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Çağla Çağlar

IBM – DEEP LEARNING AND REINFORCEMENT LEARNING

A Multi-Output Regression Approach for Predicting Material Mechanical Properties Using Deep Learning Techniques

Abstract

This study examines the prediction of material properties like tensile strength (Su) and yield strength (Sy) through a multi-output regression model approach. Different deep learning models, such as DNN (Deep Neural Network), ANN (Artificial Neural Network), and CNN (Convolutional Neural Network), were assessed in this research project. Among these models tested in the study, DNN emerged as the top performer based on its performance metrics, providing accurate predictions that can aid in material selection for industrial applications. Additionally, the feature significance was investigated using SHAP values to enhance interpretability, offering valuable insights for stakeholders in engineering and manufacturing. For those interested in replicating or delving further into this analysis, the Python code utilized in this study is included at the conclusion of the report for reference purposes.

Dataset Overview

The dataset used in this project originates from the Autodesk Material Library and contains detailed information about the mechanical properties of various materials used in machine design. It consists of 15 attributes, which describe essential material characteristics such as the material standard, unique identifiers, material types, heat treatment processes, and mechanical properties like tensile strength (Su), yield strength (Sy), elongation (A5), hardness values (Brinell and Vickers), Young's modulus (E), shear modulus (G), friction coefficient (mu), density (Ro), and pH values. Some columns, such as the description (Desc), provide additional qualitative details about the materials. This dataset represents real-world data without any synthetic or random values, making it highly reliable for material selection processes. Further details about the dataset can be found on the Kaggle page at this link: https://www.kaggle.com/datasets/purushottamnawale/materials.

Exploratory Data Analysis

The dataset contains various mechanical properties of materials that are crucial for machine design, including attributes such as tensile strength, yield strength, hardness values, and modulus values. The statistical summary of the cleaned dataset reveals that the dataset consists of 1,544 entries after handling missing data, providing a substantial base for understanding material performance.

A wide range is observed in tensile strength (Su) and yield strength (Sy), with values spanning from 69 to 2,220 MPa for Su and 28 to 2,048 MPa for Sy. The elongation at break (A5) shows a range between 0.5% and 70%, indicating variability in ductility among the materials. The Brinell hardness number (Bhn) varies significantly, with values ranging from 19 to 627, suggesting diverse hardness characteristics in the dataset.

Correlation analysis shows strong positive correlations between certain mechanical properties, such as between tensile strength and yield strength, as stronger materials typically show high values for both properties. The relationships between features are visualized using a pairplot, highlighting how different mechanical properties cluster together.

Data Cleaning and Feature Engineering

The dataset was cleaned by removing irrelevant columns such as material standard, identifiers, heat treatment, and others that were either categorical or contained a large number of missing values. All relevant columns were converted to numeric values, particularly critical features like elongation (A5), hardness (Bhn), and density (Ro), to ensure compatibility with the analysis. Missing values in the elongation and hardness columns were filled using the mean of each respective column. Additionally, a new feature, the specific strength ratio (Ro/Sy), was created to represent the strength of a material relative to its density.

Standard scaling was applied to normalize the data, ensuring that all features are on the same scale, which is essential for machine learning algorithms that are sensitive to feature scaling. The cleaned and scaled dataset was saved for further analysis.

Visualizations, such as pairplots and heatmaps, were used to explore the cleaned dataset. The pairplot provided an intuitive view of how features like elastic modulus (E), shear modulus (G), and density (Ro) interact with the target variables, tensile strength (Su) and yield strength (Sy). The heatmap revealed the correlation strengths between all features, confirming that yield strength and tensile strength are strongly correlated, while other features, such as friction coefficient (mu) and hardness (Bhn), exhibit more varied relationships.

Model Training and Evaluation

Three different deep learning models were explored for this analysis: an Artificial Neural Network (ANN), a Deep Neural Network (DNN), and a Convolutional Neural Network (CNN). Each model was built using the TensorFlow Keras library, with slight modifications in architecture to adapt to the complexity of the data.

The ANN model employed three dense layers, combined with dropout and batch normalization, to prevent overfitting. Similarly, the DNN model included more layers and higher neuron counts, making it a deeper model that incorporated regularization through dropout and L2 regularization techniques. The CNN model, typically used for spatial data, was adapted to handle the sequential nature of the data through 1D convolutional layers, followed by max pooling and dense layers.

Overfitting prevention strategies included dropout layers to randomly deactivate neurons during training, L2 regularization to penalize large weights, and the use of early stopping based on validation loss. This was combined with a learning rate reduction via ReduceLROnPlateau, which adjusted the learning rate dynamically when the model performance plateaued during training.

The models were evaluated using key regression metrics: Mean Squared Error (MSE), R-squared (R^2), and Mean Absolute Error (MAE). These metrics provide a comprehensive view of the models' predictive accuracy, with MSE measuring the average squared difference between predictions and actual values, R^2 indicating the proportion of variance captured by the model, and MAE representing the average absolute difference between predictions and actual outcomes. Each model's performance was analyzed by plotting the training and validation loss curves, which helped in identifying how well the models generalized to unseen data.

Model Recommendation

After evaluating the three models—Artificial Neural Network (ANN), Deep Neural Network (DNN), and Convolutional Neural Network (CNN)—it is evident that both the ANN and DNN models significantly outperform the CNN in terms of prediction accuracy. The evaluation metrics, including

Mean Squared Error (MSE), R-squared (R^2), and Mean Absolute Error (MAE), provide a clear comparison of their performances.

The ANN model achieved an MSE of 2857.24, an R^2 score of 0.9689, and an MAE of 36.65. These metrics indicate that the ANN model performs quite well in predicting the target values, offering a good balance between prediction accuracy and generalization. The validation loss curve suggests that the model does not suffer from significant overfitting and maintains a stable performance throughout training.

The DNN model yielded the best results overall, with an MSE of 2521.30, an R^2 score of 0.9725, and an MAE of 33.07. The lower MSE and higher R^2 indicate that this model fits the data slightly better than the ANN, capturing more variance in the target values. The validation loss curve further supports the model's robustness, showing minimal divergence from the training loss, suggesting that the DNN model generalizes well to unseen data. This makes the DNN model the optimal choice in this analysis.

In contrast, the CNN model performed the worst, with an MSE of 28936.11, an R^2 score of 0.6479, and an MAE of 112.85. The CNN model struggled to learn from the data as effectively as the other models, possibly due to its architecture being more suited for spatial data (like images) rather than the sequential data used here. Its higher error rates and lower R^2 score indicate that it is not a suitable model for this specific problem.

In conclusion, the DNN model is recommended as the final model due to its superior performance in all key metrics. The ANN model also performed well and could serve as a viable alternative if model complexity or computational resources are a concern. However, the CNN model should not be used in this context as its architecture is less suited to the task, leading to poorer predictive performance.

Key Findings and Insights

The Deep Neural Network (DNN) model was analyzed using SHAP values to understand the contribution of each feature to predicting both ultimate tensile strength (Su) and yield strength (Sy) for the first test sample. SHAP explains how features influence individual predictions, providing a more interpretable deep learning model.

For both Su and Sy, elastic modulus (E) emerged as the most important feature, positively impacting predictions. For Su, it increases the prediction by +59.52 and for Sy, by +31.23, confirming that stiffer materials typically exhibit higher strength values. The second most influential feature was the specific strength ratio (Ro/Sy), which negatively affected predictions in both cases. For Su, it reduces the prediction by -63.1 and for Sy, by -70.98, reflecting the balance between material density and strength.

Density (Ro) played a notable role, with a positive impact on Su (+61.31) and a smaller but still positive effect on Sy (+49.33). Brinell hardness (Bhn) had a negative contribution for both Su (-14.52) and Sy (-12.38), while the shear modulus (G) had a minor negative effect on Su (-14.26) and a smaller impact on Sy (-8.3). Elongation at break (A5) negatively affected both Su (-14.65) and Sy (-9.22), while the coefficient of friction (mu) slightly decreased Su (-2.52) but had a minimal positive impact on Sy (+0.24).

The SHAP analysis clarifies how the DNN model makes its predictions, with elastic modulus consistently boosting strength predictions and the specific strength ratio reducing them, aligning with physical expectations. This level of interpretability enhances transparency, making the model's predictions actionable.

In conclusion, the most critical features for predicting material strength are elastic modulus and specific strength ratio, which play opposing roles. By using SHAP, the model becomes more transparent, aiding in practical applications like material selection for engineering tasks such as electric vehicle chassis design.

Next Steps in Analysis

To further improve the model's performance and gain deeper insights, several additional analyses and enhancements could be applied. One possible approach is to optimize the model further by conducting extensive hyperparameter tuning, which could lead to significant performance improvements. Techniques like grid search or Bayesian optimization could be used to identify the best combination of parameters. Another valuable step would be the introduction of k-fold cross-validation to provide a more robust evaluation of the model's ability to generalize, reducing the reliance on a single train-test split and ensuring better performance across various subsets of the data.

Additionally, although key features such as elastic modulus and the specific strength ratio have already been identified, further feature engineering may boost the model’s performance. This could include creating interaction terms between features or applying dimensionality reduction techniques such as PCA to uncover hidden patterns. Testing alternative model architectures could also yield better results. Exploring ensemble models by combining the predictions of the DNN and ANN models, or employing hybrid models that integrate decision trees with deep learning, might enhance predictive accuracy by capturing different aspects of the data.

In cases where the dataset might contain imbalances, such as a greater number of materials with lower strength values, methods like synthetic oversampling or downsampling could be applied to prevent the model from becoming biased towards certain data ranges. Furthermore, expanding the current SHAP analysis to global methods such as SHAP summary or dependence plots would help visualize the broader impact of features across the entire dataset. This would offer a more comprehensive understanding of how features contribute to multi-output regression predictions.

Another important next step is external validation, which would involve applying the model to an unseen dataset to assess its ability to generalize beyond the current dataset. This would confirm the model’s robustness, especially in practical applications. Finally, in addition to standard metrics like MSE, R^2, and MAE, it would be beneficial to introduce domain-specific metrics such as safety factors or material-specific engineering constraints, further evaluating the model's applicability to real-world scenarios like electric vehicle chassis design. Following these steps could lead to more accurate predictions and a deeper understanding of the relationships between mechanical properties, ultimately increasing the practical utility of the results.

Appendix: Python Code for Data Analysis

The appendix contains the full Python code for data preprocessing, model training, EDA, and all generated visualizations.

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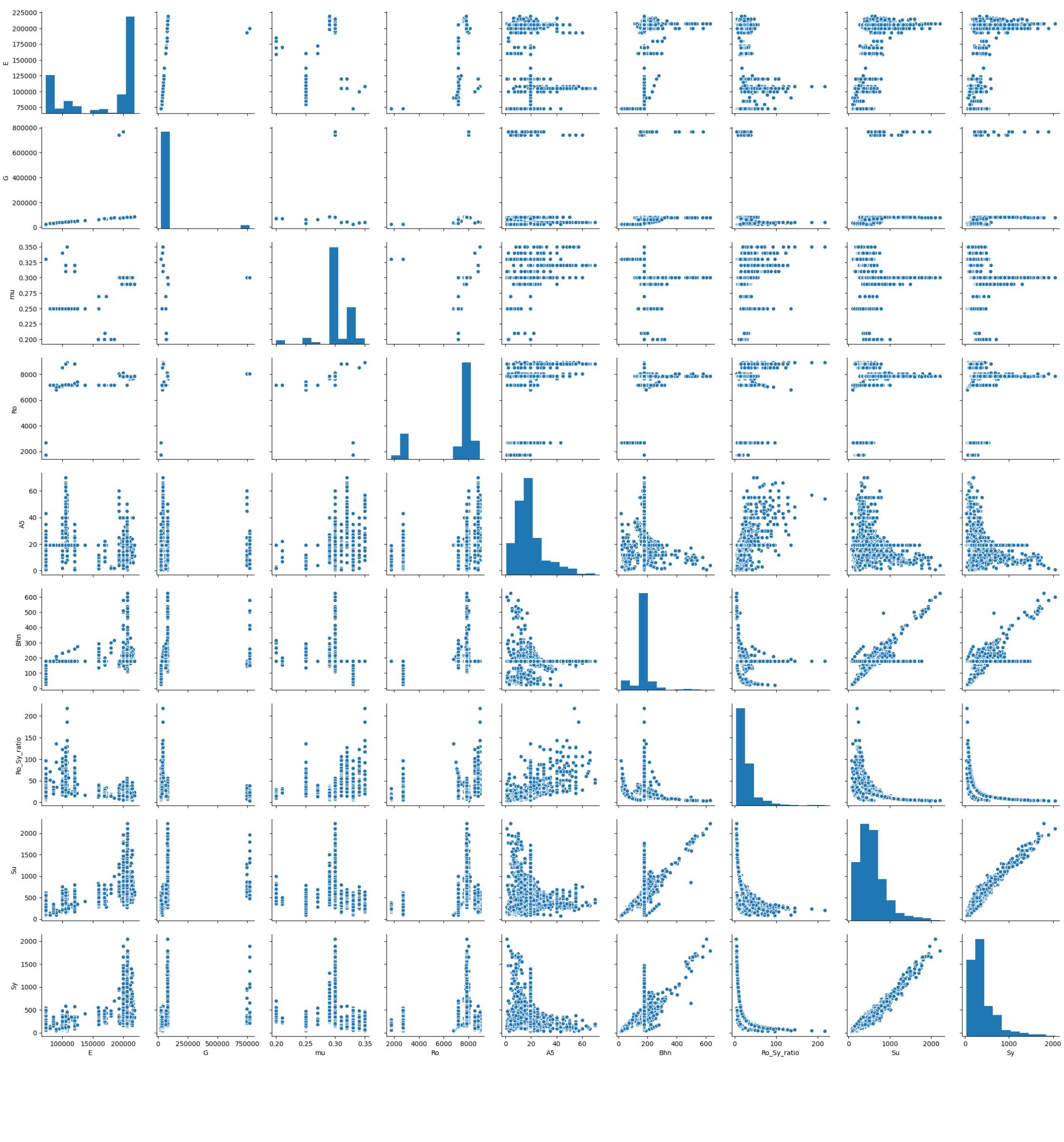
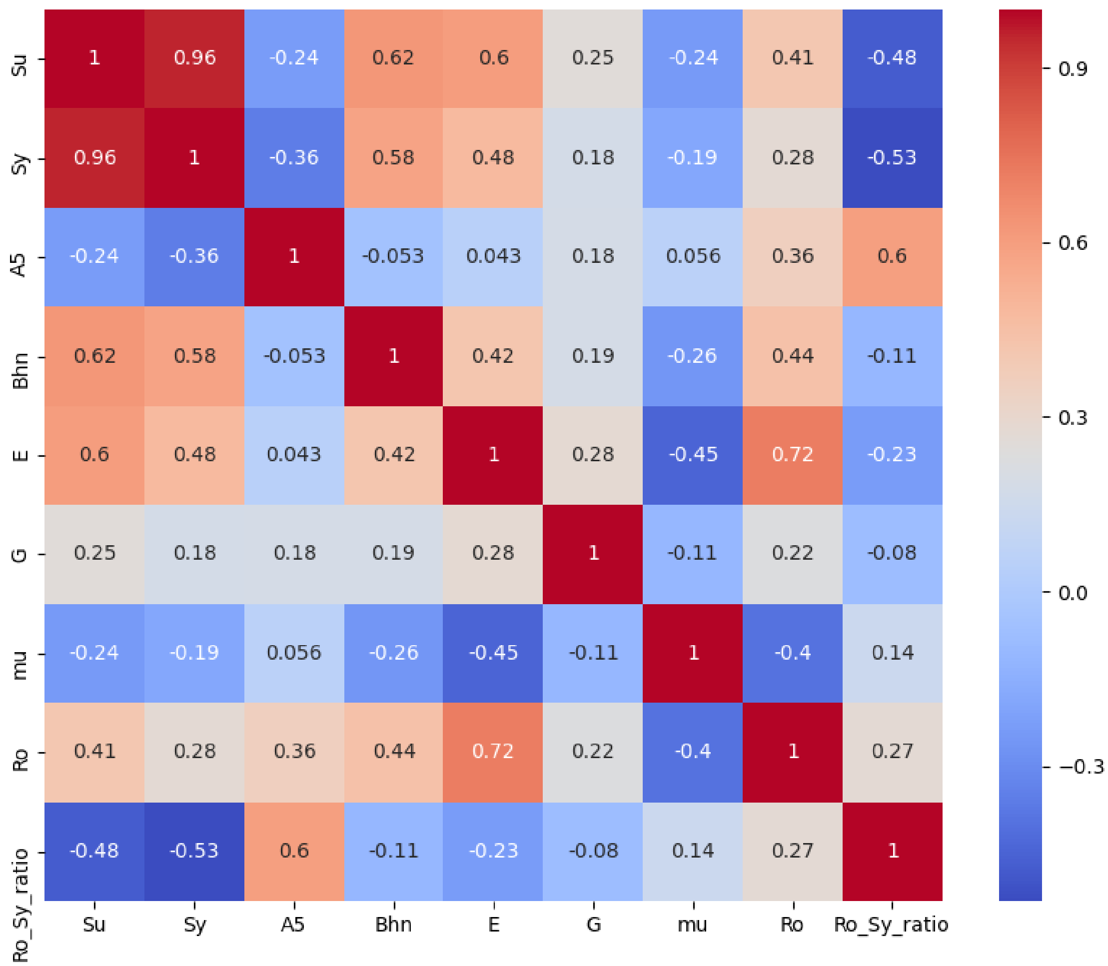
[2]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
import warnings

warnings.filterwarnings("ignore", category=DeprecationWarning)



# Load the dataset
file_path = 'materials_data.csv'
data = pd.read_csv(file_path)

# Drop irrelevant columns
data_cleaned = data.drop(columns=['Std', 'ID', 'Material', 'Heat treatment',␣
↪'pH', 'Desc', 'HV'])

# Convert columns to numeric, force errors to NaN
columns_to_convert = ['A5', 'Bhn', 'Ro', 'Sy']
for col in columns_to_convert:
    data_cleaned[col] = pd.to_numeric(data_cleaned[col], errors='coerce')

# Fill missing values with column means for A5 and Bhn
data_cleaned['A5'] = data_cleaned['A5'].fillna(data_cleaned['A5'].mean())
data_cleaned['Bhn'] = data_cleaned['Bhn'].fillna(data_cleaned['Bhn'].mean())

# # Drop rows with missing Ro or Sy
data_cleaned.dropna(subset=['Ro', 'Sy'], inplace=True)

# Create a new column for specific strength ratio
data_cleaned['Ro_Sy_ratio'] = data_cleaned['Ro'] / data_cleaned['Sy']

# Summary stats
print(data_cleaned.describe())

# Display the first 5 rows of the cleaned dataset
print(data_cleaned.head())
```

```
# Pairplot to check relationships between key variables
sns.pairplot(data_cleaned[['E', 'G', 'mu', 'Ro', 'A5', 'Bhn', 'Ro_Sy_ratio',␣
↪'Su', 'Sy']])
plt.show()

# Correlation matrix heatmap
corr_matrix = data_cleaned.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.show()

# Split features (X) and target variables (y)
X = data_cleaned[['E', 'G', 'mu', 'Ro', 'A5', 'Bhn', 'Ro_Sy_ratio']]
y = data_cleaned[['Su', 'Sy']]

# Ensure data types are float64
X = X.astype('float64')
y = y.astype('float64')

# Standard scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Convert scaled features back into a DataFrame
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

# Combine scaled features and target variables into final dataset
data_final = pd.concat([X_scaled_df, y.reset_index(drop=True)], axis=1)

# Save the final dataset to CSV
data_final.to_csv('cleaned_and_scaled_materials_data.csv', index=False)
```

```
                Su           Sy           A5          Bhn              E  \
count  1544.000000  1544.000000  1544.000000  1544.000000    1544.000000
mean    574.321891   387.762306    19.253407   177.138229  164356.865285
std     326.951396   290.036867    11.545820    62.110448   56201.219172
min      69.000000    28.000000     0.500000    19.000000   73000.000000
25%     340.000000   203.750000    12.000000   177.138229  105000.000000
50%     510.000000   310.000000    19.000000   177.138229  206000.000000
75%     707.750000   472.000000    22.000000   177.138229  206000.000000
max    2220.000000  2048.000000    70.000000   627.000000  219000.000000

                   G           mu           Ro  Ro_Sy_ratio
count    1544.000000  1544.000000  1544.000000  1544.000000
mean    85627.849741     0.302992  6925.023964    26.147465
std    125650.621278     0.024653  2119.584506    20.844076
```

```
min      26000.000000      0.200000  1750.000000     3.837891
25%      40000.000000      0.300000  7160.000000    13.043478
50%      79000.000000      0.300000  7860.000000    21.243243
75%      80000.000000      0.320000  7860.000000    31.452549
max     769000.000000      0.350000  8930.000000   217.804878
    Su     Sy    A5    Bhn       E      G   mu    Ro  Ro_Sy_ratio
0  421  314.0  39.0  126.0  207000  79000  0.3  7860    25.031847
1  424  324.0  37.0  121.0  207000  79000  0.3  7860    24.259259
2  386  284.0  37.0  111.0  207000  79000  0.3  7860    27.676056
3  448  331.0  36.0  143.0  207000  79000  0.3  7860    23.746224
4  441  346.0  35.8  131.0  207000  79000  0.3  7860    22.716763
```





[4]:
```python
import pandas as pd
import numpy as np
import warnings
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Conv1D, Flatten,␣
↪MaxPooling1D, BatchNormalization
from tensorflow.keras.optimizers import Adam, RMSprop
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.regularizers import l2

# Suppress future warnings
warnings.filterwarnings("ignore", category=FutureWarning)

# Load the dataset
```

```
file_path = 'cleaned_and_scaled_materials_data.csv'
data = pd.read_csv(file_path)

# Split features and target variables
X = data[['E', 'G', 'mu', 'Ro', 'A5', 'Bhn', 'Ro_Sy_ratio']]
y = data[['Su', 'Sy']]

# Convert to float64 to avoid potential issues with data types
X = X.astype('float64')
y = y.astype('float64')

# ANN model
def build_ann():
    model = Sequential()
    model.add(Dense(128, input_dim=X.shape[1], activation='relu',
 ↪kernel_regularizer=l2(0.001)))
    model.add(BatchNormalization())
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.4))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(2))  # Output layer for Su and Sy
    model.compile(optimizer=Adam(learning_rate=0.001), loss='mse',
 ↪metrics=['mse', 'mae'])
    return model

# DNN model with deeper architecture
def build_dnn():
    model = Sequential()
    model.add(Dense(256, input_dim=X.shape[1], activation='relu',
 ↪kernel_regularizer=l2(0.001)))
    model.add(Dropout(0.3))
    model.add(Dense(128, activation='relu'))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(2))  # Output layer for Su and Sy
    model.compile(optimizer=RMSprop(learning_rate=0.001), loss='mse',
 ↪metrics=['mse', 'mae'])
    return model

# CNN model
def build_cnn():
    model = Sequential()
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu',
 ↪input_shape=(X.shape[1], 1)))
    model.add(BatchNormalization())
    model.add(MaxPooling1D(pool_size=2))
    model.add(Flatten())
```

```
    model.add(Dense(128, activation='relu', kernel_regularizer=l2(0.001)))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(2))  # Output layer for Su and Sy
    model.compile(optimizer=Adam(learning_rate=0.001), loss='mse',␣
↪metrics=['mse', 'mae'])

    return model

# Training function for ANN and DNN
def train_and_evaluate(model, X_train, y_train, X_test, y_test):
    # Early stopping and learning rate reduction for better generalization
    callbacks = [
        EarlyStopping(monitor='val_loss', patience=10,␣
↪restore_best_weights=True),
        ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=5, min_lr=0.
↪00001)
    ]
    # Fit the model
    history = model.fit(X_train, y_train, epochs=150, validation_split=0.2,␣
↪callbacks=callbacks, verbose=1)

    # Predict and calculate metrics
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)

    return history, mse, r2, mae

# Training function for CNN
def train_and_evaluate_cnn(model, X_train, y_train, X_test, y_test):
    # Reshape input data for CNN
    X_train_cnn = X_train.values.reshape((X_train.shape[0], X_train.shape[1],␣
↪1))
    X_test_cnn = X_test.values.reshape((X_test.shape[0], X_test.shape[1], 1))

    callbacks = [
        EarlyStopping(monitor='val_loss', patience=10,␣
↪restore_best_weights=True),
        ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=5, min_lr=0.
↪00001)
    ]

    # Fit the CNN model
    history = model.fit(X_train_cnn, y_train, epochs=150, validation_split=0.2,␣
↪callbacks=callbacks, verbose=1)
```

```python
    # Predict and calculate metrics
    y_pred = model.predict(X_test_cnn)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)

    return history, mse, r2, mae

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Store results in a dictionary for each model
results = {}

# ANN model
ann_model = build_ann()
history_ann, mse_ann, r2_ann, mae_ann = train_and_evaluate(ann_model, X_train,␣
 ↪y_train, X_test, y_test)
results['ANN'] = {'MSE': mse_ann, 'R^2': r2_ann, 'MAE': mae_ann}

# DNN model
dnn_model = build_dnn()
history_dnn, mse_dnn, r2_dnn, mae_dnn = train_and_evaluate(dnn_model, X_train,␣
 ↪y_train, X_test, y_test)
results['DNN'] = {'MSE': mse_dnn, 'R^2': r2_dnn, 'MAE': mae_dnn}

# CNN model
cnn_model = build_cnn()
history_cnn, mse_cnn, r2_cnn, mae_cnn = train_and_evaluate_cnn(cnn_model,␣
 ↪X_train, y_train, X_test, y_test)
results['CNN'] = {'MSE': mse_cnn, 'R^2': r2_cnn, 'MAE': mae_cnn}

# Print final performance metrics for all models
print("\nFinal Model Performances:")
for model_name, metrics in results.items():
    print(f"{model_name} -> MSE: {metrics['MSE']}, R^2: {metrics['R^2']}, MAE:␣
 ↪{metrics['MAE']}")

# Plot training and validation loss for all models
def plot_training_loss(histories, labels):
    for history, label in zip(histories, labels):
        plt.plot(history.history['loss'], label=f'{label} Training Loss')
        plt.plot(history.history['val_loss'], label=f'{label} Validation Loss',␣
 ↪linestyle='--')
```

```
    plt.legend()
    plt.show()

# Plot training history
plot_training_loss([history_ann, history_dnn, history_cnn], ['ANN', 'DNN',␣
 ↪'CNN'])
```

```
Epoch 1/150
31/31 [==============================] - 1s 13ms/step - loss: 346958.6250 - mse:
346958.6250 - mae: 486.4286 - val_loss: 309898.1250 - val_mse: 309898.1250 -
val_mae: 466.9160 - lr: 0.0010
Epoch 2/150
31/31 [==============================] - 0s 8ms/step - loss: 332731.4062 - mse:
332731.4062 - mae: 474.9695 - val_loss: 300612.1562 - val_mse: 300612.1250 -
val_mae: 459.1653 - lr: 0.0010
Epoch 3/150
31/31 [==============================] - 0s 8ms/step - loss: 269409.1562 - mse:
269409.1562 - mae: 422.7993 - val_loss: 246460.5469 - val_mse: 246460.5312 -
val_mae: 412.6131 - lr: 0.0010
Epoch 4/150
31/31 [==============================] - 0s 7ms/step - loss: 119544.7344 - mse:
119544.7344 - mae: 259.7784 - val_loss: 113543.8594 - val_mse: 113543.8359 -
val_mae: 265.3200 - lr: 0.0010
Epoch 5/150
31/31 [==============================] - 0s 7ms/step - loss: 47487.9062 - mse:
47487.8828 - mae: 161.3738 - val_loss: 77297.0859 - val_mse: 77297.0703 -
val_mae: 207.1557 - lr: 0.0010
Epoch 6/150
31/31 [==============================] - 0s 7ms/step - loss: 41564.1914 - mse:
41564.1758 - mae: 147.7671 - val_loss: 71294.0938 - val_mse: 71294.0781 -
val_mae: 196.6705 - lr: 0.0010
Epoch 7/150
31/31 [==============================] - 0s 9ms/step - loss: 34304.7578 - mse:
34304.7422 - mae: 134.6393 - val_loss: 55904.1094 - val_mse: 55904.0859 -
val_mae: 168.7648 - lr: 0.0010
Epoch 8/150
31/31 [==============================] - 0s 7ms/step - loss: 32030.8691 - mse:
32030.8496 - mae: 130.9578 - val_loss: 52417.7578 - val_mse: 52417.7383 -
val_mae: 163.9011 - lr: 0.0010
Epoch 9/150
31/31 [==============================] - 0s 6ms/step - loss: 27598.6973 - mse:
27598.6758 - mae: 119.3643 - val_loss: 40277.2266 - val_mse: 40277.2070 -
val_mae: 136.5048 - lr: 0.0010
Epoch 10/150
31/31 [==============================] - 0s 10ms/step - loss: 26128.3379 - mse:
26128.3223 - mae: 115.2914 - val_loss: 31335.9805 - val_mse: 31335.9609 -
val_mae: 117.8369 - lr: 0.0010
```

```
Epoch 11/150
31/31 [==============================] - 0s 16ms/step - loss: 25470.3008 - mse:
25470.2852 - mae: 115.1083 - val_loss: 32498.7715 - val_mse: 32498.7539 -
val_mae: 120.0848 - lr: 0.0010
Epoch 12/150
31/31 [==============================] - 0s 13ms/step - loss: 20657.5117 - mse:
20657.4941 - mae: 103.2945 - val_loss: 24387.6602 - val_mse: 24387.6426 -
val_mae: 101.3127 - lr: 0.0010
Epoch 13/150
31/31 [==============================] - 0s 15ms/step - loss: 17637.8652 - mse:
17637.8438 - mae: 95.6876 - val_loss: 24707.8535 - val_mse: 24707.8359 -
val_mae: 101.5755 - lr: 0.0010
Epoch 14/150
31/31 [==============================] - 0s 13ms/step - loss: 18912.1934 - mse:
18912.1758 - mae: 97.9214 - val_loss: 16250.3252 - val_mse: 16250.3076 -
val_mae: 81.7623 - lr: 0.0010
Epoch 15/150
31/31 [==============================] - 0s 15ms/step - loss: 19361.1465 - mse:
19361.1289 - mae: 101.0323 - val_loss: 15263.6396 - val_mse: 15263.6191 -
val_mae: 79.6938 - lr: 0.0010
Epoch 16/150
31/31 [==============================] - 0s 15ms/step - loss: 15985.9404 - mse:
15985.9199 - mae: 90.5940 - val_loss: 17297.7812 - val_mse: 17297.7637 -
val_mae: 82.7424 - lr: 0.0010
Epoch 17/150
31/31 [==============================] - 0s 6ms/step - loss: 19545.6465 - mse:
19545.6289 - mae: 100.2851 - val_loss: 9722.5391 - val_mse: 9722.5215 - val_mae:
63.9301 - lr: 0.0010
Epoch 18/150
31/31 [==============================] - 0s 7ms/step - loss: 14186.8740 - mse:
14186.8574 - mae: 87.0687 - val_loss: 9540.5371 - val_mse: 9540.5205 - val_mae:
63.6826 - lr: 0.0010
Epoch 19/150
31/31 [==============================] - 0s 7ms/step - loss: 13726.2832 - mse:
13726.2627 - mae: 85.4965 - val_loss: 7794.0981 - val_mse: 7794.0801 - val_mae:
56.9338 - lr: 0.0010
Epoch 20/150
31/31 [==============================] - 0s 7ms/step - loss: 16102.9316 - mse:
16102.9141 - mae: 89.9202 - val_loss: 9781.8057 - val_mse: 9781.7871 - val_mae:
62.0169 - lr: 0.0010
Epoch 21/150
31/31 [==============================] - 0s 7ms/step - loss: 15777.2939 - mse:
15777.2734 - mae: 89.2567 - val_loss: 3938.8801 - val_mse: 3938.8621 - val_mae:
44.5222 - lr: 0.0010
Epoch 22/150
31/31 [==============================] - 0s 7ms/step - loss: 14400.1865 - mse:
14400.1680 - mae: 87.3086 - val_loss: 5020.4609 - val_mse: 5020.4434 - val_mae:
48.8842 - lr: 0.0010
```

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Epoch 23/150
31/31 [==============================] - 0s 7ms/step - loss: 14622.3213 - mse:
14622.3027 - mae: 86.8861 - val_loss: 4717.1714 - val_mse: 4717.1533 - val_mae:
44.2612 - lr: 0.0010
Epoch 24/150
31/31 [==============================] - 0s 7ms/step - loss: 15543.0205 - mse:
15543.0039 - mae: 90.3725 - val_loss: 4559.8115 - val_mse: 4559.7935 - val_mae:
46.4626 - lr: 0.0010
Epoch 25/150
31/31 [==============================] - 0s 9ms/step - loss: 12732.0947 - mse:
12732.0781 - mae: 81.7925 - val_loss: 4900.3965 - val_mse: 4900.3784 - val_mae:
46.2822 - lr: 0.0010
Epoch 26/150
31/31 [==============================] - 0s 7ms/step - loss: 12597.4541 - mse:
12597.4336 - mae: 81.1187 - val_loss: 2834.1855 - val_mse: 2834.1672 - val_mae:
37.6807 - lr: 0.0010
Epoch 27/150
31/31 [==============================] - 0s 6ms/step - loss: 13334.9248 - mse:
13334.9102 - mae: 81.1270 - val_loss: 3649.4717 - val_mse: 3649.4539 - val_mae:
41.2631 - lr: 0.0010
Epoch 28/150
31/31 [==============================] - 0s 7ms/step - loss: 12178.0654 - mse:
12178.0488 - mae: 79.5793 - val_loss: 2788.8157 - val_mse: 2788.7974 - val_mae:
38.5705 - lr: 0.0010
Epoch 29/150
31/31 [==============================] - 0s 7ms/step - loss: 13744.4980 - mse:
13744.4805 - mae: 83.8519 - val_loss: 2746.9043 - val_mse: 2746.8865 - val_mae:
37.7805 - lr: 0.0010
Epoch 30/150
31/31 [==============================] - 0s 7ms/step - loss: 10868.0000 - mse:
10867.9824 - mae: 76.6432 - val_loss: 3460.8313 - val_mse: 3460.8132 - val_mae:
40.7223 - lr: 0.0010
Epoch 31/150
31/31 [==============================] - 0s 6ms/step - loss: 12652.8438 - mse:
12652.8232 - mae: 82.5514 - val_loss: 2445.3240 - val_mse: 2445.3057 - val_mae:
35.1099 - lr: 0.0010
Epoch 32/150
31/31 [==============================] - 0s 7ms/step - loss: 12032.8672 - mse:
12032.8516 - mae: 80.8354 - val_loss: 3380.7502 - val_mse: 3380.7317 - val_mae:
40.4710 - lr: 0.0010
Epoch 33/150
31/31 [==============================] - 0s 7ms/step - loss: 14036.7930 - mse:
14036.7734 - mae: 82.3318 - val_loss: 2334.1887 - val_mse: 2334.1704 - val_mae:
34.2808 - lr: 0.0010
Epoch 34/150
31/31 [==============================] - 0s 7ms/step - loss: 13007.1064 - mse:
13007.0879 - mae: 81.7942 - val_loss: 2832.4919 - val_mse: 2832.4736 - val_mae:
38.5389 - lr: 0.0010
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Epoch 35/150
31/31 [==============================] - 0s 7ms/step - loss: 11839.4756 - mse:
11839.4561 - mae: 79.0096 - val_loss: 2487.5042 - val_mse: 2487.4856 - val_mae:
35.5009 - lr: 0.0010
Epoch 36/150
31/31 [==============================] - 0s 7ms/step - loss: 13049.3613 - mse:
13049.3467 - mae: 82.2309 - val_loss: 3517.4321 - val_mse: 3517.4143 - val_mae:
42.4468 - lr: 0.0010
Epoch 37/150
31/31 [==============================] - 0s 6ms/step - loss: 12799.0654 - mse:
12799.0498 - mae: 83.4640 - val_loss: 2911.8523 - val_mse: 2911.8342 - val_mae:
38.2770 - lr: 0.0010
Epoch 38/150
31/31 [==============================] - 0s 6ms/step - loss: 12925.8711 - mse:
12925.8525 - mae: 82.4073 - val_loss: 3494.8889 - val_mse: 3494.8704 - val_mae:
41.5224 - lr: 0.0010
Epoch 39/150
31/31 [==============================] - 0s 7ms/step - loss: 11578.1562 - mse:
11578.1396 - mae: 78.8233 - val_loss: 2359.9148 - val_mse: 2359.8965 - val_mae:
33.9913 - lr: 2.0000e-04
Epoch 40/150
31/31 [==============================] - 0s 6ms/step - loss: 11210.7549 - mse:
11210.7354 - mae: 78.0241 - val_loss: 2295.3862 - val_mse: 2295.3682 - val_mae:
33.4491 - lr: 2.0000e-04
Epoch 41/150
31/31 [==============================] - 0s 6ms/step - loss: 11689.0898 - mse:
11689.0723 - mae: 77.3524 - val_loss: 2542.8496 - val_mse: 2542.8315 - val_mae:
35.1530 - lr: 2.0000e-04
Epoch 42/150
31/31 [==============================] - 0s 6ms/step - loss: 10971.3066 - mse:
10971.2900 - mae: 74.4241 - val_loss: 2158.6382 - val_mse: 2158.6199 - val_mae:
32.5794 - lr: 2.0000e-04
Epoch 43/150
31/31 [==============================] - 0s 7ms/step - loss: 9284.4082 - mse:
9284.3887 - mae: 70.5203 - val_loss: 2199.5437 - val_mse: 2199.5256 - val_mae:
32.9621 - lr: 2.0000e-04
Epoch 44/150
31/31 [==============================] - 0s 6ms/step - loss: 11250.3838 - mse:
11250.3643 - mae: 79.5550 - val_loss: 2284.7979 - val_mse: 2284.7798 - val_mae:
33.4151 - lr: 2.0000e-04
Epoch 45/150
31/31 [==============================] - 0s 7ms/step - loss: 10528.7393 - mse:
10528.7197 - mae: 73.8121 - val_loss: 2185.1785 - val_mse: 2185.1602 - val_mae:
33.1997 - lr: 2.0000e-04
Epoch 46/150
31/31 [==============================] - 0s 7ms/step - loss: 11762.1426 - mse:
11762.1221 - mae: 78.4401 - val_loss: 2243.6587 - val_mse: 2243.6404 - val_mae:
33.2021 - lr: 2.0000e-04
```

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Epoch 47/150
31/31 [==============================] - 0s 7ms/step - loss: 11333.4600 - mse:
11333.4434 - mae: 76.0711 - val_loss: 2332.0696 - val_mse: 2332.0515 - val_mae:
33.6674 - lr: 2.0000e-04
Epoch 48/150
31/31 [==============================] - 0s 7ms/step - loss: 13189.2451 - mse:
13189.2266 - mae: 81.7334 - val_loss: 2374.1826 - val_mse: 2374.1646 - val_mae:
34.0510 - lr: 4.0000e-05
Epoch 49/150
31/31 [==============================] - 0s 6ms/step - loss: 11761.3936 - mse:
11761.3740 - mae: 76.9424 - val_loss: 2250.1938 - val_mse: 2250.1755 - val_mae:
33.2775 - lr: 4.0000e-05
Epoch 50/150
31/31 [==============================] - 0s 8ms/step - loss: 10933.6885 - mse:
10933.6699 - mae: 76.4759 - val_loss: 2177.8042 - val_mse: 2177.7859 - val_mae:
32.7736 - lr: 4.0000e-05
Epoch 51/150
31/31 [==============================] - 0s 7ms/step - loss: 10691.3018 - mse:
10691.2812 - mae: 75.4021 - val_loss: 2172.5344 - val_mse: 2172.5166 - val_mae:
32.8406 - lr: 4.0000e-05
Epoch 52/150
31/31 [==============================] - 0s 7ms/step - loss: 10910.2930 - mse:
10910.2725 - mae: 76.1167 - val_loss: 2184.0713 - val_mse: 2184.0532 - val_mae:
32.9440 - lr: 4.0000e-05
10/10 [==============================] - 0s 1ms/step
Epoch 1/150
31/31 [==============================] - 1s 11ms/step - loss: 329893.2500 - mse:
329893.2500 - mae: 469.8795 - val_loss: 239355.2969 - val_mse: 239355.2656 -
val_mae: 396.8409 - lr: 0.0010
Epoch 2/150
31/31 [==============================] - 0s 7ms/step - loss: 154477.2344 - mse:
154477.2031 - mae: 285.6245 - val_loss: 46401.3008 - val_mse: 46401.2695 -
val_mae: 147.7740 - lr: 0.0010
Epoch 3/150
31/31 [==============================] - 0s 6ms/step - loss: 36720.2070 - mse:
36720.1914 - mae: 127.6674 - val_loss: 23071.3008 - val_mse: 23071.2734 -
val_mae: 104.7419 - lr: 0.0010
Epoch 4/150
31/31 [==============================] - 0s 6ms/step - loss: 23753.5977 - mse:
23753.5664 - mae: 107.0821 - val_loss: 18233.7129 - val_mse: 18233.6836 -
val_mae: 93.7509 - lr: 0.0010
Epoch 5/150
31/31 [==============================] - 0s 7ms/step - loss: 21168.7441 - mse:
21168.7168 - mae: 101.0148 - val_loss: 16152.7656 - val_mse: 16152.7373 -
val_mae: 85.9462 - lr: 0.0010
Epoch 6/150
31/31 [==============================] - 0s 6ms/step - loss: 18598.6543 - mse:
18598.6211 - mae: 94.4401 - val_loss: 14610.6270 - val_mse: 14610.5986 -
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val_mae: 84.7663 - lr: 0.0010
Epoch 7/150
31/31 [==============================] - 0s 6ms/step - loss: 17654.9668 - mse:
17654.9355 - mae: 92.5293 - val_loss: 13564.8604 - val_mse: 13564.8301 -
val_mae: 81.0466 - lr: 0.0010
Epoch 8/150
31/31 [==============================] - 0s 7ms/step - loss: 16484.4707 - mse:
16484.4395 - mae: 89.6222 - val_loss: 13001.6455 - val_mse: 13001.6152 -
val_mae: 81.2706 - lr: 0.0010
Epoch 9/150
31/31 [==============================] - 0s 6ms/step - loss: 15202.8740 - mse:
15202.8447 - mae: 86.9556 - val_loss: 12681.8457 - val_mse: 12681.8145 -
val_mae: 75.7288 - lr: 0.0010
Epoch 10/150
31/31 [==============================] - 0s 6ms/step - loss: 14482.7002 - mse:
14482.6689 - mae: 85.5556 - val_loss: 11703.8701 - val_mse: 11703.8389 -
val_mae: 75.4310 - lr: 0.0010
Epoch 11/150
31/31 [==============================] - 0s 7ms/step - loss: 14188.5215 - mse:
14188.4902 - mae: 84.4222 - val_loss: 12528.0098 - val_mse: 12527.9785 -
val_mae: 84.4668 - lr: 0.0010
Epoch 12/150
31/31 [==============================] - 0s 6ms/step - loss: 14250.6318 - mse:
14250.6006 - mae: 83.4247 - val_loss: 12354.4531 - val_mse: 12354.4229 -
val_mae: 85.0907 - lr: 0.0010
Epoch 13/150
31/31 [==============================] - 0s 6ms/step - loss: 14419.8818 - mse:
14419.8496 - mae: 85.0254 - val_loss: 10516.4160 - val_mse: 10516.3848 -
val_mae: 72.1001 - lr: 0.0010
Epoch 14/150
31/31 [==============================] - 0s 6ms/step - loss: 13671.5352 - mse:
13671.5049 - mae: 81.3209 - val_loss: 10044.7666 - val_mse: 10044.7344 -
val_mae: 70.7832 - lr: 0.0010
Epoch 15/150
31/31 [==============================] - 0s 6ms/step - loss: 12081.7285 - mse:
12081.6963 - mae: 79.1937 - val_loss: 9795.7744 - val_mse: 9795.7422 - val_mae:
71.0954 - lr: 0.0010
Epoch 16/150
31/31 [==============================] - 0s 6ms/step - loss: 11754.7031 - mse:
11754.6709 - mae: 76.3043 - val_loss: 9546.7490 - val_mse: 9546.7178 - val_mae:
70.3969 - lr: 0.0010
Epoch 17/150
31/31 [==============================] - 0s 6ms/step - loss: 12260.0156 - mse:
12259.9834 - mae: 77.0559 - val_loss: 8973.9551 - val_mse: 8973.9219 - val_mae:
66.6593 - lr: 0.0010
Epoch 18/150
31/31 [==============================] - 0s 7ms/step - loss: 11927.6992 - mse:
11927.6660 - mae: 76.4031 - val_loss: 8755.6992 - val_mse: 8755.6670 - val_mae:
```

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64.0385 - lr: 0.0010
Epoch 19/150
31/31 [==============================] - 0s 8ms/step - loss: 11224.8105 - mse:
11224.7773 - mae: 73.1594 - val_loss: 10089.1143 - val_mse: 10089.0811 -
val_mae: 76.6957 - lr: 0.0010
Epoch 20/150
31/31 [==============================] - 0s 6ms/step - loss: 11133.4463 - mse:
11133.4131 - mae: 73.8204 - val_loss: 8405.5332 - val_mse: 8405.5000 - val_mae:
66.0219 - lr: 0.0010
Epoch 21/150
31/31 [==============================] - 0s 6ms/step - loss: 10526.0225 - mse:
10525.9902 - mae: 71.8254 - val_loss: 7901.8970 - val_mse: 7901.8638 - val_mae:
62.0241 - lr: 0.0010
Epoch 22/150
31/31 [==============================] - 0s 6ms/step - loss: 9966.5195 - mse:
9966.4844 - mae: 69.5239 - val_loss: 7957.6060 - val_mse: 7957.5728 - val_mae:
64.2174 - lr: 0.0010
Epoch 23/150
31/31 [==============================] - 0s 6ms/step - loss: 9984.8350 - mse:
9984.8027 - mae: 68.7209 - val_loss: 8259.7354 - val_mse: 8259.7031 - val_mae:
67.7759 - lr: 0.0010
Epoch 24/150
31/31 [==============================] - 0s 6ms/step - loss: 9725.6104 - mse:
9725.5762 - mae: 67.4588 - val_loss: 7306.8975 - val_mse: 7306.8633 - val_mae:
55.4025 - lr: 0.0010
Epoch 25/150
31/31 [==============================] - 0s 7ms/step - loss: 9365.5850 - mse:
9365.5518 - mae: 65.8610 - val_loss: 6864.9062 - val_mse: 6864.8716 - val_mae:
53.5633 - lr: 0.0010
Epoch 26/150
31/31 [==============================] - 0s 6ms/step - loss: 8677.6299 - mse:
8677.5947 - mae: 64.1779 - val_loss: 7297.6895 - val_mse: 7297.6548 - val_mae:
62.2557 - lr: 0.0010
Epoch 27/150
31/31 [==============================] - 0s 6ms/step - loss: 8745.0498 - mse:
8745.0146 - mae: 64.4600 - val_loss: 6226.7773 - val_mse: 6226.7412 - val_mae:
50.0829 - lr: 0.0010
Epoch 28/150
31/31 [==============================] - 0s 6ms/step - loss: 8540.7725 - mse:
8540.7383 - mae: 62.5294 - val_loss: 6092.6162 - val_mse: 6092.5815 - val_mae:
51.4268 - lr: 0.0010
Epoch 29/150
31/31 [==============================] - 0s 6ms/step - loss: 8319.5020 - mse:
8319.4658 - mae: 61.6276 - val_loss: 5678.2148 - val_mse: 5678.1792 - val_mae:
50.8164 - lr: 0.0010
Epoch 30/150
31/31 [==============================] - 0s 6ms/step - loss: 7889.5811 - mse:
7889.5435 - mae: 59.9743 - val_loss: 6184.6943 - val_mse: 6184.6587 - val_mae:
```

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51.1566 - lr: 0.0010
Epoch 31/150
31/31 [==============================] - 0s 6ms/step - loss: 7159.0371 - mse:
7159.0015 - mae: 57.5883 - val_loss: 5405.7251 - val_mse: 5405.6895 - val_mae:
47.4982 - lr: 0.0010
Epoch 32/150
31/31 [==============================] - 0s 6ms/step - loss: 7692.1743 - mse:
7692.1382 - mae: 58.7060 - val_loss: 5185.3804 - val_mse: 5185.3447 - val_mae:
48.6302 - lr: 0.0010
Epoch 33/150
31/31 [==============================] - 0s 6ms/step - loss: 7081.0830 - mse:
7081.0459 - mae: 56.9929 - val_loss: 6855.6113 - val_mse: 6855.5747 - val_mae:
60.5217 - lr: 0.0010
Epoch 34/150
31/31 [==============================] - 0s 6ms/step - loss: 7031.5127 - mse:
7031.4766 - mae: 56.4593 - val_loss: 4980.1582 - val_mse: 4980.1226 - val_mae:
44.9204 - lr: 0.0010
Epoch 35/150
31/31 [==============================] - 0s 6ms/step - loss: 7827.0112 - mse:
7826.9736 - mae: 57.9577 - val_loss: 5531.7983 - val_mse: 5531.7622 - val_mae:
47.1939 - lr: 0.0010
Epoch 36/150
31/31 [==============================] - 0s 6ms/step - loss: 6928.9229 - mse:
6928.8892 - mae: 54.8751 - val_loss: 4590.3809 - val_mse: 4590.3452 - val_mae:
44.1536 - lr: 0.0010
Epoch 37/150
31/31 [==============================] - 0s 6ms/step - loss: 6481.8193 - mse:
6481.7832 - mae: 54.1130 - val_loss: 4538.6426 - val_mse: 4538.6064 - val_mae:
42.7801 - lr: 0.0010
Epoch 38/150
31/31 [==============================] - 0s 6ms/step - loss: 6698.7959 - mse:
6698.7598 - mae: 53.9537 - val_loss: 5036.5938 - val_mse: 5036.5576 - val_mae:
41.9475 - lr: 0.0010
Epoch 39/150
31/31 [==============================] - 0s 6ms/step - loss: 6380.8994 - mse:
6380.8628 - mae: 53.4174 - val_loss: 4804.2393 - val_mse: 4804.2036 - val_mae:
43.1995 - lr: 0.0010
Epoch 40/150
31/31 [==============================] - 0s 6ms/step - loss: 6299.9717 - mse:
6299.9351 - mae: 52.2654 - val_loss: 4092.2170 - val_mse: 4092.1802 - val_mae:
42.8153 - lr: 0.0010
Epoch 41/150
31/31 [==============================] - 0s 6ms/step - loss: 7027.0010 - mse:
7026.9634 - mae: 54.8182 - val_loss: 3973.6919 - val_mse: 3973.6553 - val_mae:
40.5918 - lr: 0.0010
Epoch 42/150
31/31 [==============================] - 0s 7ms/step - loss: 6008.1816 - mse:
6008.1445 - mae: 52.2545 - val_loss: 3908.4373 - val_mse: 3908.4011 - val_mae:
```

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41.5282 - lr: 0.0010
Epoch 43/150
31/31 [==============================] - 0s 6ms/step - loss: 5797.7803 - mse:
5797.7427 - mae: 50.4728 - val_loss: 3850.8259 - val_mse: 3850.7891 - val_mae:
43.0322 - lr: 0.0010
Epoch 44/150
31/31 [==============================] - 0s 6ms/step - loss: 6236.6592 - mse:
6236.6221 - mae: 53.0202 - val_loss: 3626.5396 - val_mse: 3626.5027 - val_mae:
39.0909 - lr: 0.0010
Epoch 45/150
31/31 [==============================] - 0s 6ms/step - loss: 5686.5518 - mse:
5686.5137 - mae: 49.6462 - val_loss: 5386.2617 - val_mse: 5386.2246 - val_mae:
47.2939 - lr: 0.0010
Epoch 46/150
31/31 [==============================] - 0s 8ms/step - loss: 5491.2324 - mse:
5491.1953 - mae: 50.7689 - val_loss: 3704.2603 - val_mse: 3704.2234 - val_mae:
38.2375 - lr: 0.0010
Epoch 47/150
31/31 [==============================] - 0s 7ms/step - loss: 5180.2837 - mse:
5180.2480 - mae: 48.9995 - val_loss: 3563.5181 - val_mse: 3563.4805 - val_mae:
40.9467 - lr: 0.0010
Epoch 48/150
31/31 [==============================] - 0s 7ms/step - loss: 5283.1367 - mse:
5283.1006 - mae: 48.3786 - val_loss: 3594.6116 - val_mse: 3594.5745 - val_mae:
40.6520 - lr: 0.0010
Epoch 49/150
31/31 [==============================] - 0s 7ms/step - loss: 5288.3530 - mse:
5288.3154 - mae: 48.9005 - val_loss: 4008.9639 - val_mse: 4008.9263 - val_mae:
46.1254 - lr: 0.0010
Epoch 50/150
31/31 [==============================] - 0s 6ms/step - loss: 4977.0474 - mse:
4977.0107 - mae: 47.8510 - val_loss: 4204.0601 - val_mse: 4204.0220 - val_mae:
47.8103 - lr: 0.0010
Epoch 51/150
31/31 [==============================] - 0s 6ms/step - loss: 5343.0718 - mse:
5343.0337 - mae: 48.5577 - val_loss: 3205.9910 - val_mse: 3205.9534 - val_mae:
38.1960 - lr: 0.0010
Epoch 52/150
31/31 [==============================] - 0s 7ms/step - loss: 5317.8066 - mse:
5317.7686 - mae: 48.6663 - val_loss: 3007.1541 - val_mse: 3007.1167 - val_mae:
35.8259 - lr: 0.0010
Epoch 53/150
31/31 [==============================] - 0s 6ms/step - loss: 5126.8452 - mse:
5126.8081 - mae: 47.9930 - val_loss: 2962.5266 - val_mse: 2962.4888 - val_mae:
36.2724 - lr: 0.0010
Epoch 54/150
31/31 [==============================] - 0s 6ms/step - loss: 4881.8379 - mse:
4881.8008 - mae: 47.8212 - val_loss: 2901.3564 - val_mse: 2901.3188 - val_mae:
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35.2232 - lr: 0.0010
Epoch 55/150
31/31 [==============================] - 0s 6ms/step - loss: 5118.9258 - mse:
5118.8877 - mae: 47.5580 - val_loss: 2916.8792 - val_mse: 2916.8420 - val_mae:
35.7929 - lr: 0.0010
Epoch 56/150
31/31 [==============================] - 0s 6ms/step - loss: 4624.8247 - mse:
4624.7886 - mae: 46.3196 - val_loss: 2958.2546 - val_mse: 2958.2168 - val_mae:
36.3642 - lr: 0.0010
Epoch 57/150
31/31 [==============================] - 0s 6ms/step - loss: 4937.5786 - mse:
4937.5415 - mae: 46.7076 - val_loss: 3161.0859 - val_mse: 3161.0483 - val_mae:
39.7126 - lr: 0.0010
Epoch 58/150
31/31 [==============================] - 0s 7ms/step - loss: 4886.0889 - mse:
4886.0522 - mae: 46.0190 - val_loss: 3804.1123 - val_mse: 3804.0750 - val_mae:
45.3283 - lr: 0.0010
Epoch 59/150
31/31 [==============================] - 0s 6ms/step - loss: 4681.0088 - mse:
4680.9712 - mae: 46.3619 - val_loss: 2766.8733 - val_mse: 2766.8357 - val_mae:
35.6958 - lr: 0.0010
Epoch 60/150
31/31 [==============================] - 0s 6ms/step - loss: 4856.5415 - mse:
4856.5039 - mae: 45.5498 - val_loss: 3001.1165 - val_mse: 3001.0786 - val_mae:
35.9782 - lr: 0.0010
Epoch 61/150
31/31 [==============================] - 0s 6ms/step - loss: 4413.0986 - mse:
4413.0610 - mae: 45.0485 - val_loss: 2671.8398 - val_mse: 2671.8027 - val_mae:
34.0773 - lr: 0.0010
Epoch 62/150
31/31 [==============================] - 0s 6ms/step - loss: 4690.7207 - mse:
4690.6836 - mae: 45.9335 - val_loss: 2593.9104 - val_mse: 2593.8728 - val_mae:
34.5544 - lr: 0.0010
Epoch 63/150
31/31 [==============================] - 0s 7ms/step - loss: 4476.9365 - mse:
4476.8989 - mae: 45.2498 - val_loss: 2575.1211 - val_mse: 2575.0837 - val_mae:
34.5725 - lr: 0.0010
Epoch 64/150
31/31 [==============================] - 0s 6ms/step - loss: 4251.1050 - mse:
4251.0669 - mae: 43.8199 - val_loss: 2911.3650 - val_mse: 2911.3274 - val_mae:
39.9471 - lr: 0.0010
Epoch 65/150
31/31 [==============================] - 0s 6ms/step - loss: 4117.7104 - mse:
4117.6729 - mae: 44.2961 - val_loss: 2527.7019 - val_mse: 2527.6641 - val_mae:
35.5818 - lr: 0.0010
Epoch 66/150
31/31 [==============================] - 0s 6ms/step - loss: 4562.7349 - mse:
4562.6963 - mae: 45.5674 - val_loss: 3786.6191 - val_mse: 3786.5815 - val_mae:
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45.7800 - lr: 0.0010
Epoch 67/150
31/31 [==============================] - 0s 7ms/step - loss: 4264.3745 - mse:
4264.3374 - mae: 43.7143 - val_loss: 2508.9731 - val_mse: 2508.9358 - val_mae:
34.2627 - lr: 0.0010
Epoch 68/150
31/31 [==============================] - 0s 6ms/step - loss: 4456.0312 - mse:
4455.9927 - mae: 45.0960 - val_loss: 2416.1045 - val_mse: 2416.0674 - val_mae:
33.5212 - lr: 0.0010
Epoch 69/150
31/31 [==============================] - 0s 6ms/step - loss: 4380.2178 - mse:
4380.1812 - mae: 45.0627 - val_loss: 2434.4519 - val_mse: 2434.4148 - val_mae:
34.0261 - lr: 0.0010
Epoch 70/150
31/31 [==============================] - 0s 6ms/step - loss: 4040.8452 - mse:
4040.8076 - mae: 43.1759 - val_loss: 2419.1584 - val_mse: 2419.1208 - val_mae:
34.6370 - lr: 0.0010
Epoch 71/150
31/31 [==============================] - 0s 6ms/step - loss: 4129.4019 - mse:
4129.3647 - mae: 43.9592 - val_loss: 3198.0020 - val_mse: 3197.9646 - val_mae:
41.5203 - lr: 0.0010
Epoch 72/150
31/31 [==============================] - 0s 6ms/step - loss: 4401.1338 - mse:
4401.0967 - mae: 44.5434 - val_loss: 2290.5874 - val_mse: 2290.5500 - val_mae:
32.4315 - lr: 0.0010
Epoch 73/150
31/31 [==============================] - 0s 8ms/step - loss: 4329.6299 - mse:
4329.5918 - mae: 44.4763 - val_loss: 2469.9458 - val_mse: 2469.9087 - val_mae:
34.9285 - lr: 0.0010
Epoch 74/150
31/31 [==============================] - 0s 6ms/step - loss: 3952.6150 - mse:
3952.5774 - mae: 43.4945 - val_loss: 2370.7446 - val_mse: 2370.7070 - val_mae:
32.9314 - lr: 0.0010
Epoch 75/150
31/31 [==============================] - 0s 6ms/step - loss: 4017.7104 - mse:
4017.6733 - mae: 42.9656 - val_loss: 2269.8423 - val_mse: 2269.8052 - val_mae:
32.5962 - lr: 0.0010
Epoch 76/150
31/31 [==============================] - 0s 6ms/step - loss: 3974.7766 - mse:
3974.7397 - mae: 43.3286 - val_loss: 3069.8223 - val_mse: 3069.7854 - val_mae:
39.3442 - lr: 0.0010
Epoch 77/150
31/31 [==============================] - 0s 6ms/step - loss: 3819.2998 - mse:
3819.2627 - mae: 42.4898 - val_loss: 2431.4792 - val_mse: 2431.4419 - val_mae:
32.8776 - lr: 0.0010
Epoch 78/150
31/31 [==============================] - 0s 7ms/step - loss: 3757.3118 - mse:
3757.2737 - mae: 42.3253 - val_loss: 3717.7056 - val_mse: 3717.6685 - val_mae:
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43.3385 - lr: 0.0010
Epoch 79/150
31/31 [==============================] - 0s 6ms/step - loss: 3918.1965 - mse:
3918.1604 - mae: 43.4719 - val_loss: 2476.1055 - val_mse: 2476.0686 - val_mae:
34.3939 - lr: 0.0010
Epoch 80/150
31/31 [==============================] - 0s 6ms/step - loss: 3795.0613 - mse:
3795.0237 - mae: 42.3314 - val_loss: 2439.3047 - val_mse: 2439.2671 - val_mae:
33.2737 - lr: 0.0010
Epoch 81/150
31/31 [==============================] - 0s 6ms/step - loss: 3504.4773 - mse:
3504.4399 - mae: 40.0190 - val_loss: 2137.5776 - val_mse: 2137.5405 - val_mae:
31.9331 - lr: 2.0000e-04
Epoch 82/150
31/31 [==============================] - 0s 7ms/step - loss: 3316.6470 - mse:
3316.6094 - mae: 39.6899 - val_loss: 2103.2024 - val_mse: 2103.1648 - val_mae:
31.5418 - lr: 2.0000e-04
Epoch 83/150
31/31 [==============================] - 0s 6ms/step - loss: 3413.4253 - mse:
3413.3877 - mae: 40.1100 - val_loss: 2098.9744 - val_mse: 2098.9365 - val_mae:
31.5028 - lr: 2.0000e-04
Epoch 84/150
31/31 [==============================] - 0s 7ms/step - loss: 3172.2424 - mse:
3172.2051 - mae: 39.0554 - val_loss: 2069.6628 - val_mse: 2069.6255 - val_mae:
31.2687 - lr: 2.0000e-04
Epoch 85/150
31/31 [==============================] - 0s 6ms/step - loss: 3450.7371 - mse:
3450.7002 - mae: 39.6932 - val_loss: 2062.6819 - val_mse: 2062.6448 - val_mae:
31.3742 - lr: 2.0000e-04
Epoch 86/150
31/31 [==============================] - 0s 7ms/step - loss: 3409.8237 - mse:
3409.7876 - mae: 40.2885 - val_loss: 2070.7927 - val_mse: 2070.7554 - val_mae:
31.3398 - lr: 2.0000e-04
Epoch 87/150
31/31 [==============================] - 0s 7ms/step - loss: 3515.3423 - mse:
3515.3049 - mae: 40.1394 - val_loss: 2149.4976 - val_mse: 2149.4602 - val_mae:
31.9920 - lr: 2.0000e-04
Epoch 88/150
31/31 [==============================] - 0s 6ms/step - loss: 3432.0459 - mse:
3432.0078 - mae: 39.5243 - val_loss: 2128.5474 - val_mse: 2128.5098 - val_mae:
32.1456 - lr: 2.0000e-04
Epoch 89/150
31/31 [==============================] - 0s 7ms/step - loss: 3454.6221 - mse:
3454.5847 - mae: 39.9904 - val_loss: 2041.0194 - val_mse: 2040.9822 - val_mae:
31.2879 - lr: 2.0000e-04
Epoch 90/150
31/31 [==============================] - 0s 6ms/step - loss: 3547.8931 - mse:
3547.8552 - mae: 40.5610 - val_loss: 2054.7744 - val_mse: 2054.7371 - val_mae:
```

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31.3359 - lr: 2.0000e-04
Epoch 91/150
31/31 [==============================] - 0s 6ms/step - loss: 3246.4800 - mse:
3246.4434 - mae: 39.3018 - val_loss: 2116.3496 - val_mse: 2116.3123 - val_mae:
32.3421 - lr: 2.0000e-04
Epoch 92/150
31/31 [==============================] - 0s 6ms/step - loss: 3580.9031 - mse:
3580.8662 - mae: 40.9997 - val_loss: 2102.1289 - val_mse: 2102.0916 - val_mae:
31.9633 - lr: 2.0000e-04
Epoch 93/150
31/31 [==============================] - 0s 6ms/step - loss: 3482.6797 - mse:
3482.6426 - mae: 39.8022 - val_loss: 2102.3752 - val_mse: 2102.3379 - val_mae:
31.6432 - lr: 2.0000e-04
Epoch 94/150
31/31 [==============================] - 0s 7ms/step - loss: 3456.2981 - mse:
3456.2607 - mae: 39.6324 - val_loss: 2040.5162 - val_mse: 2040.4790 - val_mae:
31.5622 - lr: 2.0000e-04
Epoch 95/150
31/31 [==============================] - 0s 7ms/step - loss: 3263.3538 - mse:
3263.3169 - mae: 39.0220 - val_loss: 2036.9316 - val_mse: 2036.8942 - val_mae:
31.3115 - lr: 2.0000e-04
Epoch 96/150
31/31 [==============================] - 0s 7ms/step - loss: 3362.0337 - mse:
3361.9968 - mae: 40.2098 - val_loss: 2032.5797 - val_mse: 2032.5424 - val_mae:
31.7611 - lr: 2.0000e-04
Epoch 97/150
31/31 [==============================] - 0s 6ms/step - loss: 3473.1279 - mse:
3473.0898 - mae: 40.2907 - val_loss: 2050.2363 - val_mse: 2050.1987 - val_mae:
31.7298 - lr: 2.0000e-04
Epoch 98/150
31/31 [==============================] - 0s 8ms/step - loss: 3652.3364 - mse:
3652.2993 - mae: 40.8551 - val_loss: 2098.0447 - val_mse: 2098.0073 - val_mae:
31.5918 - lr: 2.0000e-04
Epoch 99/150
31/31 [==============================] - 0s 7ms/step - loss: 3467.8989 - mse:
3467.8611 - mae: 39.8621 - val_loss: 2016.6190 - val_mse: 2016.5818 - val_mae:
31.1564 - lr: 2.0000e-04
Epoch 100/150
31/31 [==============================] - 0s 7ms/step - loss: 3364.6667 - mse:
3364.6294 - mae: 39.2603 - val_loss: 2040.7704 - val_mse: 2040.7330 - val_mae:
31.4744 - lr: 2.0000e-04
Epoch 101/150
31/31 [==============================] - 0s 7ms/step - loss: 3525.5254 - mse:
3525.4880 - mae: 39.7322 - val_loss: 2101.1958 - val_mse: 2101.1582 - val_mae:
32.3782 - lr: 2.0000e-04
Epoch 102/150
31/31 [==============================] - 0s 7ms/step - loss: 3335.0862 - mse:
3335.0491 - mae: 39.6779 - val_loss: 2076.7549 - val_mse: 2076.7175 - val_mae:
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32.1894 - lr: 2.0000e-04
Epoch 103/150
31/31 [==============================] - 0s 6ms/step - loss: 3423.4170 - mse:
3423.3796 - mae: 40.3640 - val_loss: 2098.8887 - val_mse: 2098.8516 - val_mae:
31.8181 - lr: 2.0000e-04
Epoch 104/150
31/31 [==============================] - 0s 6ms/step - loss: 3477.8398 - mse:
3477.8022 - mae: 39.7403 - val_loss: 2119.9553 - val_mse: 2119.9177 - val_mae:
32.3312 - lr: 2.0000e-04
Epoch 105/150
31/31 [==============================] - 0s 6ms/step - loss: 3158.2708 - mse:
3158.2341 - mae: 38.7100 - val_loss: 2035.6986 - val_mse: 2035.6611 - val_mae:
31.3068 - lr: 4.0000e-05
Epoch 106/150
31/31 [==============================] - 0s 6ms/step - loss: 3274.6802 - mse:
3274.6436 - mae: 39.1338 - val_loss: 2032.8169 - val_mse: 2032.7797 - val_mae:
31.3014 - lr: 4.0000e-05
Epoch 107/150
31/31 [==============================] - 0s 6ms/step - loss: 3327.8765 - mse:
3327.8391 - mae: 38.9879 - val_loss: 2036.4883 - val_mse: 2036.4510 - val_mae:
31.2478 - lr: 4.0000e-05
Epoch 108/150
31/31 [==============================] - 0s 6ms/step - loss: 3464.8696 - mse:
3464.8330 - mae: 39.7068 - val_loss: 2019.1460 - val_mse: 2019.1089 - val_mae:
31.1970 - lr: 4.0000e-05
Epoch 109/150
31/31 [==============================] - 0s 6ms/step - loss: 3359.3325 - mse:
3359.2954 - mae: 39.3376 - val_loss: 2011.9851 - val_mse: 2011.9479 - val_mae:
31.1263 - lr: 4.0000e-05
Epoch 110/150
31/31 [==============================] - 0s 6ms/step - loss: 3036.4778 - mse:
3036.4407 - mae: 38.7299 - val_loss: 2020.0867 - val_mse: 2020.0493 - val_mae:
31.0581 - lr: 4.0000e-05
Epoch 111/150
31/31 [==============================] - 0s 7ms/step - loss: 3029.5784 - mse:
3029.5410 - mae: 37.7099 - val_loss: 2001.7147 - val_mse: 2001.6772 - val_mae:
31.1320 - lr: 4.0000e-05
Epoch 112/150
31/31 [==============================] - 0s 7ms/step - loss: 3397.3457 - mse:
3397.3081 - mae: 39.7807 - val_loss: 1996.4663 - val_mse: 1996.4292 - val_mae:
30.9527 - lr: 4.0000e-05
Epoch 113/150
31/31 [==============================] - 0s 6ms/step - loss: 3231.7095 - mse:
3231.6721 - mae: 39.2993 - val_loss: 2003.3776 - val_mse: 2003.3402 - val_mae:
30.9997 - lr: 4.0000e-05
Epoch 114/150
31/31 [==============================] - 0s 7ms/step - loss: 3196.7434 - mse:
3196.7068 - mae: 38.6561 - val_loss: 2004.4542 - val_mse: 2004.4171 - val_mae:
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30.9197 - lr: 4.0000e-05
Epoch 115/150
31/31 [==============================] - 0s 6ms/step - loss: 3435.0920 - mse:
3435.0552 - mae: 39.5763 - val_loss: 2014.9985 - val_mse: 2014.9612 - val_mae:
30.9743 - lr: 4.0000e-05
Epoch 116/150
31/31 [==============================] - 0s 6ms/step - loss: 3313.7463 - mse:
3313.7090 - mae: 38.7422 - val_loss: 1990.4938 - val_mse: 1990.4564 - val_mae:
30.7941 - lr: 4.0000e-05
Epoch 117/150
31/31 [==============================] - 0s 7ms/step - loss: 3157.3718 - mse:
3157.3347 - mae: 38.1448 - val_loss: 1985.6031 - val_mse: 1985.5659 - val_mae:
30.8348 - lr: 4.0000e-05
Epoch 118/150
31/31 [==============================] - 0s 6ms/step - loss: 3427.0928 - mse:
3427.0554 - mae: 39.7838 - val_loss: 1998.4103 - val_mse: 1998.3729 - val_mae:
30.9573 - lr: 4.0000e-05
Epoch 119/150
31/31 [==============================] - 0s 6ms/step - loss: 3290.6709 - mse:
3290.6328 - mae: 39.4190 - val_loss: 1974.6152 - val_mse: 1974.5780 - val_mae:
30.9256 - lr: 4.0000e-05
Epoch 120/150
31/31 [==============================] - 0s 6ms/step - loss: 3257.4395 - mse:
3257.4021 - mae: 38.9081 - val_loss: 1990.4102 - val_mse: 1990.3727 - val_mae:
31.2431 - lr: 4.0000e-05
Epoch 121/150
31/31 [==============================] - 0s 6ms/step - loss: 3161.7654 - mse:
3161.7283 - mae: 38.3926 - val_loss: 1976.1956 - val_mse: 1976.1584 - val_mae:
30.8726 - lr: 4.0000e-05
Epoch 122/150
31/31 [==============================] - 0s 6ms/step - loss: 3277.5930 - mse:
3277.5559 - mae: 38.5876 - val_loss: 1971.7278 - val_mse: 1971.6903 - val_mae:
30.9360 - lr: 4.0000e-05
Epoch 123/150
31/31 [==============================] - 0s 6ms/step - loss: 3103.4214 - mse:
3103.3840 - mae: 38.8865 - val_loss: 1967.6289 - val_mse: 1967.5918 - val_mae:
30.8229 - lr: 4.0000e-05
Epoch 124/150
31/31 [==============================] - 0s 6ms/step - loss: 3197.1851 - mse:
3197.1472 - mae: 38.3742 - val_loss: 1966.8290 - val_mse: 1966.7916 - val_mae:
30.7904 - lr: 4.0000e-05
Epoch 125/150
31/31 [==============================] - 0s 8ms/step - loss: 3190.5476 - mse:
3190.5098 - mae: 37.9396 - val_loss: 1964.9192 - val_mse: 1964.8818 - val_mae:
30.8426 - lr: 4.0000e-05
Epoch 126/150
31/31 [==============================] - 0s 6ms/step - loss: 3174.0837 - mse:
3174.0469 - mae: 39.0554 - val_loss: 1968.3934 - val_mse: 1968.3561 - val_mae:
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30.8641 - lr: 4.0000e-05
Epoch 127/150
31/31 [==============================] - 0s 7ms/step - loss: 3339.9717 - mse:
3339.9333 - mae: 39.4309 - val_loss: 1962.7822 - val_mse: 1962.7449 - val_mae:
30.9246 - lr: 4.0000e-05
Epoch 128/150
31/31 [==============================] - 0s 6ms/step - loss: 3165.4065 - mse:
3165.3696 - mae: 38.9061 - val_loss: 1954.2085 - val_mse: 1954.1711 - val_mae:
30.7418 - lr: 4.0000e-05
Epoch 129/150
31/31 [==============================] - 0s 6ms/step - loss: 3259.5288 - mse:
3259.4919 - mae: 38.5142 - val_loss: 1965.7915 - val_mse: 1965.7543 - val_mae:
30.8139 - lr: 4.0000e-05
Epoch 130/150
31/31 [==============================] - 0s 6ms/step - loss: 3167.0852 - mse:
3167.0476 - mae: 38.0241 - val_loss: 1964.2682 - val_mse: 1964.2311 - val_mae:
30.7129 - lr: 4.0000e-05
Epoch 131/150
31/31 [==============================] - 0s 6ms/step - loss: 3301.5203 - mse:
3301.4834 - mae: 38.8844 - val_loss: 1960.3615 - val_mse: 1960.3241 - val_mae:
30.8035 - lr: 4.0000e-05
Epoch 132/150
31/31 [==============================] - 0s 6ms/step - loss: 2990.1250 - mse:
2990.0874 - mae: 38.4982 - val_loss: 1952.2698 - val_mse: 1952.2327 - val_mae:
30.6357 - lr: 4.0000e-05
Epoch 133/150
31/31 [==============================] - 0s 6ms/step - loss: 3263.5542 - mse:
3263.5164 - mae: 39.2960 - val_loss: 1945.2925 - val_mse: 1945.2550 - val_mae:
30.6103 - lr: 4.0000e-05
Epoch 134/150
31/31 [==============================] - 0s 6ms/step - loss: 3197.8289 - mse:
3197.7917 - mae: 38.4836 - val_loss: 1943.9031 - val_mse: 1943.8657 - val_mae:
30.6045 - lr: 4.0000e-05
Epoch 135/150
31/31 [==============================] - 0s 7ms/step - loss: 3146.3184 - mse:
3146.2805 - mae: 38.6327 - val_loss: 1957.8262 - val_mse: 1957.7891 - val_mae:
30.5999 - lr: 4.0000e-05
Epoch 136/150
31/31 [==============================] - 0s 7ms/step - loss: 2999.2842 - mse:
2999.2463 - mae: 37.7860 - val_loss: 1947.4231 - val_mse: 1947.3857 - val_mae:
30.5725 - lr: 4.0000e-05
Epoch 137/150
31/31 [==============================] - 0s 7ms/step - loss: 3187.2825 - mse:
3187.2451 - mae: 38.7553 - val_loss: 1956.0270 - val_mse: 1955.9895 - val_mae:
30.8376 - lr: 4.0000e-05
Epoch 138/150
31/31 [==============================] - 0s 7ms/step - loss: 3275.2908 - mse:
3275.2537 - mae: 39.1694 - val_loss: 1951.9969 - val_mse: 1951.9594 - val_mae:
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30.6002 - lr: 4.0000e-05
Epoch 139/150
31/31 [==============================] - 0s 6ms/step - loss: 3258.8010 - mse:
3258.7642 - mae: 39.1884 - val_loss: 1953.8242 - val_mse: 1953.7870 - val_mae:
30.6184 - lr: 4.0000e-05
Epoch 140/150
31/31 [==============================] - 0s 6ms/step - loss: 3282.8286 - mse:
3282.7910 - mae: 39.2737 - val_loss: 1951.0366 - val_mse: 1950.9993 - val_mae:
30.6029 - lr: 1.0000e-05
Epoch 141/150
31/31 [==============================] - 0s 6ms/step - loss: 3269.6035 - mse:
3269.5667 - mae: 38.9951 - val_loss: 1949.3661 - val_mse: 1949.3290 - val_mae:
30.6222 - lr: 1.0000e-05
Epoch 142/150
31/31 [==============================] - 0s 6ms/step - loss: 3532.6392 - mse:
3532.6021 - mae: 40.1966 - val_loss: 1951.2091 - val_mse: 1951.1720 - val_mae:
30.6580 - lr: 1.0000e-05
Epoch 143/150
31/31 [==============================] - 0s 6ms/step - loss: 3213.2847 - mse:
3213.2473 - mae: 39.4023 - val_loss: 1951.2986 - val_mse: 1951.2614 - val_mae:
30.6308 - lr: 1.0000e-05
Epoch 144/150
31/31 [==============================] - 0s 6ms/step - loss: 3432.8689 - mse:
3432.8318 - mae: 38.9006 - val_loss: 1957.1174 - val_mse: 1957.0802 - val_mae:
30.6472 - lr: 1.0000e-05
10/10 [==============================] - 0s 2ms/step
Epoch 1/150
31/31 [==============================] - 2s 15ms/step - loss: 340786.6562 - mse:
340786.5625 - mae: 479.2112 - val_loss: 304594.5000 - val_mse: 304594.4062 -
val_mae: 461.1436 - lr: 0.0010
Epoch 2/150
31/31 [==============================] - 0s 10ms/step - loss: 271110.5625 - mse:
271110.4062 - mae: 406.1664 - val_loss: 242447.0938 - val_mse: 242446.9375 -
val_mae: 392.2988 - lr: 0.0010
Epoch 3/150
31/31 [==============================] - 0s 10ms/step - loss: 125870.9219 - mse:
125870.7188 - mae: 264.4988 - val_loss: 139470.5469 - val_mse: 139470.3125 -
val_mae: 266.1722 - lr: 0.0010
Epoch 4/150
31/31 [==============================] - 0s 9ms/step - loss: 70029.1250 - mse:
70028.8906 - mae: 189.8358 - val_loss: 116095.9688 - val_mse: 116095.7422 -
val_mae: 235.0649 - lr: 0.0010
Epoch 5/150
31/31 [==============================] - 0s 9ms/step - loss: 49421.8711 - mse:
49421.6328 - mae: 164.6550 - val_loss: 105172.7734 - val_mse: 105172.5469 -
val_mae: 221.7375 - lr: 0.0010
Epoch 6/150
31/31 [==============================] - 0s 8ms/step - loss: 43463.1953 - mse:
```

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43462.9531 - mae: 152.7132 - val_loss: 91091.4922 - val_mse: 91091.2500 -
val_mae: 202.8798 - lr: 0.0010
Epoch 7/150
31/31 [==============================] - 0s 9ms/step - loss: 40601.4727 - mse:
40601.2227 - mae: 144.3562 - val_loss: 83472.5703 - val_mse: 83472.3125 -
val_mae: 193.5264 - lr: 0.0010
Epoch 8/150
31/31 [==============================] - 0s 8ms/step - loss: 39587.9062 - mse:
39587.6484 - mae: 146.0729 - val_loss: 82321.1328 - val_mse: 82320.8906 -
val_mae: 194.8771 - lr: 0.0010
Epoch 9/150
31/31 [==============================] - 0s 8ms/step - loss: 37422.1562 - mse:
37421.8945 - mae: 136.6111 - val_loss: 69272.0938 - val_mse: 69271.8281 -
val_mae: 176.3061 - lr: 0.0010
Epoch 10/150
31/31 [==============================] - 0s 8ms/step - loss: 36478.3789 - mse:
36478.1094 - mae: 135.8015 - val_loss: 63235.5938 - val_mse: 63235.3359 -
val_mae: 167.7070 - lr: 0.0010
Epoch 11/150
31/31 [==============================] - 0s 8ms/step - loss: 36048.7695 - mse:
36048.5039 - mae: 134.7435 - val_loss: 54648.8047 - val_mse: 54648.5312 -
val_mae: 155.7641 - lr: 0.0010
Epoch 12/150
31/31 [==============================] - 0s 8ms/step - loss: 34408.2461 - mse:
34407.9844 - mae: 133.2737 - val_loss: 53040.1523 - val_mse: 53039.8828 -
val_mae: 154.7737 - lr: 0.0010
Epoch 13/150
31/31 [==============================] - 0s 8ms/step - loss: 33989.0391 - mse:
33988.7617 - mae: 130.4467 - val_loss: 39587.1836 - val_mse: 39586.8945 -
val_mae: 133.5513 - lr: 0.0010
Epoch 14/150
31/31 [==============================] - 0s 9ms/step - loss: 34386.9805 - mse:
34386.6992 - mae: 132.0977 - val_loss: 39474.3633 - val_mse: 39474.0859 -
val_mae: 133.2299 - lr: 0.0010
Epoch 15/150
31/31 [==============================] - 0s 9ms/step - loss: 33143.8242 - mse:
33143.5391 - mae: 128.3131 - val_loss: 35851.8750 - val_mse: 35851.5781 -
val_mae: 127.7500 - lr: 0.0010
Epoch 16/150
31/31 [==============================] - 0s 9ms/step - loss: 33904.5352 - mse:
33904.2422 - mae: 129.9962 - val_loss: 33787.6602 - val_mse: 33787.3633 -
val_mae: 124.3465 - lr: 0.0010
Epoch 17/150
31/31 [==============================] - 0s 8ms/step - loss: 33642.7617 - mse:
33642.4609 - mae: 129.2782 - val_loss: 29800.4336 - val_mse: 29800.1348 -
val_mae: 118.3554 - lr: 0.0010
Epoch 18/150
31/31 [==============================] - 0s 9ms/step - loss: 33040.5039 - mse:
```

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33040.1992 - mae: 127.5704 - val_loss: 28669.0645 - val_mse: 28668.7578 -
val_mae: 115.9390 - lr: 0.0010
Epoch 19/150
31/31 [==============================] - 0s 10ms/step - loss: 32504.6230 - mse:
32504.3184 - mae: 127.2049 - val_loss: 28173.5078 - val_mse: 28173.2031 -
val_mae: 114.9096 - lr: 0.0010
Epoch 20/150
31/31 [==============================] - 0s 8ms/step - loss: 31507.4648 - mse:
31507.1582 - mae: 125.8713 - val_loss: 27472.0879 - val_mse: 27471.7734 -
val_mae: 114.0623 - lr: 0.0010
Epoch 21/150
31/31 [==============================] - 0s 8ms/step - loss: 32699.4238 - mse:
32699.1113 - mae: 126.9405 - val_loss: 27192.9531 - val_mse: 27192.6367 -
val_mae: 113.8537 - lr: 0.0010
Epoch 22/150
31/31 [==============================] - 0s 8ms/step - loss: 31248.6152 - mse:
31248.2988 - mae: 123.8823 - val_loss: 27020.8867 - val_mse: 27020.5684 -
val_mae: 112.9310 - lr: 0.0010
Epoch 23/150
31/31 [==============================] - 0s 8ms/step - loss: 32272.5430 - mse:
32272.2129 - mae: 125.8442 - val_loss: 27392.2793 - val_mse: 27391.9609 -
val_mae: 111.7787 - lr: 0.0010
Epoch 24/150
31/31 [==============================] - 0s 9ms/step - loss: 32145.5156 - mse:
32145.1934 - mae: 125.2631 - val_loss: 26910.9141 - val_mse: 26910.5938 -
val_mae: 111.4131 - lr: 0.0010
Epoch 25/150
31/31 [==============================] - 0s 8ms/step - loss: 32439.0352 - mse:
32438.7109 - mae: 123.6500 - val_loss: 26952.3711 - val_mse: 26952.0469 -
val_mae: 111.3270 - lr: 0.0010
Epoch 26/150
31/31 [==============================] - 0s 9ms/step - loss: 33347.1641 - mse:
33346.8359 - mae: 125.9983 - val_loss: 27150.6270 - val_mse: 27150.2969 -
val_mae: 114.8244 - lr: 0.0010
Epoch 27/150
31/31 [==============================] - 0s 9ms/step - loss: 31449.9355 - mse:
31449.5996 - mae: 123.3338 - val_loss: 27211.0215 - val_mse: 27210.6855 -
val_mae: 114.5531 - lr: 0.0010
Epoch 28/150
31/31 [==============================] - 0s 9ms/step - loss: 31257.0332 - mse:
31256.6992 - mae: 123.0651 - val_loss: 27112.5391 - val_mse: 27112.2031 -
val_mae: 114.7302 - lr: 0.0010
Epoch 29/150
31/31 [==============================] - 0s 8ms/step - loss: 32306.0645 - mse:
32305.7305 - mae: 123.9230 - val_loss: 26331.0352 - val_mse: 26330.6934 -
val_mae: 111.4154 - lr: 0.0010
Epoch 30/150
31/31 [==============================] - 0s 9ms/step - loss: 31119.2754 - mse:
```
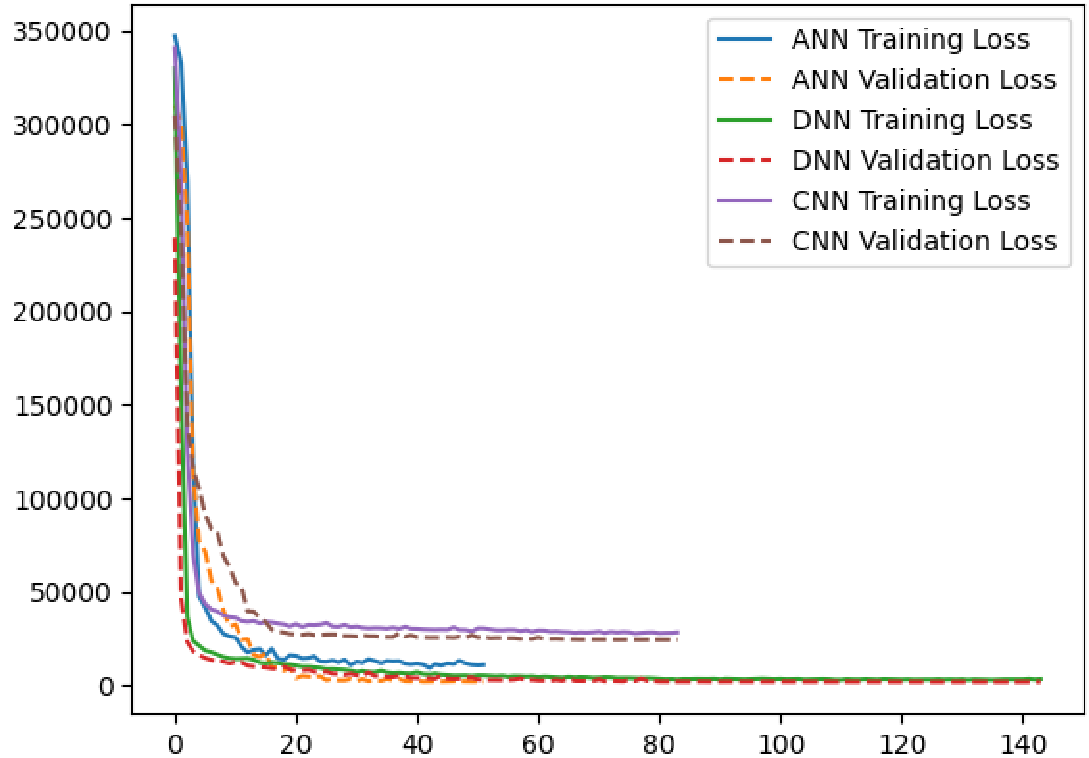

```
31118.9355 - mae: 122.6219 - val_loss: 26260.8887 - val_mse: 26260.5488 -
val_mae: 109.3945 - lr: 0.0010
Epoch 31/150
31/31 [==============================] - 0s 8ms/step - loss: 31395.8242 - mse:
31395.4824 - mae: 121.6387 - val_loss: 26086.0527 - val_mse: 26085.7109 -
val_mae: 109.8728 - lr: 0.0010
Epoch 32/150
31/31 [==============================] - 0s 8ms/step - loss: 30777.8535 - mse:
30777.5098 - mae: 121.5072 - val_loss: 26613.0488 - val_mse: 26612.7051 -
val_mae: 111.7257 - lr: 0.0010
Epoch 33/150
31/31 [==============================] - 0s 9ms/step - loss: 30452.2344 - mse:
30451.8867 - mae: 120.3382 - val_loss: 26226.0312 - val_mse: 26225.6797 -
val_mae: 110.6052 - lr: 0.0010
Epoch 34/150
31/31 [==============================] - 0s 9ms/step - loss: 30648.9238 - mse:
30648.5664 - mae: 121.0176 - val_loss: 26195.9121 - val_mse: 26195.5586 -
val_mae: 111.1153 - lr: 0.0010
Epoch 35/150
31/31 [==============================] - 0s 9ms/step - loss: 30571.0371 - mse:
30570.6797 - mae: 121.8005 - val_loss: 25782.8789 - val_mse: 25782.5215 -
val_mae: 108.1416 - lr: 0.0010
Epoch 36/150
31/31 [==============================] - 0s 9ms/step - loss: 30266.2227 - mse:
30265.8633 - mae: 120.0380 - val_loss: 25779.4648 - val_mse: 25779.1055 -
val_mae: 108.3005 - lr: 0.0010
Epoch 37/150
31/31 [==============================] - 0s 8ms/step - loss: 30826.8945 - mse:
30826.5352 - mae: 122.1493 - val_loss: 25732.9902 - val_mse: 25732.6309 -
val_mae: 108.4324 - lr: 0.0010
Epoch 38/150
31/31 [==============================] - 0s 8ms/step - loss: 30193.7578 - mse:
30193.3984 - mae: 119.5503 - val_loss: 27956.9668 - val_mse: 27956.6016 -
val_mae: 117.0692 - lr: 0.0010
Epoch 39/150
31/31 [==============================] - 0s 10ms/step - loss: 31322.1348 - mse:
31321.7695 - mae: 122.7605 - val_loss: 25979.6562 - val_mse: 25979.2949 -
val_mae: 109.7097 - lr: 0.0010
Epoch 40/150
31/31 [==============================] - 0s 8ms/step - loss: 30270.4082 - mse:
30270.0469 - mae: 119.9877 - val_loss: 26718.0137 - val_mse: 26717.6504 -
val_mae: 107.2453 - lr: 0.0010
Epoch 41/150
31/31 [==============================] - 0s 9ms/step - loss: 30190.8730 - mse:
30190.5020 - mae: 119.8945 - val_loss: 25695.4297 - val_mse: 25695.0586 -
val_mae: 108.3681 - lr: 0.0010
Epoch 42/150
31/31 [==============================] - 0s 9ms/step - loss: 29937.0723 - mse:
```

```
29936.7051 - mae: 120.5954 - val_loss: 25633.8984 - val_mse: 25633.5254 -
val_mae: 105.9023 - lr: 0.0010
Epoch 43/150
31/31 [==============================] - 0s 9ms/step - loss: 29808.3828 - mse:
29808.0117 - mae: 118.3278 - val_loss: 25496.6914 - val_mse: 25496.3203 -
val_mae: 107.3251 - lr: 0.0010
Epoch 44/150
31/31 [==============================] - 0s 9ms/step - loss: 29740.4141 - mse:
29740.0391 - mae: 118.3561 - val_loss: 25535.6699 - val_mse: 25535.2949 -
val_mae: 105.8842 - lr: 0.0010
Epoch 45/150
31/31 [==============================] - 0s 8ms/step - loss: 29832.1758 - mse:
29831.7988 - mae: 117.5888 - val_loss: 25384.6836 - val_mse: 25384.3086 -
val_mae: 105.8840 - lr: 0.0010
Epoch 46/150
31/31 [==============================] - 0s 9ms/step - loss: 29756.6270 - mse:
29756.2539 - mae: 117.0348 - val_loss: 25626.1719 - val_mse: 25625.7910 -
val_mae: 107.9983 - lr: 0.0010
Epoch 47/150
31/31 [==============================] - 0s 8ms/step - loss: 30979.4453 - mse:
30979.0664 - mae: 121.5326 - val_loss: 25456.0762 - val_mse: 25455.6992 -
val_mae: 108.4533 - lr: 0.0010
Epoch 48/150
31/31 [==============================] - 0s 9ms/step - loss: 29699.0332 - mse:
29698.6484 - mae: 118.9246 - val_loss: 25941.5684 - val_mse: 25941.1836 -
val_mae: 110.7018 - lr: 0.0010
Epoch 49/150
31/31 [==============================] - 0s 8ms/step - loss: 29606.4512 - mse:
29606.0684 - mae: 118.1181 - val_loss: 25237.7090 - val_mse: 25237.3262 -
val_mae: 105.1359 - lr: 0.0010
Epoch 50/150
31/31 [==============================] - 0s 8ms/step - loss: 28848.1211 - mse:
28847.7383 - mae: 115.7153 - val_loss: 26837.4434 - val_mse: 26837.0527 -
val_mae: 115.2867 - lr: 0.0010
Epoch 51/150
31/31 [==============================] - 0s 8ms/step - loss: 30469.2773 - mse:
30468.8926 - mae: 119.9952 - val_loss: 25503.0918 - val_mse: 25502.7012 -
val_mae: 108.9857 - lr: 0.0010
Epoch 52/150
31/31 [==============================] - 0s 8ms/step - loss: 30442.7754 - mse:
30442.3789 - mae: 120.7184 - val_loss: 26147.4766 - val_mse: 26147.0859 -
val_mae: 105.4175 - lr: 0.0010
Epoch 53/150
31/31 [==============================] - 0s 8ms/step - loss: 29972.7188 - mse:
29972.3281 - mae: 119.5303 - val_loss: 25192.0391 - val_mse: 25191.6445 -
val_mae: 105.9860 - lr: 0.0010
Epoch 54/150
31/31 [==============================] - 0s 8ms/step - loss: 29462.2266 - mse:
```

```
29461.8340 - mae: 117.2234 - val_loss: 25350.7051 - val_mse: 25350.3066 -
val_mae: 107.1112 - lr: 0.0010
Epoch 55/150
31/31 [==============================] - 0s 8ms/step - loss: 29385.7559 - mse:
29385.3633 - mae: 118.3214 - val_loss: 25303.7148 - val_mse: 25303.3184 -
val_mae: 106.8243 - lr: 0.0010
Epoch 56/150
31/31 [==============================] - 0s 8ms/step - loss: 29628.5547 - mse:
29628.1641 - mae: 119.2185 - val_loss: 25180.7324 - val_mse: 25180.3340 -
val_mae: 103.6822 - lr: 0.0010
Epoch 57/150
31/31 [==============================] - 0s 9ms/step - loss: 29603.0410 - mse:
29602.6406 - mae: 117.0545 - val_loss: 25184.4316 - val_mse: 25184.0312 -
val_mae: 105.4991 - lr: 0.0010
Epoch 58/150
31/31 [==============================] - 0s 8ms/step - loss: 29006.7949 - mse:
29006.3926 - mae: 117.1214 - val_loss: 24806.7383 - val_mse: 24806.3359 -
val_mae: 104.6072 - lr: 0.0010
Epoch 59/150
31/31 [==============================] - 0s 8ms/step - loss: 29413.6172 - mse:
29413.2109 - mae: 116.2225 - val_loss: 25098.4590 - val_mse: 25098.0527 -
val_mae: 104.0605 - lr: 0.0010
Epoch 60/150
31/31 [==============================] - 0s 9ms/step - loss: 28617.5977 - mse:
28617.1914 - mae: 115.5518 - val_loss: 24680.7285 - val_mse: 24680.3242 -
val_mae: 103.3373 - lr: 0.0010
Epoch 61/150
31/31 [==============================] - 0s 8ms/step - loss: 29302.6133 - mse:
29302.2012 - mae: 115.4802 - val_loss: 25660.9512 - val_mse: 25660.5449 -
val_mae: 102.9766 - lr: 0.0010
Epoch 62/150
31/31 [==============================] - 0s 8ms/step - loss: 29225.7988 - mse:
29225.3965 - mae: 116.4944 - val_loss: 24687.5449 - val_mse: 24687.1328 -
val_mae: 104.6165 - lr: 0.0010
Epoch 63/150
31/31 [==============================] - 0s 9ms/step - loss: 28689.3594 - mse:
28688.9492 - mae: 114.0043 - val_loss: 24790.2617 - val_mse: 24789.8516 -
val_mae: 105.3340 - lr: 0.0010
Epoch 64/150
31/31 [==============================] - 0s 8ms/step - loss: 28801.3711 - mse:
28800.9531 - mae: 116.7408 - val_loss: 24857.5625 - val_mse: 24857.1484 -
val_mae: 104.3179 - lr: 0.0010
Epoch 65/150
31/31 [==============================] - 0s 8ms/step - loss: 28529.9238 - mse:
28529.5137 - mae: 113.4560 - val_loss: 24692.8711 - val_mse: 24692.4570 -
val_mae: 104.4376 - lr: 0.0010
Epoch 66/150
31/31 [==============================] - 0s 10ms/step - loss: 28400.9609 - mse:
```

```
28400.5488 - mae: 115.3429 - val_loss: 24524.5039 - val_mse: 24524.0898 -
val_mae: 103.5621 - lr: 2.0000e-04
Epoch 67/150
31/31 [==============================] - 0s 9ms/step - loss: 28035.0977 - mse:
28034.6895 - mae: 114.0194 - val_loss: 24477.5918 - val_mse: 24477.1797 -
val_mae: 103.1200 - lr: 2.0000e-04
Epoch 68/150
31/31 [==============================] - 0s 10ms/step - loss: 28266.9766 - mse:
28266.5605 - mae: 114.0694 - val_loss: 24399.6973 - val_mse: 24399.2793 -
val_mae: 102.3610 - lr: 2.0000e-04
Epoch 69/150
31/31 [==============================] - 0s 10ms/step - loss: 28148.5566 - mse:
28148.1406 - mae: 113.5834 - val_loss: 24394.3008 - val_mse: 24393.8867 -
val_mae: 102.9561 - lr: 2.0000e-04
Epoch 70/150
31/31 [==============================] - 0s 9ms/step - loss: 28337.7402 - mse:
28337.3223 - mae: 114.8002 - val_loss: 24424.3281 - val_mse: 24423.9141 -
val_mae: 102.2197 - lr: 2.0000e-04
Epoch 71/150
31/31 [==============================] - 0s 9ms/step - loss: 28706.2188 - mse:
28705.8105 - mae: 114.6321 - val_loss: 24420.1445 - val_mse: 24419.7305 -
val_mae: 102.4314 - lr: 2.0000e-04
Epoch 72/150
31/31 [==============================] - 0s 10ms/step - loss: 27955.2051 - mse:
27954.7910 - mae: 113.2164 - val_loss: 24397.5918 - val_mse: 24397.1758 -
val_mae: 102.9010 - lr: 2.0000e-04
Epoch 73/150
31/31 [==============================] - 0s 9ms/step - loss: 28547.5605 - mse:
28547.1484 - mae: 114.5860 - val_loss: 24353.9590 - val_mse: 24353.5449 -
val_mae: 103.0866 - lr: 2.0000e-04
Epoch 74/150
31/31 [==============================] - 0s 10ms/step - loss: 28229.0449 - mse:
28228.6191 - mae: 114.2043 - val_loss: 24300.6758 - val_mse: 24300.2617 -
val_mae: 102.6486 - lr: 2.0000e-04
Epoch 75/150
31/31 [==============================] - 0s 8ms/step - loss: 28470.8223 - mse:
28470.3984 - mae: 114.4973 - val_loss: 24329.1230 - val_mse: 24328.7051 -
val_mae: 102.7451 - lr: 2.0000e-04
Epoch 76/150
31/31 [==============================] - 0s 8ms/step - loss: 28349.2734 - mse:
28348.8535 - mae: 114.3672 - val_loss: 24332.1719 - val_mse: 24331.7559 -
val_mae: 102.2644 - lr: 2.0000e-04
Epoch 77/150
31/31 [==============================] - 0s 10ms/step - loss: 27739.3164 - mse:
27738.8984 - mae: 113.0110 - val_loss: 24339.9668 - val_mse: 24339.5488 -
val_mae: 102.3332 - lr: 2.0000e-04
Epoch 78/150
31/31 [==============================] - 0s 8ms/step - loss: 28009.5332 - mse:
```

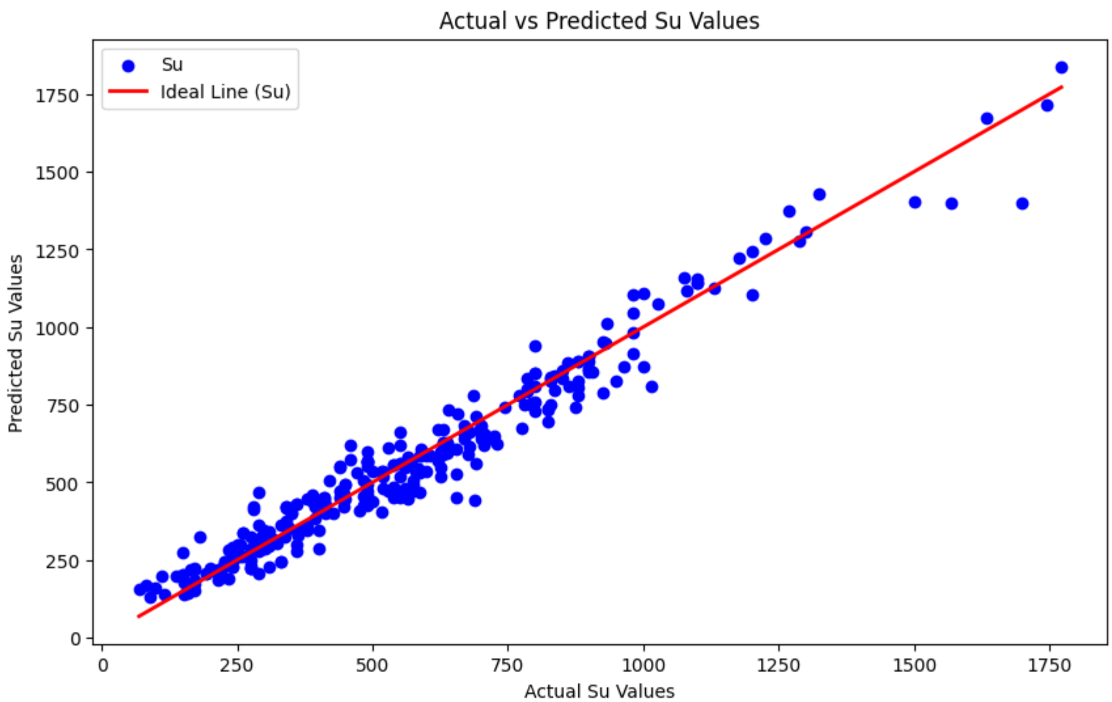
```
28009.1152 - mae: 114.4641 - val_loss: 24304.8711 - val_mse: 24304.4531 -
val_mae: 101.9929 - lr: 2.0000e-04
Epoch 79/150
31/31 [==============================] - 0s 10ms/step - loss: 28233.6602 - mse:
28233.2402 - mae: 113.3782 - val_loss: 24346.6133 - val_mse: 24346.1973 -
val_mae: 102.1313 - lr: 2.0000e-04
Epoch 80/150
31/31 [==============================] - 0s 12ms/step - loss: 28274.3379 - mse:
28273.9180 - mae: 113.6779 - val_loss: 24327.0430 - val_mse: 24326.6250 -
val_mae: 102.2804 - lr: 4.0000e-05
Epoch 81/150
31/31 [==============================] - 0s 15ms/step - loss: 27860.4219 - mse:
27860.0098 - mae: 113.8861 - val_loss: 24307.1738 - val_mse: 24306.7578 -
val_mae: 102.3794 - lr: 4.0000e-05
Epoch 82/150
31/31 [==============================] - 1s 17ms/step - loss: 27962.4043 - mse:
27961.9805 - mae: 113.2739 - val_loss: 24304.3105 - val_mse: 24303.8945 -
val_mae: 102.3588 - lr: 4.0000e-05
Epoch 83/150
31/31 [==============================] - 1s 18ms/step - loss: 28027.3887 - mse:
28026.9668 - mae: 113.3447 - val_loss: 24305.1562 - val_mse: 24304.7383 -
val_mae: 102.5155 - lr: 4.0000e-05
Epoch 84/150
31/31 [==============================] - 1s 18ms/step - loss: 28269.7285 - mse:
28269.3125 - mae: 114.4923 - val_loss: 24311.9453 - val_mse: 24311.5293 -
val_mae: 102.6076 - lr: 4.0000e-05
10/10 [==============================] - 0s 2ms/step

Final Model Performances:
ANN -> MSE: 2857.238186953973, R^2: 0.9688756392120368, MAE: 36.647934095759226
DNN -> MSE: 2521.3009123192924, R^2: 0.9725271792876777, MAE: 33.072109963130025
CNN -> MSE: 28936.108978082037, R^2: 0.6478957555119651, MAE: 112.85480675188083
```

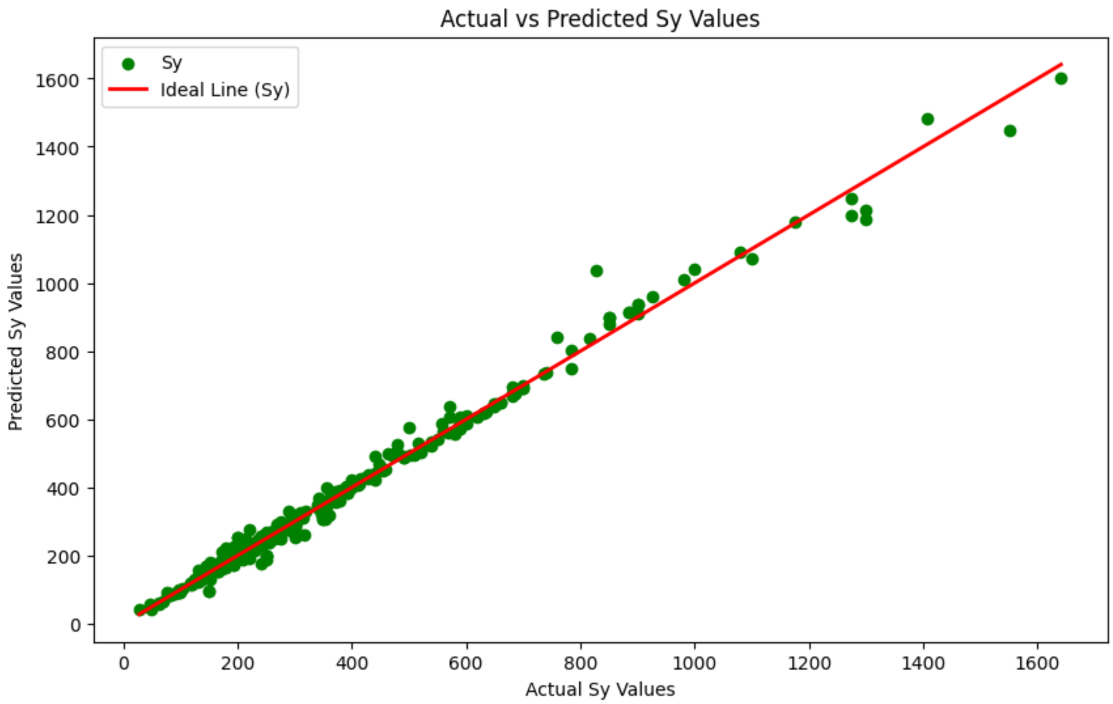


[5]:
```python
import matplotlib.pyplot as plt

# Make predictions with the DNN model
y_pred = dnn_model.predict(X_test)

# Visualize the real vs predicted 'Su' values
plt.figure(figsize=(10, 6))
plt.scatter(y_test['Su'], y_pred[:, 0], label='Su', color='blue')
plt.plot([y_test['Su'].min(), y_test['Su'].max()], [y_test['Su'].min(),␣
↪y_test['Su'].max()], color='red', lw=2, label='Ideal Line (Su)')
plt.xlabel('Actual Su Values')
plt.ylabel('Predicted Su Values')
plt.title('Actual vs Predicted Su Values')
plt.legend()
plt.show()

# Visualize the real vs predicted 'Sy' values
plt.figure(figsize=(10, 6))
plt.scatter(y_test['Sy'], y_pred[:, 1], label='Sy', color='green')
plt.plot([y_test['Sy'].min(), y_test['Sy'].max()], [y_test['Sy'].min(),␣
↪y_test['Sy'].max()], color='red', lw=2, label='Ideal Line (Sy)')
plt.xlabel('Actual Sy Values')
```

```
plt.ylabel('Predicted Sy Values')
plt.title('Actual vs Predicted Sy Values')
plt.legend()
plt.show()
```

```
10/10 [==============================] - 0s 2ms/step
```

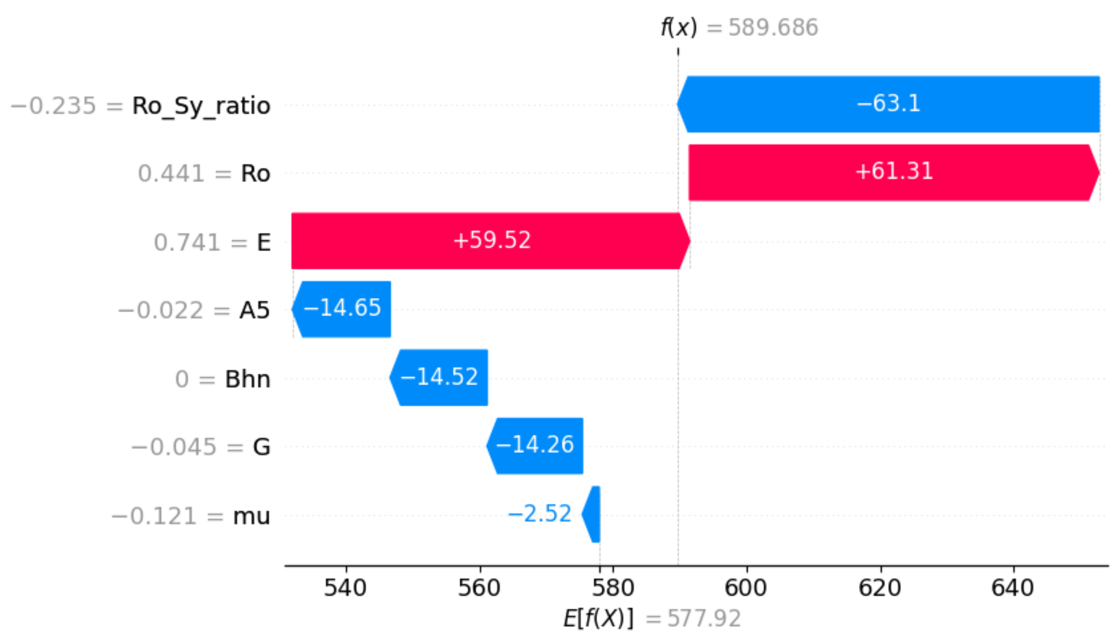




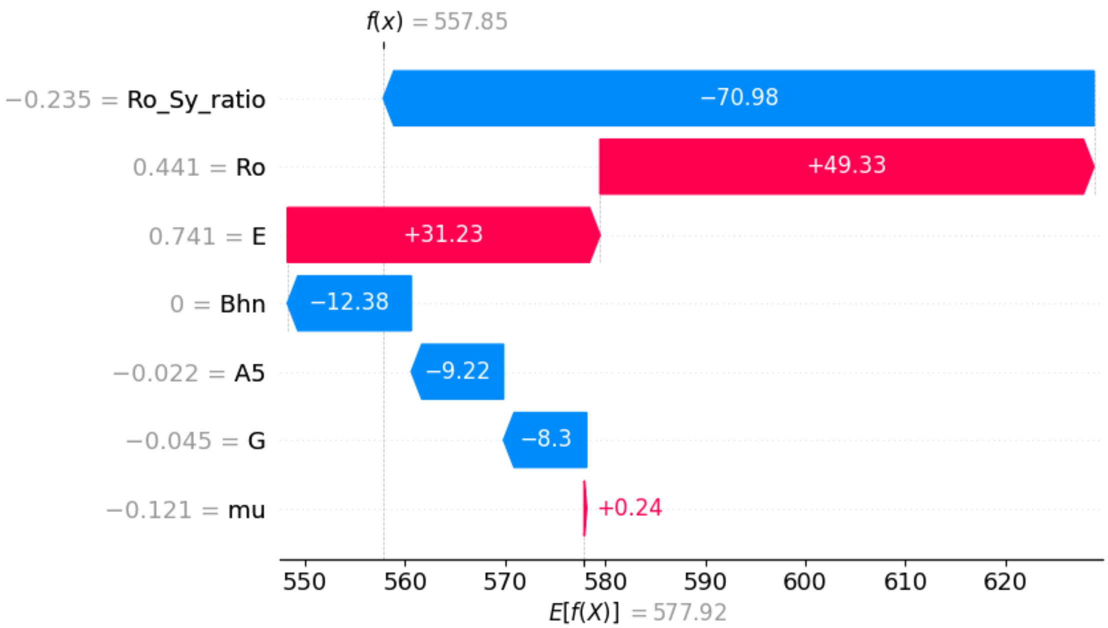
[10]:
```python
import shap
import numpy as np
import matplotlib.pyplot as plt

# Convert X_test to a NumPy array, ensuring compatibility with SHAP
X_test_shap = X_test.to_numpy()
feature_names = X_test.columns  # Extract feature names from the DataFrame

# Initialize the SHAP DeepExplainer using the trained DNN model and training␣
↪data
explainer = shap.DeepExplainer(dnn_model, X_train.to_numpy())

# Compute SHAP values for the test data, handling each output separately
shap_values = explainer.shap_values(X_test_shap)

# Handle base values appropriately, ensuring compatibility with multi-output␣
↪models
if isinstance(explainer.expected_value, list):
    base_values_su = explainer.expected_value[0]  # Base value for the 'Su'␣
↪output
    base_values_sy = explainer.expected_value[1]  # Base value for the 'Sy'␣
↪output
else:
    base_values_su = explainer.expected_value
```

```
    base_values_sy = explainer.expected_value

# Flatten base values to ensure they are scalars
base_values_su = np.array(base_values_su).flatten()[0]
base_values_sy = np.array(base_values_sy).flatten()[0]

# Generate SHAP waterfall plot for the 'Su' output
print("SHAP Waterfall Plot for Su:")
plt.figure(figsize=(15, 6))
shap.waterfall_plot(shap.Explanation(values=shap_values[0][0],␣
  ↪base_values=base_values_su, feature_names=feature_names,␣
  ↪data=X_test_shap[0]))
plt.show()

# Generate SHAP waterfall plot for the 'Sy' output
print("SHAP Waterfall Plot for Sy:")
plt.figure(figsize=(15, 6))
shap.waterfall_plot(shap.Explanation(values=shap_values[1][0],␣
  ↪base_values=base_values_sy, feature_names=feature_names,␣
  ↪data=X_test_shap[0]))
plt.show()
```

SHAP Waterfall Plot for Su:



SHAP Waterfall Plot for Sy:



f(x) = 557.85
−0.235 = Ro_Sy_ratio
−70.98
0.441 = Ro
+49.33
0.741 = E
+31.23
0 = Bhn
−12.38
−0.022 = A5
−9.22
−0.045 = G
−8.3
−0.121 = mu
+0.24
550
560
570
580
590
600
610
620
E[f(X)] = 577.92