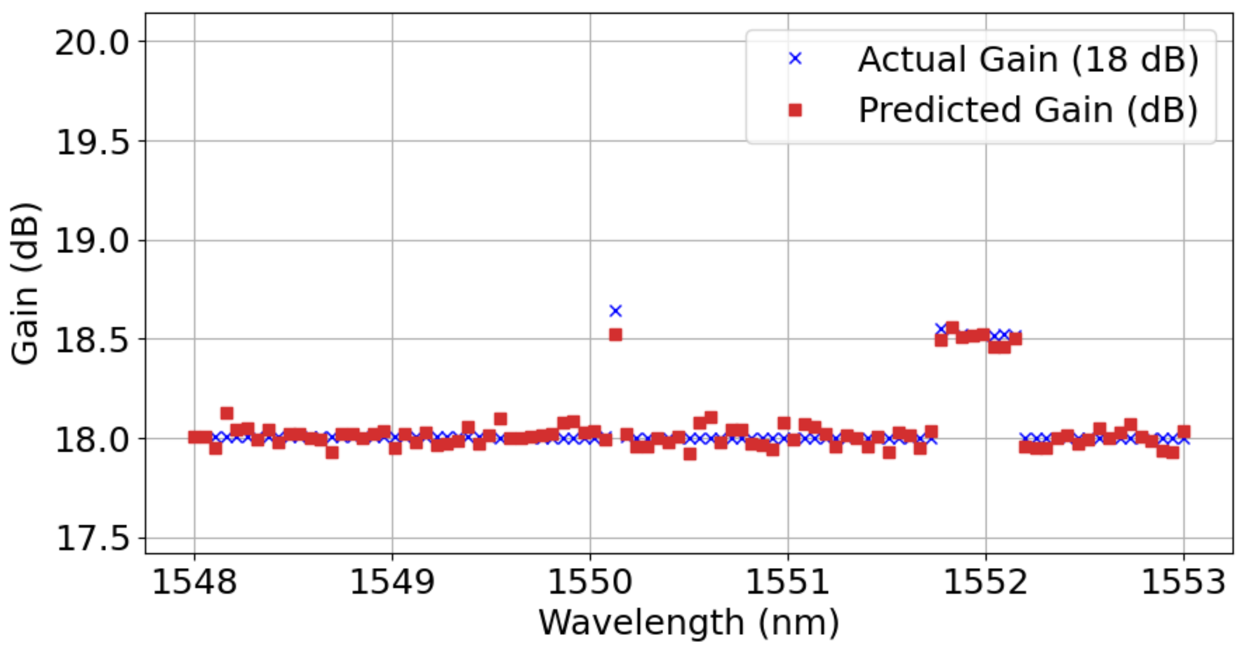
```
plt.legend(fontsize=18)
plt.xticks(fontsize=18)
plt.yticks(fontsize=18)

plt.tight_layout()
plt.show()
```

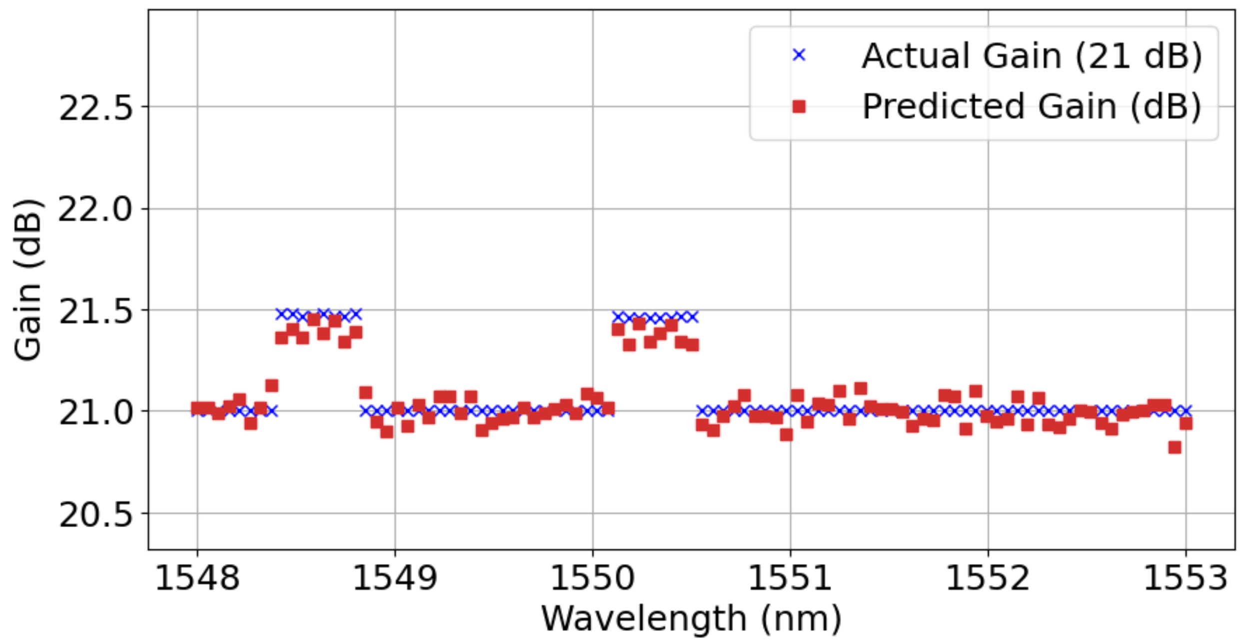



```
import pandas as pd
import numpy as np
import pickle
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt

db_values = [15, 18, 21, 24, 27]

# Load the saved variables including the scaler
with open('dnn_results.pkl', 'rb') as f:
    results = pickle.load(f)

# Extract the saved data
mae_train_list_dnn = results['mae_train_list_dnn']
mse_train_list_dnn = results['mse_train_list_dnn']
mae_random_list_dnn = results['mae_random_list_dnn']
mse_random_list_dnn = results['mse_random_list_dnn']
mae_goalpost_list_dnn = results['mae_goalpost_list_dnn']
mse_goalpost_list_dnn = results['mse_goalpost_list_dnn']
actual_gains_dnn = results['actual_gains_dnn']
dnn_predicted_gains = results['dnn_predicted_gains']
scaler = results['scaler']  # Load the saved scaler

# Loop through each dB value
for db in db_values:
    # Example of new data with 190 features
    # Concatenating the actual gains and predicted gains for each dB
level as new data
```

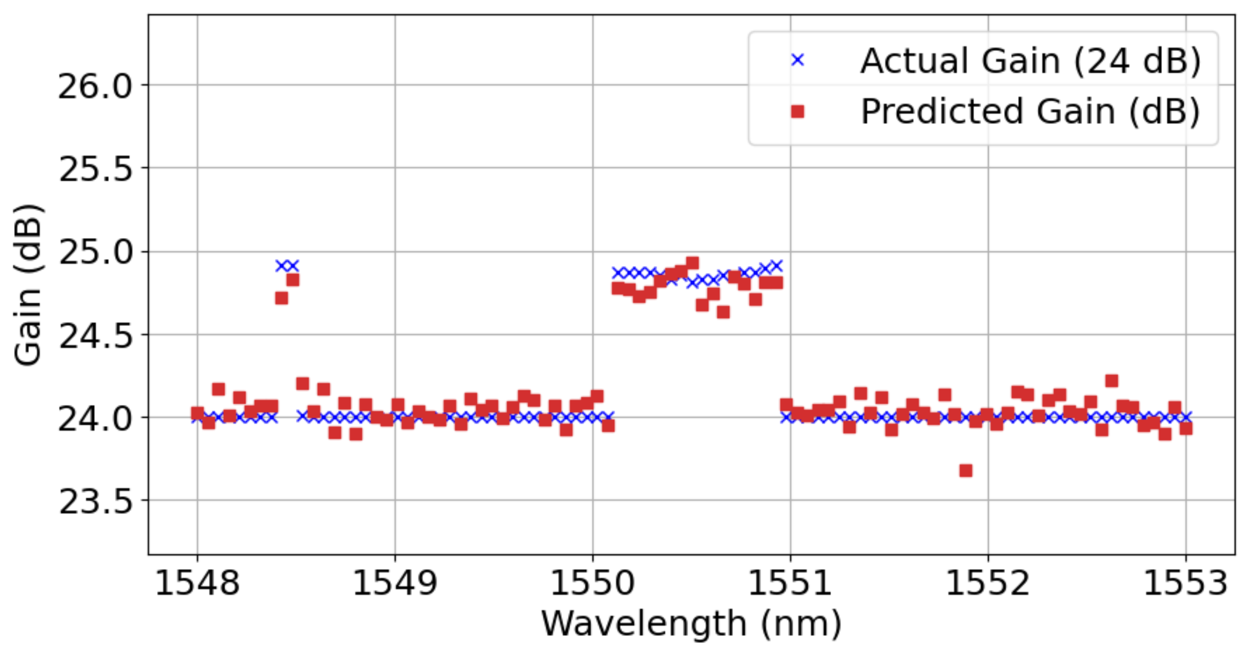
```
    new_data = np.concatenate([actual_gains_dnn[db][:95].reshape(1, -
1), dnn_predicted_gains[db][:95].reshape(1, -1)], axis=1)

    # Scaling the new data using the loaded scaler
    new_data_scaled = scaler.transform(new_data)

    # Inverse transform the scaled data back to the original scale
    predictions_original_scale =
scaler.inverse_transform(new_data_scaled)

    # Add dB offset to the predictions and actual gains
    actual_gains_with_offset = predictions_original_scale[0, :95] + db
    predicted_gains_with_offset = predictions_original_scale[0, 95:] +
db

    # Plotting actual vs predicted gains without MAE and MSE
    wavelengths = np.linspace(1548, 1553, 95)  # Assuming 95 channels

    plt.figure(figsize=(10, 5))

    # Plot actual gains with dB value in the label
    plt.plot(wavelengths, actual_gains_with_offset, 'x',
label=f'Actual Gain ({db} dB)', color='blue')

    # Plot predicted gains with dB value in the label
    plt.plot(wavelengths, predicted_gains_with_offset, 's',
label=f'Predicted Gain (dB)', color='#D32F2F')

    # Increase font size for labels
    plt.xlabel('Wavelength (nm)', fontsize=18)
    plt.ylabel('Gain (dB)', fontsize=18)

    # Increase font size for the legend and show the dB gain in it
    plt.legend(fontsize=18)
    plt.grid(True)

    # Set the y-axis limit with an additional gain (dB) value
    y_min = min(min(actual_gains_with_offset),
min(predicted_gains_with_offset)) - 0.5
    y_max = max(max(actual_gains_with_offset),
max(predicted_gains_with_offset)) + 1.5
    plt.ylim(y_min, y_max)

    # Increase font size for tick labels
    plt.xticks(fontsize=18)
    plt.yticks(fontsize=18)

    # Show the plot
    plt.show()
```


Actual Gain (15 dB)
Predicted Gain (dB)
Gain (dB)
Wavelength (nm)
16.50
16.25
16.00
15.75
15.50
15.25
15.00
14.75
14.50
1548
1549
1550
1551
1552
1553

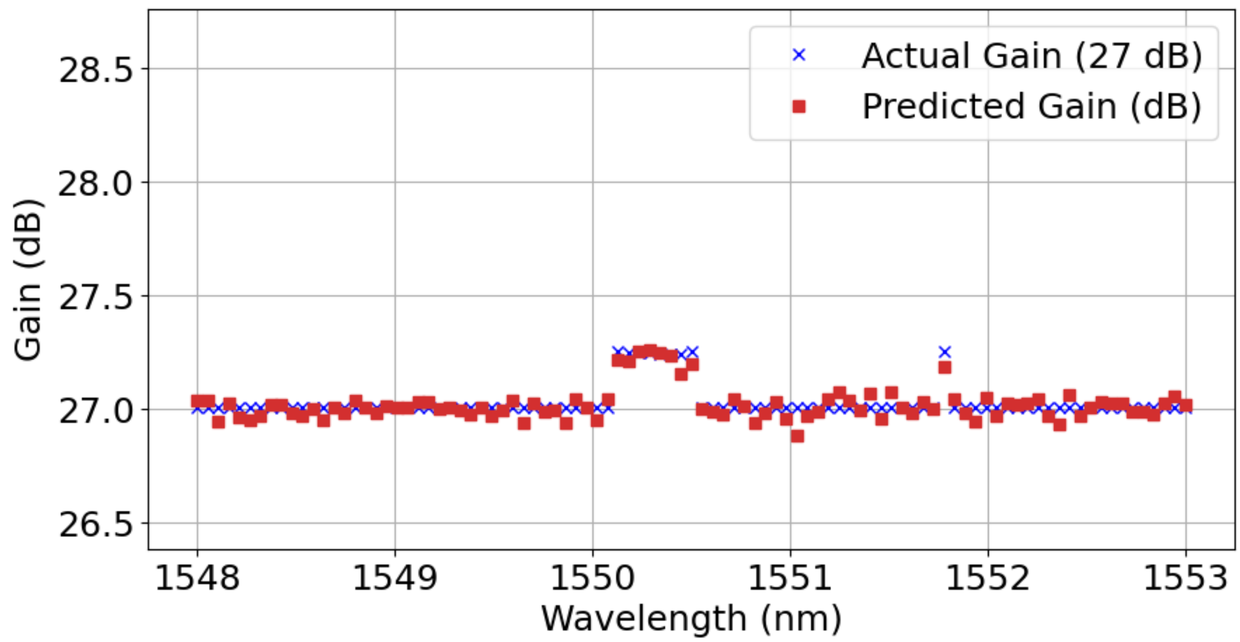

Actual Gain (18 dB)
Predicted Gain (dB)
Gain (dB)
Wavelength (nm)
20.0
19.5
19.0
18.5
18.0
17.5
1548
1549
1550
1551
1552
1553



Actual Gain (21 dB)
Predicted Gain (dB)
Gain (dB)
22.5
22.0
21.5
21.0
20.5
1548
1549
1550
1551
1552
1553
Wavelength (nm)

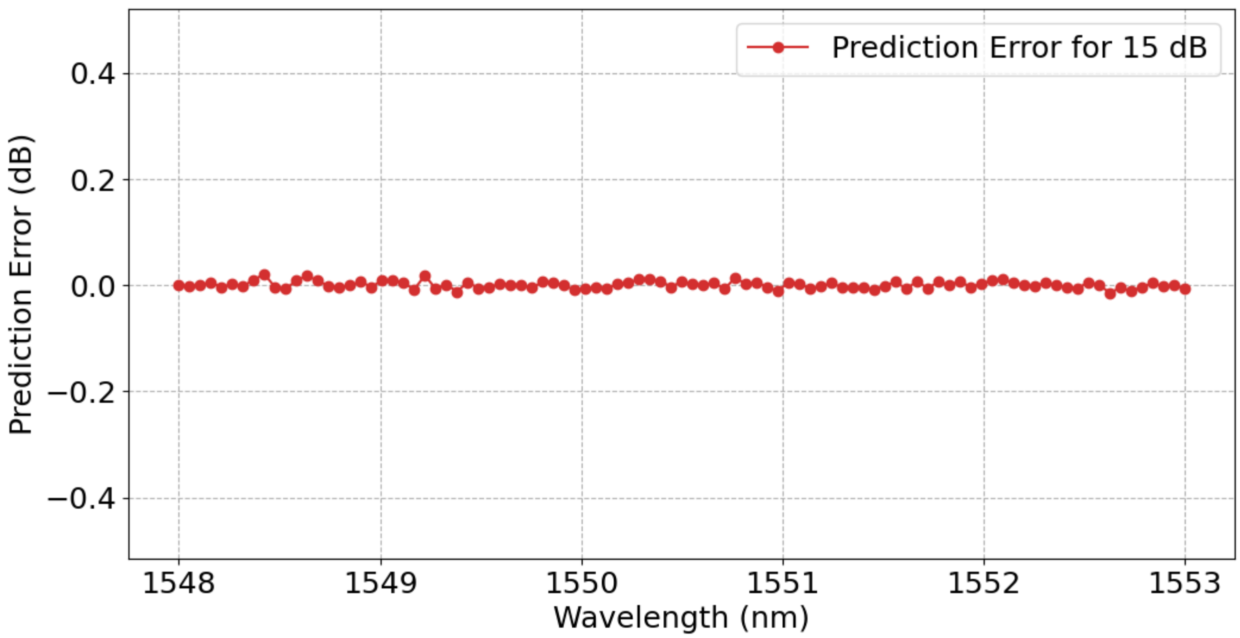


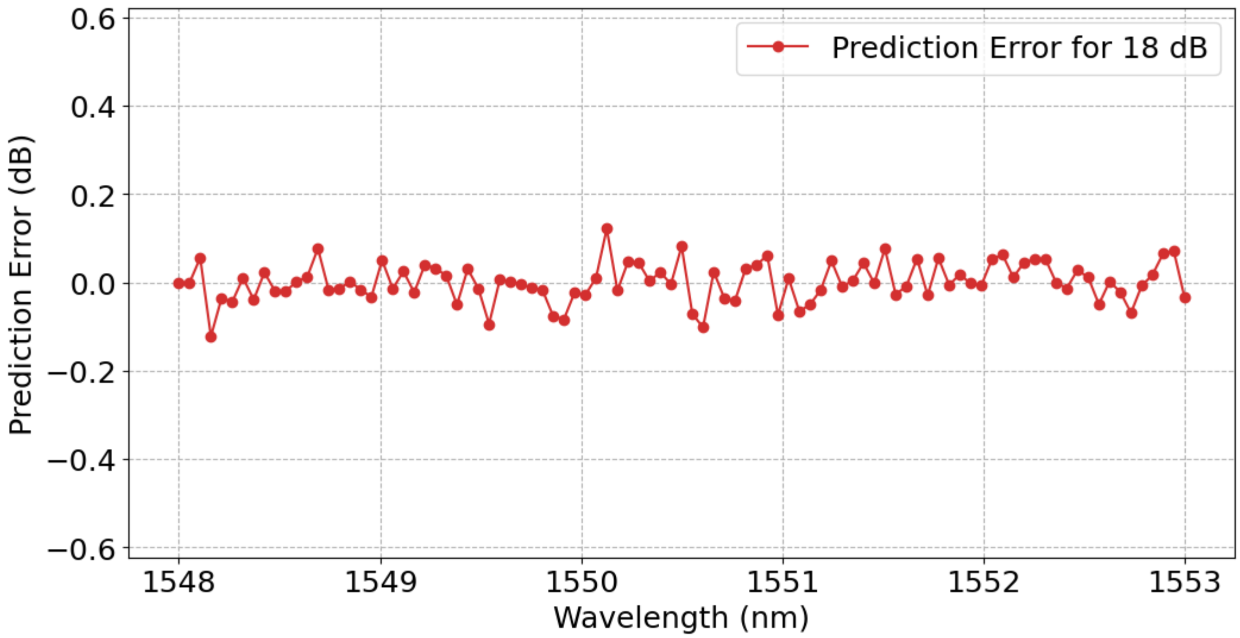
Actual Gain (24 dB)
Predicted Gain (dB)
Gain (dB)
26.0
25.5
25.0
24.5
24.0
23.5
1548
1549
1550
1551
1552
1553
Wavelength (nm)

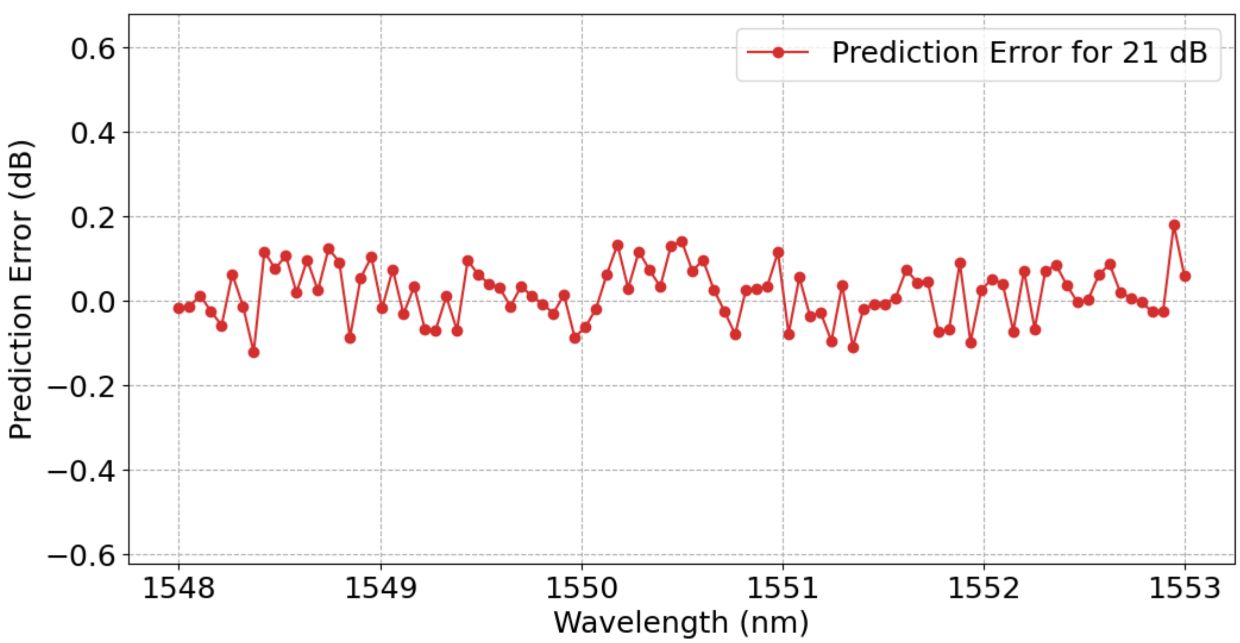


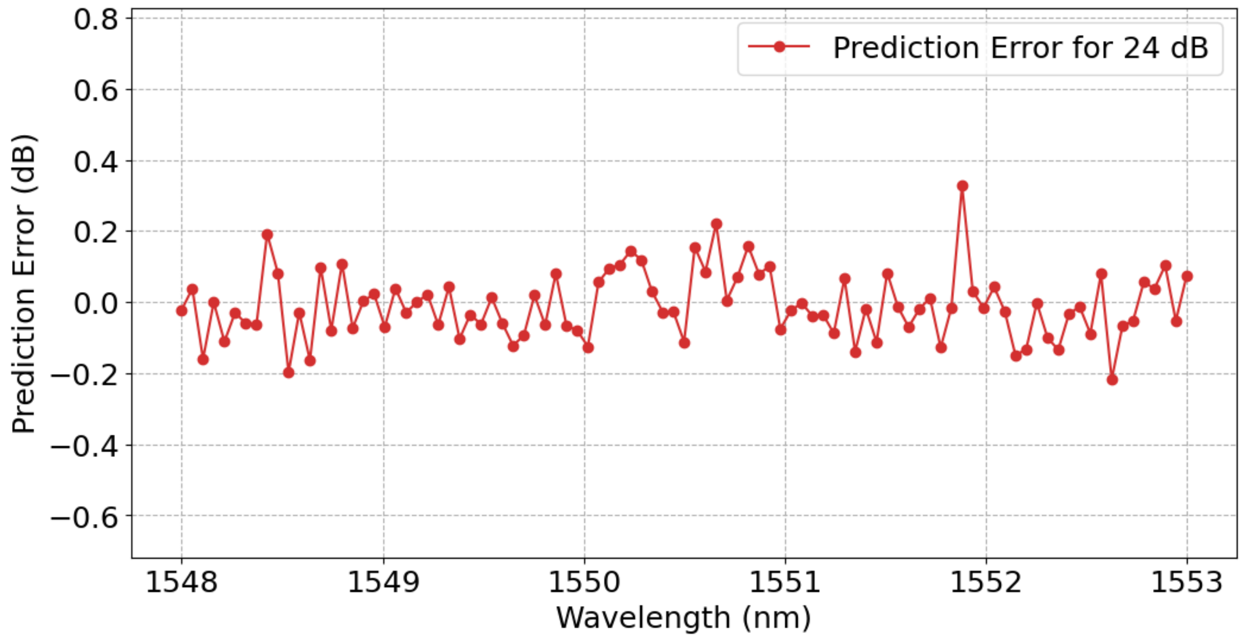

```
import pandas as pd
import numpy as np
import pickle
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt

db_values = [15, 18, 21, 24, 27]
wavelengths = np.linspace(1548, 1553, 95)  # Assuming 95 wavelength
channels

# Load the saved variables including the scaler
with open('dnn_results.pkl', 'rb') as f:
    results = pickle.load(f)

# Extract the saved data
actual_gains_dnn = results['actual_gains_dnn']
dnn_predicted_gains = results['dnn_predicted_gains']
scaler = results['scaler']  # Load the saved scaler

# Loop through each dB value
for db in db_values:
    # Extract the actual and predicted gains
    actual_gains = actual_gains_dnn[db][:95]
    predicted_gains = dnn_predicted_gains[db][:95]

    # Calculate prediction error
    prediction_error = actual_gains - predicted_gains

    # Plotting prediction error vs wavelength
```

```
    plt.figure(figsize=(12, 6))
    plt.plot(wavelengths, prediction_error, label=f'Prediction Error
for {db} dB', color='#D32F2F', marker='o')

    plt.xlabel('Wavelength (nm)', fontsize=18)
    plt.ylabel('Prediction Error (dB)', fontsize=18)

    # Set y-axis limits with 0.5 dB buffer on both sides
    y_min = min(prediction_error) - 0.5
    y_max = max(prediction_error) + 0.5
    plt.ylim(y_min, y_max)

    # Add grid and legend for clarity
    plt.grid(True, which="both", ls="--")
    plt.legend(fontsize=18)
    plt.xticks(fontsize=18)
    plt.yticks(fontsize=18)

    plt.show()
```

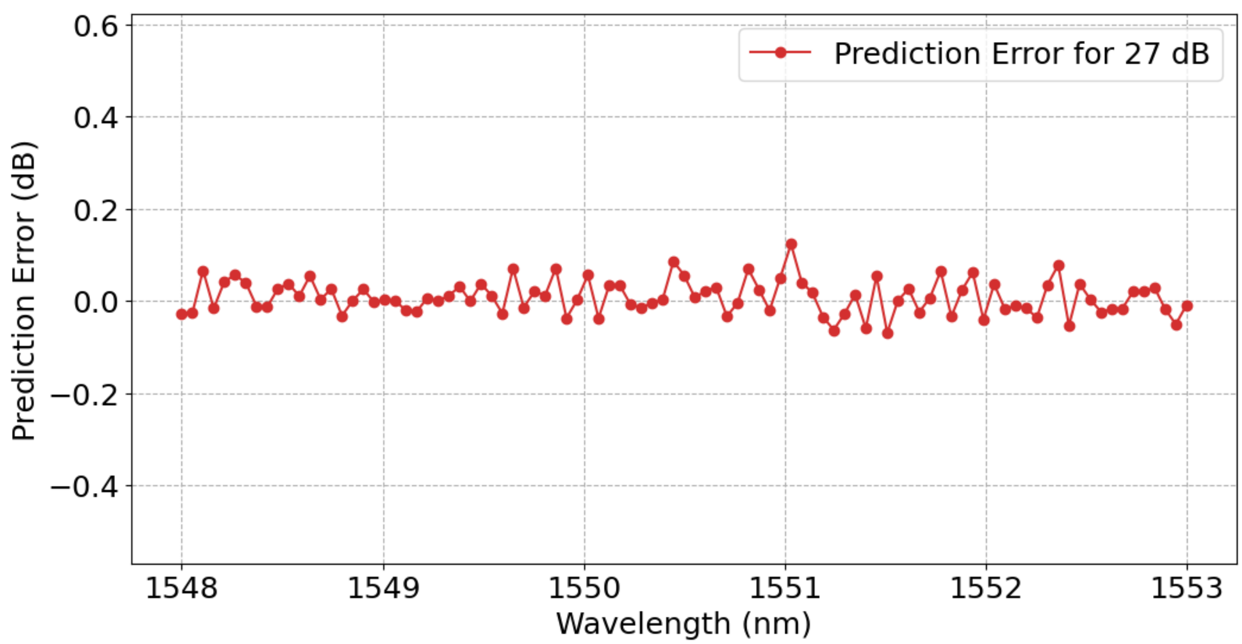



Prediction Error for 18 dB
Prediction Error (dB)
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
1548
1549
1550
1551
1552
1553
Wavelength (nm)


Prediction Error for 21 dB
Prediction Error (dB)
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
1548
1549
1550
1551
1552
1553
Wavelength (nm)



Prediction Error for 24 dB
Prediction Error (dB)
Wavelength (nm)
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
1548
1549
1550
1551
1552
1553



Prediction Error for 27 dB
Prediction Error (dB)
Wavelength (nm)
0.6
0.4
0.2
0.0
−0.2
−0.4
1548
1549
1550
1551
1552
1553