Python Exercises for Petroleum Engineers: Set 2

Novin Nekuee

Student_id: 403134029

Welcome to the second homework for your "Introduction to Machine Learning" course. In this assignment, you will be working with a real well-logging dataset. Your task is to build a machine learning model that can predict water saturation using the appropriate set of logs.

In this homework, you will have the opportunity to solve a realistic machine learning problem step by step. To begin, you will need to import your well-logging data into Python and use appropriate tools to describe the data. You will then perform several preprocessing steps, such as

> 1. data cleaning,
>
> 2. normalization,
>
> 3. exploratory data analysis,
>
> 4. and feature selection,

to ensure that the data is ready to be used in a machine learning model.

Next, you should design an ANN model using Keras or Pytorch Lightning libraries. You will then train the neural network with different configurations, including varying the number of layers, number of neurons, learning rates, activation functions, and number of epochs.

During training, you will analyze the loss versus iteration curves to determine the best configuration for your model. You will also need to identify cases of overfitting and underfitting, which can negatively impact the performance of your model. Through this process, you will gain valuable experience in designing and training neural networks, and learn how to optimize their performance for a specific problem.

This homework will provide you with a hands-on experience in solving a realistic machine learning problem and help you develop important skills in data preprocessing, neural network training, and performance analysis. By completing this assignment, you will be well-prepared to tackle more complex machine learning problems in your future career as a petroleum engineer.

So, let's get started and dive into the exercises!

Task 1: Data Import

You have been provided with a well logging data set *FullSet_HW2.las*. This file is an *ASCII* file, which means you can load it by notepad to see what does it contain. Contact me if you had problem with understanding the data file.

Find a way to import this file into Python.

In [1]:

```
# First of all lets read las file and save it as excel file
import lasio
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import warnings

warnings.filterwarnings('ignore')

las = lasio.read("./FullSet_HW2.las")

df = las.df()
```

```
df = df.reset_index()
df.head()

# df.to_excel("FullSet_HW2.xlsx", engine='openpyxl')   # For save it to excel
```

Out[1]:

	DEPTH	CALIPER	DRHO	DT	DTS	GR	MSFR	NPHI	PEF	POTA	RHOB	RLLD	RLLS	SWE	THOR	URAN
0	27.000	NaN	NaN	NaN	NaN	13.4222	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	27.125	NaN	NaN	NaN	NaN	14.2646	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	27.250	NaN	NaN	NaN	NaN	14.7782	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	27.375	NaN	NaN	NaN	NaN	14.8532	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	27.500	NaN	NaN	NaN	NaN	14.5207	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [2]:
```
print(las.curves)  # For more information about the data set
```

```
Mnemonic  Unit  Value  Description
--------  ----  -----  -----------
DEPTH     M            {F}
CALIPER   MM           Caliper    {F}
DRHO      K/M3         Delta rho    {F}
DT        US/M         Delta Time    {F}
DTS       US/M         Shear Interval Transit Time    {F}
GR        GAPI         Gamma Ray    {F}
MSFR                   {F}
NPHI      V/V          Neutron porosity    {F}
PEF       B/E          Photo-electric factor    {F}
POTA      %            Potassium    {F}
RHOB      K/M3         Bulk Density    {F}
RLLD                   {F}
RLLS                   {F}
SWE       V/V          Effective Water Saturation    {F}
THOR      PPM          Thorium    {F}
URAN      PPM          Uranium    {F}
```

Task 2: Data Description

Describe the provided dataset. Your description should contain

1. shape of the dataset,
2. number of nulls of each column,
3. descriptive statistics (similar to Figure 3-3 "Machine Learning in the

Oil and Gas Industry"), 4. and your suggested depth interval to develope the model.

Task2-1: Shape of the dataset

In [3]:
```
df.shape
```

Out[3]:
```
(25899, 16)
```

Task2-2: number of null values in each column

There is two ways to solve this problem, one is to use the `isnull()` function to count the number of null values in each column, and the other ways is to get the count of Non-Null values by getting data information (`info()`)

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25899 entries, 0 to 25898
Data columns (total 16 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   DEPTH    25899 non-null  float64
 1   CALIPER  25458 non-null  float64
 2   DRHO     7742 non-null   float64
 3   DT       25173 non-null  float64
 4   DTS      3688 non-null   float64
 5   GR       25752 non-null  float64
 6   MSFR     5827 non-null   float64
 7   NPHI     8244 non-null   float64
 8   PEF      7742 non-null   float64
 9   POTA     8110 non-null   float64
 10  RHOB     7742 non-null   float64
 11  RLLD     8007 non-null   float64
 12  RLLS     8015 non-null   float64
 13  SWE      1729 non-null   float64
 14  THOR     8110 non-null   float64
 15  URAN     8110 non-null   float64
dtypes: float64(16)
memory usage: 3.2 MB
```

In [5]:
```python
df.isnull().sum()
```

Out[5]:
```
DEPTH          0
CALIPER      441
DRHO       18157
DT           726
DTS        22211
GR           147
MSFR       20072
NPHI       17655
PEF        18157
POTA       17789
RHOB       18157
RLLD       17892
RLLS       17884
SWE        24170
THOR       17789
URAN       17789
dtype: int64
```

Task2-3: Descriptive Statistics

In this step, we generate a descriptive statistical summary of the dataset using the `describe()` method. This provides key metrics for each well log, such as the `count`, `mean`, `standard deviation`, `minimum`, `maximum`, and `quartile values`.

In [6]:
```python
df.describe().transpose()  # I used transpose due to the width limitation of final pdf file
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
DEPTH	25899.0	1645.625000	934.567706	27.000000	836.312500	1645.625000	2454.937500	3264.250000
CALIPER	25458.0	14.212401	4.640448	7.693300	9.034050	12.831900	18.367575	21.816300
DRHO	7742.0	0.079707	0.145116	-1.313353	0.024000	0.038656	0.115264	0.680282
DT	25173.0	90.548042	26.977269	37.998200	67.309000	86.735200	109.608500	205.452000
DTS	3688.0	127.695462	18.901311	78.234800	117.553275	125.568900	133.161425	258.181300
GR	25752.0	31.114276	12.340763	4.701200	23.512075	31.085500	36.661550	169.565600
MSFR	5827.0	3.041833	3.738093	0.293000	1.367500	2.544600	4.124700	150.617000
NPHI	8244.0	0.195071	0.104171	-0.002580	0.123149	0.178814	0.242792	0.876141
PEF	7742.0	6.721218	6.441028	1.952300	3.597025	4.483900	5.358875	51.169400
POTA	8110.0	0.746082	0.345081	0.012600	0.520250	0.741200	0.949775	3.221400
RHOB	7742.0	2.524475	0.192477	1.221000	2.465000	2.552000	2.615000	3.109800
RLLD	8007.0	182.406811	2292.058902	0.011000	2.829500	5.198000	8.444000	40000.000000
RLLS	8015.0	43.692169	805.204005	0.044000	2.476500	5.022000	8.648500	25000.000000
SWE	1729.0	0.491855	0.237953	0.000000	0.317000	0.474000	0.645900	1.000000
THOR	8110.0	1.965749	2.572671	0.044600	0.505275	1.005400	2.065400	26.531900
URAN	8110.0	1.841279	1.762433	0.001900	0.755900	1.396650	2.266975	19.926700

Task 2-4: Depth Interval Selection

For training our model in supervised learning or neural networks we require complete, non-null data. Therefore, we must identify a continuous depth interval where the log data is valid.

For this initial analysis, we are selecting an interval based on the availability of all existing logs. The goal here is to find the most data-rich zone where every single column contains a valid measurement. This approach considers the presence or absence of data across all features, without yet prioritizing the importance of specific logs or the target variable (`SW`). This gives us a foundational, "fully-populated" interval to begin our analysis.

In [7]:

```python
key_columns = df.columns

cleaned_df = df.dropna(subset=key_columns)

valid_depths = cleaned_df['DEPTH']
valid_indices = cleaned_df.index

# Find the start and end of this continuous block of data
start_depth = valid_depths.min()
end_depth = valid_depths.max()

start_index = valid_indices.min()
end_index = valid_indices.max()

print("Suggested Depth Interval:")
print(f"\nSuggested modeling interval starts at: {start_depth:.2f}m with index of {start_index}")
print(f"Suggested modeling interval ends at:   {end_depth:.2f}m with index of {end_index}")
```

```
Suggested Depth Interval:

Suggested modeling interval starts at: 2279.00m with index of 18016
Suggested modeling interval ends at:   2495.00m with index of 19744
```

Pandas Profiling Report

To supplement our initial analysis, we employed the pandas-profiling library to generate a detailed and automated EDA report. This report provides a comprehensive overview of the dataset, including in-depth analysis of each variable's statistics, distribution, correlations, and missing value patterns.

For a complete, interactive exploration of the data, please see the `data_report.html` file accompanying this notebook.

In [ ]:
```
from pandas_profiling import ProfileReport

profile = ProfileReport(df, title="Full Data Profiling")

profile.to_file("data_report.html")
```

Task 2: Data Preparation

You should perform multiple steps of data preparation through this task. The required data preprocessings are:

1. Data cleaning: In this step you will need to identify and deal with any issues or anomalies in the dataset, to ensure that the data is accurate and consistent. Also you should keep an appropriate interval (a continous interval) of logs and delete the rest of them.

2. Feature selection: You will analyze the data and choose the best set of logs to use as input features for your machine learning model. This step will help you eliminate irrelevant or redundant features, which can negatively impact the performance of your model.

   You should use **your domain knowledge** and **feautre selection methods** to choose the best set of the input logs. Also you should plot correlation heatmap of features and pair plots using seaborn, pandas and/or matplotlib libraries (like Figure 3-3 "Machine Learning in the

Oil and Gas Industry")

3. Data normalization

4. Data splitting: Split your data randomly into *Train*, *Test*, and *Validation* sets. Choose a reasonable ratio to split the data.

Task 2-1: Data cleaning

In this step, the dataset is filtered to retain only the continuous depth interval identified in the previous analysis (from start_depth to end_depth). This removes data points outside the high-quality region. Any remaining rows with null values in this interval are also removed to ensure that the dataset is complete and ready for feature selection.

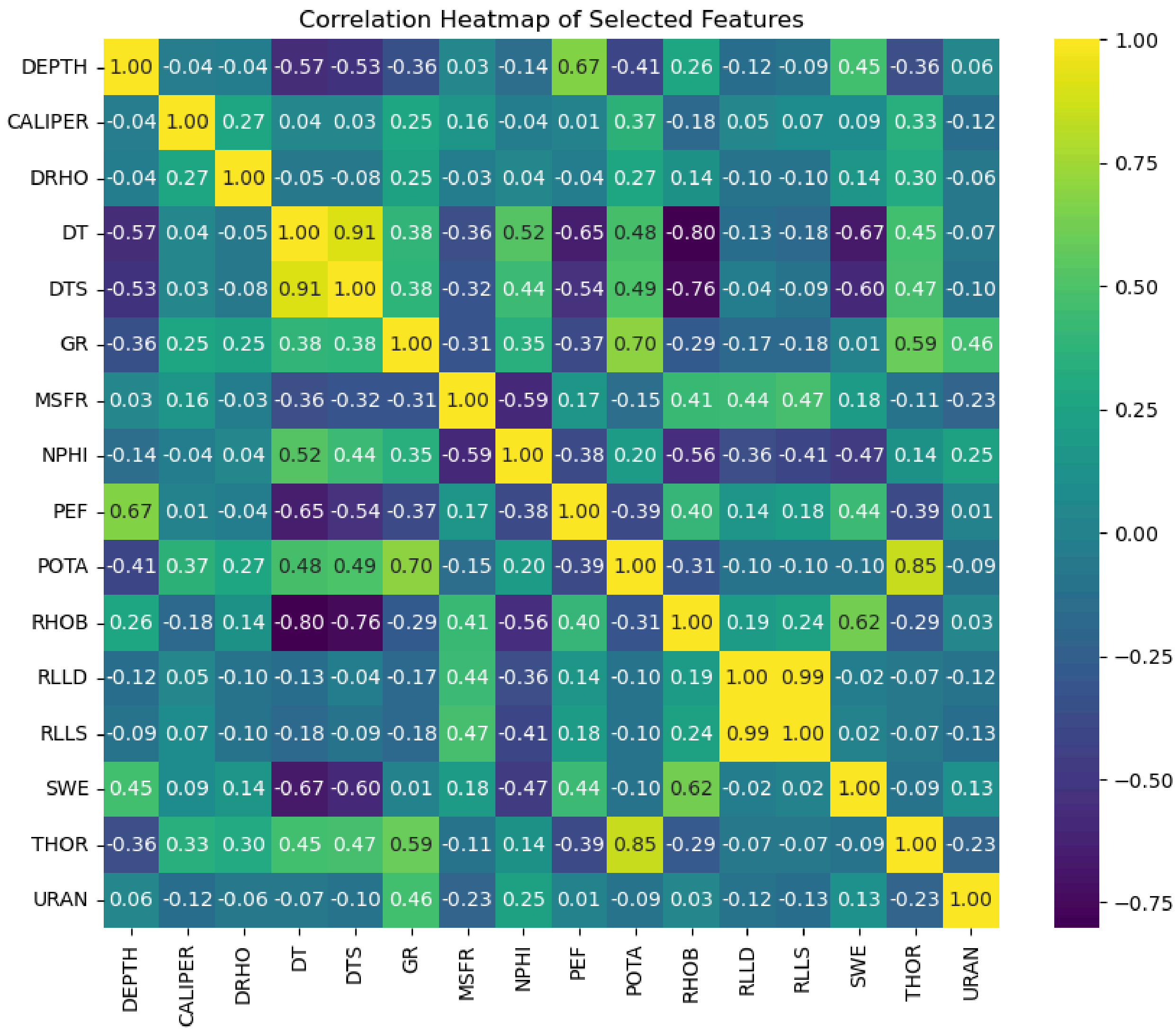
Another way is to use `dropna()` on the entire dataset to recognize non-empty data as a table, as in Part 3 of the previous task (which we did in Part 3 of the previous task, and now we want to do something different).

In [8]:
```
df_interval = df.loc[start_index:end_index].copy()
cleaned_df = df_interval.dropna()

print(f"Full Data Shape: {df.shape}")
print(f"Cleaned Data Shape: {cleaned_df.shape}")
```

```
Full Data Shape: (25899, 16)
Cleaned Data Shape: (1729, 16)
```

Task 2-2: Feature Selection

In [9]:
```
import seaborn as sns
import matplotlib.pyplot as plt

correlation_matrix = cleaned_df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='viridis', fmt='.2f')
plt.title('Correlation Heatmap of Selected Features')
plt.show()
```



In [10]:
```python
print(correlation_matrix['SWE'].sort_values(ascending=False))
```

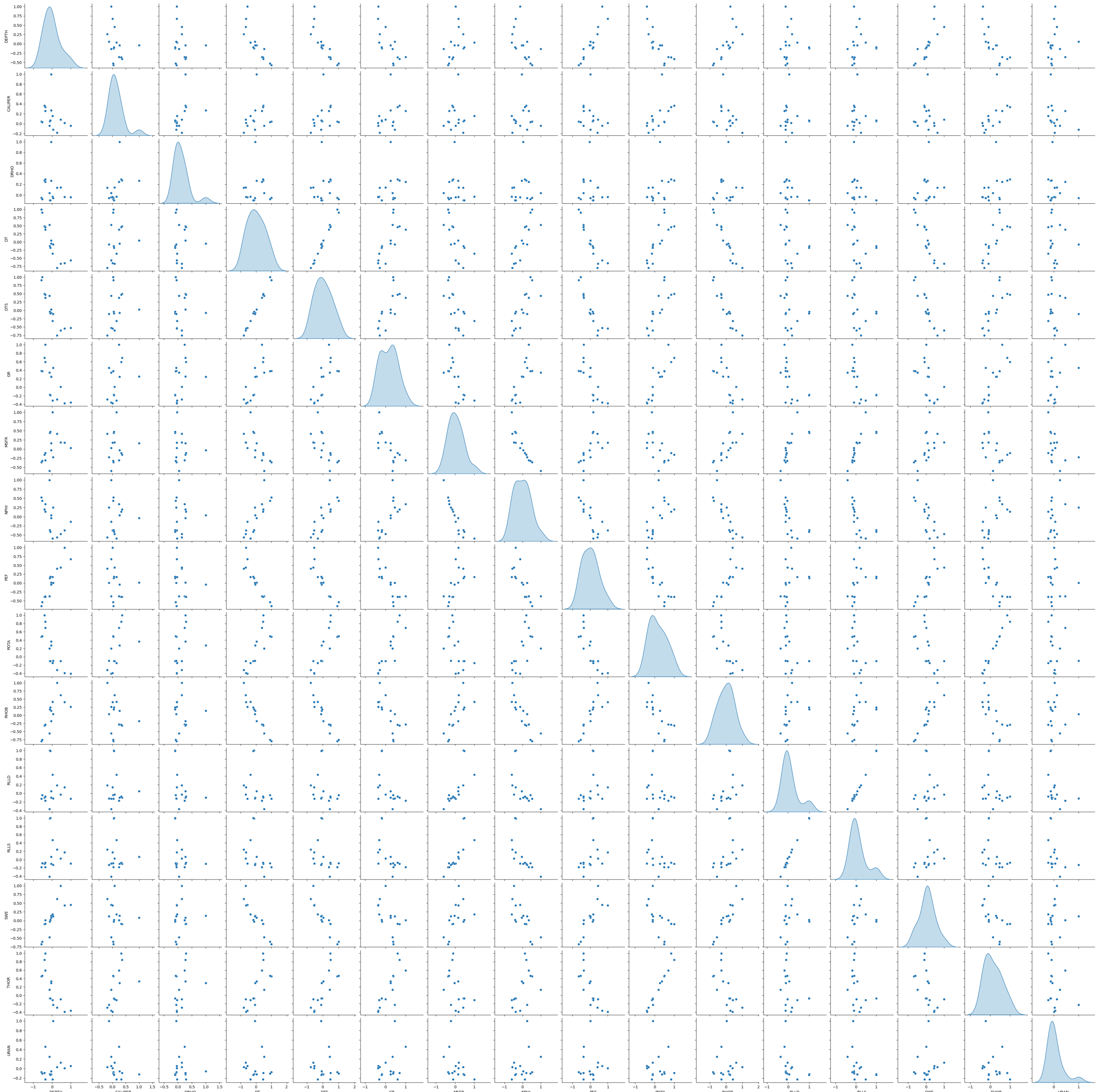
```
SWE        1.000000
RHOB       0.623229
DEPTH      0.454973
PEF        0.435940
MSFR       0.182287
DRHO       0.141433
URAN       0.125743
CALIPER    0.085070
RLLS       0.024209
GR         0.009662
RLLD      -0.024621
THOR      -0.089208
POTA      -0.100132
NPHI      -0.470558
DTS       -0.603210
DT        -0.673495
Name: SWE, dtype: float64
```

So based on the correlation heatmap analysis, a new subset of features was selected for the model. The columns `DRHO`, `DTS`, `GR`, `MSFR`, `POTA`, `RLLS`, `THOR`, `URAN`, and `CALIPER` were dropped for the following reasons:

- Low Correlation with Target: These logs showed a very weak linear correlation with our target variable, `SW`. Including them would likely add noise rather than predictive value.
- Redundancy: Some of the dropped features were highly correlated with other input features, making them redundant.

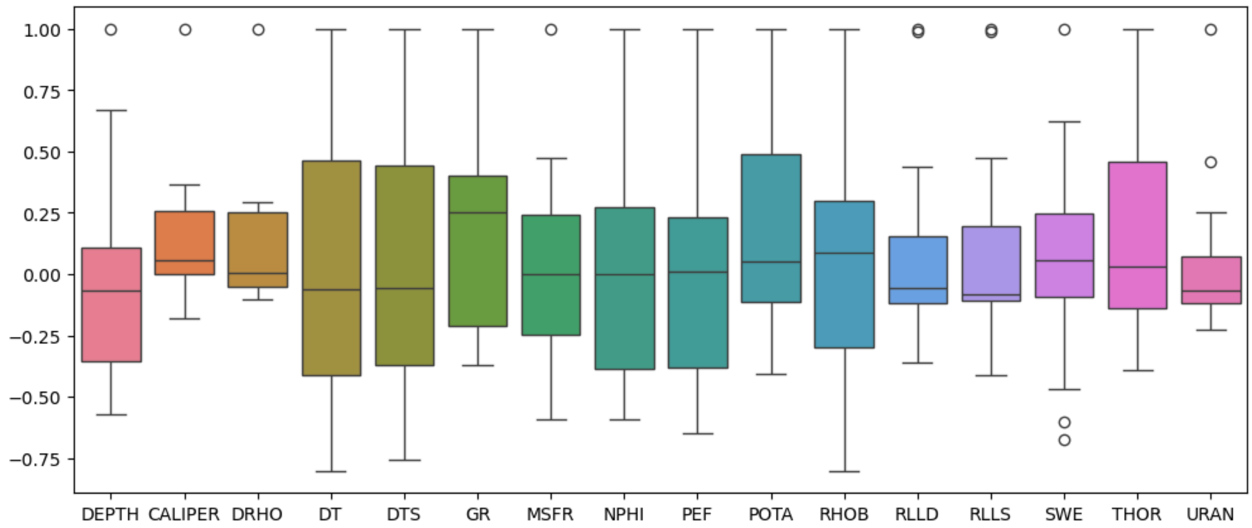
By removing these columns, we create a more focused and simpler model that relies on the most impactful features, which can improve performance and reduce the risk of overfitting.

In [11]:
```python
sns.pairplot(cleaned_df.corr() , diag_kind='kde')
plt.show()
```



Now lets see the boxplot for outliers existant

In [12]:
```python
plt.figure(figsize = (12, 5))
sns.boxplot(cleaned_df.corr())
plt.show()
```



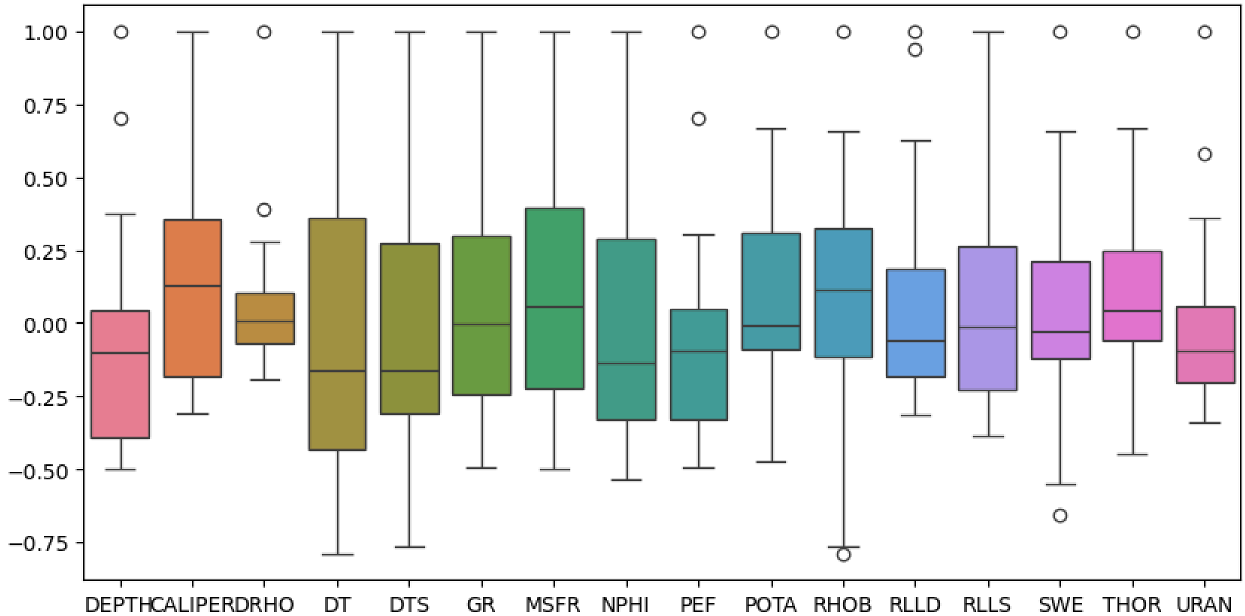
Based on the above boxplot we can see there are many outliers that can affect our prediction and training process, so we have to remove them from our dataset

In [13]:
```
def remove_outliers(df):

    cleaned_df = pd.DataFrame(columns = df.columns)

    for col in df.columns:

        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1

        lower_bound = Q1 - 1.5*IQR
        upper_bound = Q3 + 1.5*IQR

        col_cleaned = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)][col]

        cleaned_df[col] = col_cleaned
    return cleaned_df

cleaned_df = remove_outliers(cleaned_df)
```

In [14]:
```
print(cleaned_df.isnull().sum())
cleaned_df.dropna(inplace=True)
```

```
DEPTH        0
CALIPER    153
DRHO       142
DT          90
DTS         95
GR         100
MSFR        53
NPHI        23
PEF          6
POTA       153
RHOB        15
RLLD       152
RLLS       152
SWE          0
THOR       153
URAN        96
dtype: int64
```

In [15]:
```
plt.figure(figsize = (10 , 5))
sns.boxplot(cleaned_df.corr())
plt.show()
```



Before Normalization we should split our data to train, test, validation and the normalize them, so we do Data splitting before normalization

Task 2-3: Data splitting

Firs lets select our features and remove the features we dont need.

In [16]:
```
selected_data = cleaned_df.drop(columns=["DRHO" , "DTS" , "GR" , "MSFR" , "POTA" , "RLLS" , "THOR" , "URAN"
selected_data.describe()
```

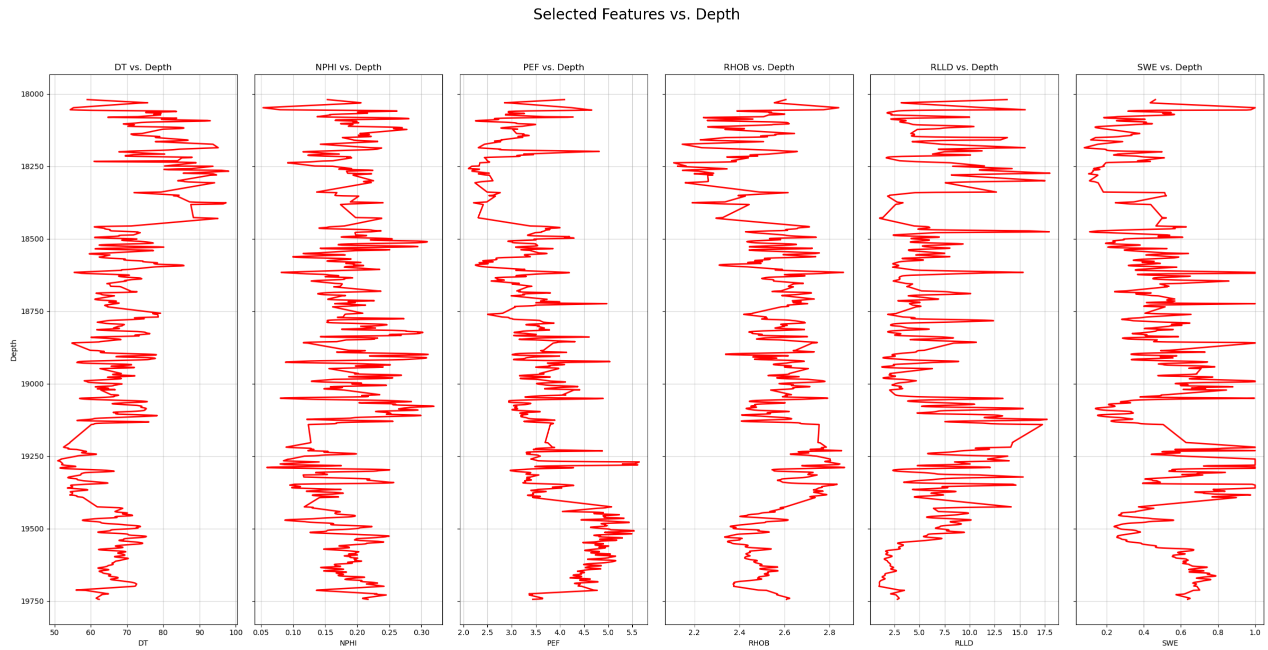
Out[16]:

	DEPTH	DT	NPHI	PEF	RHOB	RLLD	SWE
count	1066.000000	1066.000000	1066.000000	1066.000000	1066.000000	1066.000000	1066.000000
mean	2398.152908	68.234893	0.190980	3.709300	2.542235	5.653699	0.483124
std	60.737737	8.408757	0.048319	0.797805	0.133942	3.532724	0.210770
min	2279.500000	50.878300	0.053319	2.104200	2.108000	0.944000	0.079500
25%	2349.906250	62.889475	0.159483	3.169600	2.449250	2.686750	0.321750
50%	2401.187500	67.492550	0.189737	3.532750	2.539000	4.840000	0.460650
75%	2455.343750	72.778450	0.221353	4.404750	2.632750	7.812250	0.625875
max	2495.000000	98.033800	0.319646	5.644100	2.867000	18.018000	1.000000

This figure provides a side-by-side visualization of the selected features used as input for the model. Each subplot displays a single well log on the horizontal axis plotted against valid Depth on the shared vertical axis. This layout allows for a comprehensive visual inspection and comparison of the data along the wellbore.

In [17]:
```
data_to_plot = selected_data

columns_to_plot = data_to_plot.columns[1:]

num_plots = len(columns_to_plot)

fig, axs = plt.subplots(1, num_plots, figsize=(num_plots * 4, 12), sharey=True)

fig.suptitle('Selected Features vs. Depth', fontsize=20, y=1.02)

for i, col_name in enumerate(columns_to_plot):
    ax = axs[i]
```

```python
    ax.plot(data_to_plot[col_name], data_to_plot.index, linewidth=2, color='red')
    ax.set_xlabel(col_name)
    ax.set_title(f'{col_name} vs. Depth')
    ax.grid(True, alpha=0.5)

axs[0].set_ylabel('Depth')
axs[0].invert_yaxis()

plt.tight_layout(rect=[0, 0, 1, 0.98])

plt.show()
```



The data is first partitioned into training (70%), validation (15%), and test (15%) sets using train_test_split. The test set is held out to provide an unbiased final evaluation of the model. The validation set is used to monitor performance during training.

This is a standard and widely accepted convention in machine learning that provides a strong balance between model training and evaluation.

In addition, considering the amount of data, it is better to use more data for training.

In [18]:
```python
from sklearn.model_selection import train_test_split

TARGET_COLUMN = 'SWE'

X = selected_data.drop(TARGET_COLUMN, axis=1)
y = selected_data[TARGET_COLUMN]

# Splitting the test and a rest data for next step (validation and train)
X_train_val, X_test, y_train_val, y_test = train_test_split(
    X, y, test_size=0.15, random_state=42
)

# Splitting the train and validation
X_train, X_val, y_train, y_val = train_test_split(
    X_train_val, y_train_val, test_size=0.1765, random_state=42 # 0.15 / 0.85 = 0.1765
)

print("Data Shapes After Splitting:")
print(f"\nX_train shape: {X_train.shape}")
print(f"X_val shape:   {X_val.shape}")
print(f"X_test shape:  {X_test.shape}")
```

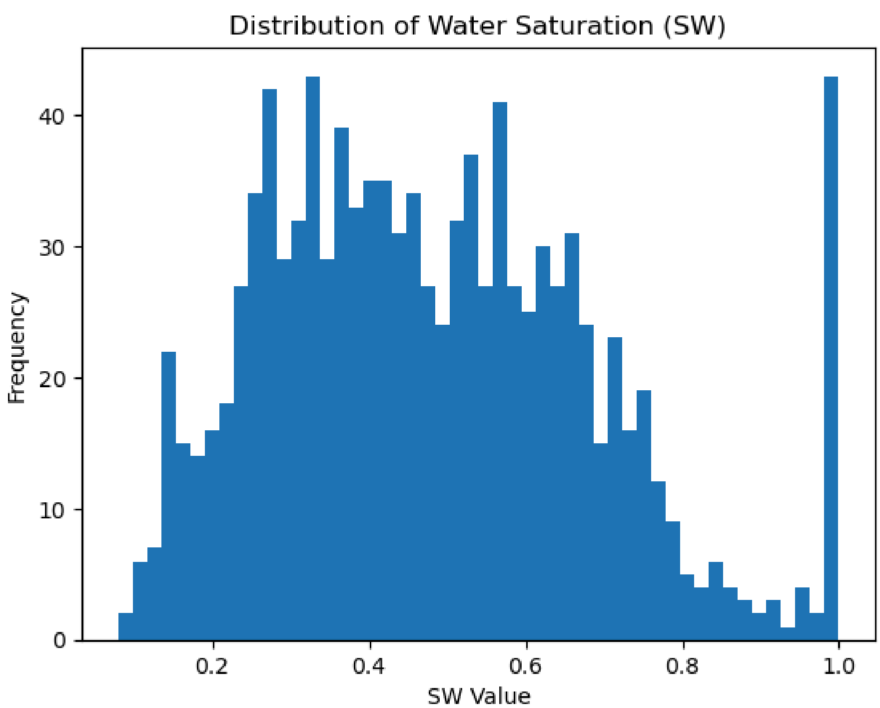
```
Data Shapes After Splitting:

X_train shape: (746, 6)
X_val shape:   (160, 6)
X_test shape:  (160, 6)
```

This histogram illustrates the frequency distribution of the target variable, Water Saturation (SW). The horizontal axis shows the range of SW values, grouped into 50 bins, while the vertical axis represents the frequency, or count, of data points within each bin. This plot is essential for understanding the underlying characteristics of the target data, such as its central tendency, spread, and skewness.

If you look at the histogram, you'll notice that the distribution of SW values is between [0,1], so there is no need to normalize the target data.

In [19]:

```
plt.hist(y, bins=50)
plt.title('Distribution of Water Saturation (SW)')
plt.xlabel('SW Value')
plt.ylabel('Frequency')
plt.show()
```



Task 2-4: Data Normalization

To ensure all features are on a common scale, `MinMaxScaler` is applied. Crucially, the scaler is fitted only on the training data. The learned scaling parameters (min and max values) are then used to transform the training, validation, and test sets. This ensures that no information from the validation or test sets influences the transformation, providing a realistic simulation of how the model would perform on new, unseen data.

In [20]:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

# Scale transorm for each data set
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

# For better readability, convert scaled arrays back to DataFrames
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train.columns, index=X_train.index)
X_val_scaled = pd.DataFrame(X_val_scaled, columns=X_val.columns, index=X_val.index)
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X_test.columns, index=X_test.index)
```

```python
print("\n--- Data After Normalization ---")
print("First 5 rows of scaled training data:")
print(X_train_scaled.head())
print("\nFirst 5 rows of scaled test data:")
print(X_test_scaled.head())
print("\nFirst 5 rows of scaled validation data:")
print(X_val_scaled.head())
```

```
--- Data After Normalization ---
First 5 rows of scaled training data:
          DEPTH        DT      NPHI       PEF      RHOB      RLLD
19447  0.827726  0.404532  0.391825  0.753778  0.518767  0.523955
18991  0.563225  0.160624  0.248999  0.480748  0.894102  0.207450
18098  0.045244  0.523445  0.504075  0.214469  0.635389  0.130432
18142  0.070766  0.441637  0.563410  0.325631  0.608579  0.206103
18160  0.081206  0.762700  0.506245  0.196503  0.195710  0.488755

First 5 rows of scaled test data:
          DEPTH        DT      NPHI       PEF      RHOB      RLLD
18087  0.038863  0.616085  0.783037  0.166050  0.471850  0.069462
19445  0.826566  0.391469  0.394838  0.789966  0.538874  0.507321
18822  0.465197  0.503880  0.920182  0.280516  0.447721  0.053122
19665  0.954176  0.311455  0.479944  0.662279  0.524129  0.022197
19426  0.815545  0.273764  0.240403  0.824967  0.655496  0.602261

First 5 rows of scaled validation data:
          DEPTH        DT      NPHI       PEF      RHOB      RLLD
19371  0.783643  0.100285  0.216026  0.435069  0.888740  0.441080
18927  0.526102  0.111665  0.126741  0.537360  0.694370  0.311878
19241  0.708237  0.187942  0.511688  0.349191  0.747989  0.284643
18466  0.258701  0.275732  0.385692  0.454052  0.722520  0.231112
18505  0.281323  0.374463  0.629274  0.361055  0.583110  0.294893
```

Task 3: Preparing your ANN code

Prepare a Multi-layer Perceptron (MLP) model with keras or pytorch.

Task 3.1: Prepare your initial architecture

Use the following function (*generate_nn_architecture*) to generate an architecture for you. Implement the generated architecture as a module of the library of your choice (keras or pytorch).

```python
import random

def generate_nn_architecture(student_number,initial_input_dim):
    # Set random seed based on student number
    random.seed(student_number)

    # Initialize list to store layers
    nn_architecture = []

    # Generate random number of layers between 3 and 7
    num_layers = random.randint(3, 7)

    # Generate layers
    input_dim = initial_input_dim  # Initial input dimension (number of features which have you selected in the preprocessing step)
    for i in range(num_layers):
        # Generate random number of neurons between 3 and 5
        output_dim = random.randint(5, 15)
        # Generate random activation function
        activation = random.choice(["relu", "tanh", "sigmoid" , "leaky relu"])
        # Append layer to architecture list
        nn_architecture.append({"input_dim": input_dim, "output_dim": output_dim, "activation": activation})
        # Update input dimension for next layer
        input_dim = output_dim
```

```
    # Add final layer with sigmoid activation for binary classification
    nn_architecture.append({"input_dim": input_dim, "output_dim": 1, "activation": "sigmoid"})

    return nn_architecture
```

> *initial_input_dim* value is the number of features that you have selected in the **feature selection** step.

Usage example:

```
student_number = 123456
initial_input_dim = 3 # Number of selected features
nn_architecture = generate_nn_architecture(student_number, initial_input_dim)
print(nn_architecture)
```

In [21]:

```
import random
import tensorflow as tf
from tensorflow import keras

def generate_nn_architecture(student_number,initial_input_dim):
    # Set random seed based on student number
    random.seed(student_number)

    # Initialize list to store layers
    nn_architecture = []

    # Generate random number of layers between 3 and 7
    num_layers = random.randint(3, 7)

    # Generate layers
    input_dim = initial_input_dim  # Initial input dimension (number of features which have you selected in
    for i in range(num_layers):
        # Generate random number of neurons between 3 and 5
        output_dim = random.randint(5, 15)
        # Generate random activation function
        activation = random.choice(["relu", "tanh", "sigmoid" , "leaky relu"])
        # Append layer to architecture list
        nn_architecture.append({"input_dim": input_dim, "output_dim": output_dim, "activation": activation})
        # Update input dimension for next layer
        input_dim = output_dim

    # Add final layer with sigmoid activation for binary classification
    nn_architecture.append({"input_dim": input_dim, "output_dim": 1, "activation": "sigmoid"})

    return nn_architecture

student_number = 403134029
initial_input_dim = X_train_scaled.shape[1]
nn_architecture = generate_nn_architecture(student_number, initial_input_dim)
print("NN architecture for each layer:\n")
for i, layer in enumerate(nn_architecture):
    print(f"Layer {i+1}: {layer}")
```

```
NN architecture for each layer:

Layer 1: {'input_dim': 6, 'output_dim': 9, 'activation': 'sigmoid'}
Layer 2: {'input_dim': 9, 'output_dim': 12, 'activation': 'relu'}
Layer 3: {'input_dim': 12, 'output_dim': 10, 'activation': 'relu'}
Layer 4: {'input_dim': 10, 'output_dim': 1, 'activation': 'sigmoid'}
```

Task 4: Training and analyzing your ANN

Task 4.1: Training your ANN

Consider values for number of epochs and learning rate and train your network.

1. Plot overlay scatter of train cost and validation cost versus epochs,
2. scatter of SWE_pred versus SWE,

3. overlay scatter of SWE_pred versus depth and SWE versus depth.

In [22]:
```
from keras.models import Sequential # type: ignore
from keras.layers import Dense, Dropout, Activation, Flatten, BatchNormalization # type: ignore
from tensorflow.keras.optimizers import Adam # type: ignore

n_features_in = X_train_scaled.shape[1]
n_features_out = 1


def build_model_from_architecture(architecture, learning_rate=0.001):
    model = Sequential()

    for i, layer_params in enumerate(architecture):
        if i == 0:
            model.add(Dense(
                units=layer_params['output_dim'],
                activation=layer_params['activation'],
                input_dim=layer_params['input_dim']
            ))
        else:
            model.add(Dense(
                units=layer_params['output_dim'],
                activation=layer_params['activation']
            ))

    optimizer = Adam(learning_rate=learning_rate)
    model.compile(
        loss='mean_squared_error',
        optimizer=optimizer,
        metrics=['mean_absolute_error']
    )
    return model

model = build_model_from_architecture(nn_architecture, learning_rate=0.001)
```

Model Structure: The architecture consists of:

- Three hidden Dense layers with `128`, `64`, and `32` neurons, using the `ReLU` activation function. ReLU was chosen for its computational efficiency and effectiveness in handling non-linear relationships.
- One Dense output layer with a single neuron and a `sigmoid` activation function.

While a linear activation is the standard convention for regression tasks, an alternative approach using `sigmoid` was tested. This decision was motivated by the physical nature of the target variable, Water Saturation (SW), which is naturally bounded between `0 and 1`. The `sigmoid` function inherently constrains the model's output to this valid range.

In [23]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 9)	63
dense_1 (Dense)	(None, 12)	120
dense_2 (Dense)	(None, 10)	130
dense_3 (Dense)	(None, 1)	11

Total params: 324 (1.27 KB)

Trainable params: 324 (1.27 KB)

Non-trainable params: 0 (0.00 B)

The `model.summary()` method provided a concise blueprint of the model's architecture. It detailed the sequence of layers, the output shape after each transformation, and the number of trainable parameters, confirming the model's complexity and structure.

In [24]:
```
history = model.fit(
    X_train_scaled,
    y_train,
    epochs=200,
    batch_size=16,
    validation_data=(X_val_scaled, y_val),
    verbose=1
)
```

```
Epoch 1/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - loss: 0.0392 - mean_absolute_error: 0.1644 - val_loss: 0.0409 - val_
mean_absolute_error: 0.1672
Epoch 2/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0405 - mean_absolute_error: 0.1663 - val_loss: 0.0388 - val_
mean_absolute_error: 0.1634
Epoch 3/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0381 - mean_absolute_error: 0.1611 - val_loss: 0.0365 - val_
mean_absolute_error: 0.1593
Epoch 4/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0346 - mean_absolute_error: 0.1546 - val_loss: 0.0344 - val_
mean_absolute_error: 0.1543
Epoch 5/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0332 - mean_absolute_error: 0.1530 - val_loss: 0.0313 - val_
mean_absolute_error: 0.1494
Epoch 6/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0303 - mean_absolute_error: 0.1463 - val_loss: 0.0283 - val_
mean_absolute_error: 0.1422
Epoch 7/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0276 - mean_absolute_error: 0.1382 - val_loss: 0.0256 - val_
mean_absolute_error: 0.1365
Epoch 8/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0231 - mean_absolute_error: 0.1266 - val_loss: 0.0225 - val_
mean_absolute_error: 0.1284
Epoch 9/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0220 - mean_absolute_error: 0.1228 - val_loss: 0.0205 - val_
mean_absolute_error: 0.1217
Epoch 10/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0181 - mean_absolute_error: 0.1107 - val_loss: 0.0182 - val_
mean_absolute_error: 0.1151
Epoch 11/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0169 - mean_absolute_error: 0.1079 - val_loss: 0.0172 - val_
mean_absolute_error: 0.1105
Epoch 12/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0172 - mean_absolute_error: 0.1087 - val_loss: 0.0155 - val_
mean_absolute_error: 0.1046
Epoch 13/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0151 - mean_absolute_error: 0.0990 - val_loss: 0.0141 - val_
mean_absolute_error: 0.0987
Epoch 14/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0155 - mean_absolute_error: 0.0994 - val_loss: 0.0135 - val_
mean_absolute_error: 0.0974
Epoch 15/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0141 - mean_absolute_error: 0.0961 - val_loss: 0.0138 - val_
mean_absolute_error: 0.1000
Epoch 16/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0114 - mean_absolute_error: 0.0847 - val_loss: 0.0113 - val_
mean_absolute_error: 0.0867
Epoch 17/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0132 - mean_absolute_error: 0.0874 - val_loss: 0.0105 - val_
mean_absolute_error: 0.0832
Epoch 18/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0108 - mean_absolute_error: 0.0818 - val_loss: 0.0099 - val_
mean_absolute_error: 0.0803
Epoch 19/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0105 - mean_absolute_error: 0.0787 - val_loss: 0.0096 - val_
mean_absolute_error: 0.0751
Epoch 20/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0117 - mean_absolute_error: 0.0818 - val_loss: 0.0092 - val_
mean_absolute_error: 0.0725
Epoch 21/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0100 - mean_absolute_error: 0.0750 - val_loss: 0.0088 - val_
mean_absolute_error: 0.0709
Epoch 22/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0089 - mean_absolute_error: 0.0696 - val_loss: 0.0085 - val_
mean_absolute_error: 0.0697
Epoch 23/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0097 - mean_absolute_error: 0.0714 - val_loss: 0.0087 - val_
mean_absolute_error: 0.0673
Epoch 24/200
```

```
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0102 - mean_absolute_error: 0.0735 - val_loss: 0.0084 - val_
mean_absolute_error: 0.0666
Epoch 25/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0113 - mean_absolute_error: 0.0746 - val_loss: 0.0080 - val_
mean_absolute_error: 0.0693
Epoch 26/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0098 - mean_absolute_error: 0.0700 - val_loss: 0.0079 - val_
mean_absolute_error: 0.0668
Epoch 27/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0099 - mean_absolute_error: 0.0696 - val_loss: 0.0079 - val_
mean_absolute_error: 0.0653
Epoch 28/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0079 - mean_absolute_error: 0.0656 - val_loss: 0.0077 - val_
mean_absolute_error: 0.0675
Epoch 29/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0086 - mean_absolute_error: 0.0662 - val_loss: 0.0076 - val_
mean_absolute_error: 0.0660
Epoch 30/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0098 - mean_absolute_error: 0.0714 - val_loss: 0.0075 - val_
mean_absolute_error: 0.0642
Epoch 31/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0101 - mean_absolute_error: 0.0709 - val_loss: 0.0075 - val_
mean_absolute_error: 0.0623
Epoch 32/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0101 - mean_absolute_error: 0.0700 - val_loss: 0.0073 - val_
mean_absolute_error: 0.0615
Epoch 33/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0082 - mean_absolute_error: 0.0654 - val_loss: 0.0070 - val_
mean_absolute_error: 0.0641
Epoch 34/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0078 - mean_absolute_error: 0.0656 - val_loss: 0.0070 - val_
mean_absolute_error: 0.0613
Epoch 35/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0081 - mean_absolute_error: 0.0633 - val_loss: 0.0073 - val_
mean_absolute_error: 0.0675
Epoch 36/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0081 - mean_absolute_error: 0.0642 - val_loss: 0.0074 - val_
mean_absolute_error: 0.0679
Epoch 37/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0092 - mean_absolute_error: 0.0702 - val_loss: 0.0068 - val_
mean_absolute_error: 0.0638
Epoch 38/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0079 - mean_absolute_error: 0.0626 - val_loss: 0.0067 - val_
mean_absolute_error: 0.0633
Epoch 39/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0077 - mean_absolute_error: 0.0645 - val_loss: 0.0075 - val_
mean_absolute_error: 0.0611
Epoch 40/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0076 - mean_absolute_error: 0.0581 - val_loss: 0.0071 - val_
mean_absolute_error: 0.0665
Epoch 41/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0079 - mean_absolute_error: 0.0646 - val_loss: 0.0069 - val_
mean_absolute_error: 0.0646
Epoch 42/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0081 - mean_absolute_error: 0.0656 - val_loss: 0.0067 - val_
mean_absolute_error: 0.0599
Epoch 43/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0090 - mean_absolute_error: 0.0679 - val_loss: 0.0071 - val_
mean_absolute_error: 0.0601
Epoch 44/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0069 - mean_absolute_error: 0.0569 - val_loss: 0.0065 - val_
mean_absolute_error: 0.0620
Epoch 45/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0075 - mean_absolute_error: 0.0601 - val_loss: 0.0066 - val_
mean_absolute_error: 0.0628
Epoch 46/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0083 - mean_absolute_error: 0.0644 - val_loss: 0.0064 - val_
mean_absolute_error: 0.0601
Epoch 47/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0082 - mean_absolute_error: 0.0660 - val_loss: 0.0064 - val_
```

```
mean_absolute_error: 0.0612
Epoch 48/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0086 - mean_absolute_error: 0.0642 - val_loss: 0.0063 - val_
mean_absolute_error: 0.0599
Epoch 49/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0068 - mean_absolute_error: 0.0585 - val_loss: 0.0063 - val_
mean_absolute_error: 0.0597
Epoch 50/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0084 - mean_absolute_error: 0.0623 - val_loss: 0.0068 - val_
mean_absolute_error: 0.0581
Epoch 51/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0086 - mean_absolute_error: 0.0642 - val_loss: 0.0063 - val_
mean_absolute_error: 0.0584
Epoch 52/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0071 - mean_absolute_error: 0.0599 - val_loss: 0.0063 - val_
mean_absolute_error: 0.0618
Epoch 53/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0084 - mean_absolute_error: 0.0657 - val_loss: 0.0062 - val_
mean_absolute_error: 0.0605
Epoch 54/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0080 - mean_absolute_error: 0.0629 - val_loss: 0.0061 - val_
mean_absolute_error: 0.0600
Epoch 55/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0078 - mean_absolute_error: 0.0632 - val_loss: 0.0061 - val_
mean_absolute_error: 0.0584
Epoch 56/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0078 - mean_absolute_error: 0.0624 - val_loss: 0.0060 - val_
mean_absolute_error: 0.0581
Epoch 57/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0068 - mean_absolute_error: 0.0575 - val_loss: 0.0060 - val_
mean_absolute_error: 0.0595
Epoch 58/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0067 - mean_absolute_error: 0.0587 - val_loss: 0.0059 - val_
mean_absolute_error: 0.0592
Epoch 59/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0076 - mean_absolute_error: 0.0637 - val_loss: 0.0059 - val_
mean_absolute_error: 0.0597
Epoch 60/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0073 - mean_absolute_error: 0.0633 - val_loss: 0.0059 - val_
mean_absolute_error: 0.0591
Epoch 61/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0073 - mean_absolute_error: 0.0614 - val_loss: 0.0058 - val_
mean_absolute_error: 0.0592
Epoch 62/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0067 - mean_absolute_error: 0.0599 - val_loss: 0.0060 - val_
mean_absolute_error: 0.0616
Epoch 63/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0061 - mean_absolute_error: 0.0576 - val_loss: 0.0056 - val_
mean_absolute_error: 0.0565
Epoch 64/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0068 - mean_absolute_error: 0.0599 - val_loss: 0.0058 - val_
mean_absolute_error: 0.0557
Epoch 65/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0073 - mean_absolute_error: 0.0589 - val_loss: 0.0056 - val_
mean_absolute_error: 0.0586
Epoch 66/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0069 - mean_absolute_error: 0.0584 - val_loss: 0.0055 - val_
mean_absolute_error: 0.0583
Epoch 67/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0068 - mean_absolute_error: 0.0597 - val_loss: 0.0054 - val_
mean_absolute_error: 0.0567
Epoch 68/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0074 - mean_absolute_error: 0.0597 - val_loss: 0.0053 - val_
mean_absolute_error: 0.0568
Epoch 69/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0067 - mean_absolute_error: 0.0586 - val_loss: 0.0060 - val_
mean_absolute_error: 0.0615
Epoch 70/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0063 - mean_absolute_error: 0.0589 - val_loss: 0.0053 - val_
mean_absolute_error: 0.0531
```

```
Epoch 71/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0064 - mean_absolute_error: 0.0552 - val_loss: 0.0054 - val_
mean_absolute_error: 0.0585
Epoch 72/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0064 - mean_absolute_error: 0.0570 - val_loss: 0.0054 - val_
mean_absolute_error: 0.0582
Epoch 73/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0058 - mean_absolute_error: 0.0549 - val_loss: 0.0049 - val_
mean_absolute_error: 0.0535
Epoch 74/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0067 - mean_absolute_error: 0.0584 - val_loss: 0.0050 - val_
mean_absolute_error: 0.0560
Epoch 75/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0056 - mean_absolute_error: 0.0552 - val_loss: 0.0048 - val_
mean_absolute_error: 0.0518
Epoch 76/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0057 - mean_absolute_error: 0.0528 - val_loss: 0.0047 - val_
mean_absolute_error: 0.0534
Epoch 77/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0053 - mean_absolute_error: 0.0520 - val_loss: 0.0051 - val_
mean_absolute_error: 0.0558
Epoch 78/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0057 - mean_absolute_error: 0.0545 - val_loss: 0.0047 - val_
mean_absolute_error: 0.0534
Epoch 79/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0060 - mean_absolute_error: 0.0555 - val_loss: 0.0045 - val_
mean_absolute_error: 0.0502
Epoch 80/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0050 - mean_absolute_error: 0.0474 - val_loss: 0.0046 - val_
mean_absolute_error: 0.0531
Epoch 81/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0052 - mean_absolute_error: 0.0528 - val_loss: 0.0051 - val_
mean_absolute_error: 0.0578
Epoch 82/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0051 - mean_absolute_error: 0.0517 - val_loss: 0.0046 - val_
mean_absolute_error: 0.0530
Epoch 83/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0055 - mean_absolute_error: 0.0520 - val_loss: 0.0044 - val_
mean_absolute_error: 0.0475
Epoch 84/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0051 - mean_absolute_error: 0.0490 - val_loss: 0.0040 - val_
mean_absolute_error: 0.0471
Epoch 85/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0046 - mean_absolute_error: 0.0482 - val_loss: 0.0040 - val_
mean_absolute_error: 0.0486
Epoch 86/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0051 - mean_absolute_error: 0.0506 - val_loss: 0.0038 - val_
mean_absolute_error: 0.0471
Epoch 87/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0048 - mean_absolute_error: 0.0468 - val_loss: 0.0037 - val_
mean_absolute_error: 0.0451
Epoch 88/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0048 - mean_absolute_error: 0.0499 - val_loss: 0.0037 - val_
mean_absolute_error: 0.0454
Epoch 89/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0042 - mean_absolute_error: 0.0463 - val_loss: 0.0037 - val_
mean_absolute_error: 0.0457
Epoch 90/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0041 - mean_absolute_error: 0.0468 - val_loss: 0.0038 - val_
mean_absolute_error: 0.0476
Epoch 91/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0041 - mean_absolute_error: 0.0454 - val_loss: 0.0034 - val_
mean_absolute_error: 0.0432
Epoch 92/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0047 - mean_absolute_error: 0.0464 - val_loss: 0.0035 - val_
mean_absolute_error: 0.0432
Epoch 93/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0045 - mean_absolute_error: 0.0451 - val_loss: 0.0033 - val_
mean_absolute_error: 0.0438
Epoch 94/200
```

```
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0038 - mean_absolute_error: 0.0435 - val_loss: 0.0032 - val_
mean_absolute_error: 0.0419
Epoch 95/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0040 - mean_absolute_error: 0.0437 - val_loss: 0.0032 - val_
mean_absolute_error: 0.0417
Epoch 96/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0036 - mean_absolute_error: 0.0417 - val_loss: 0.0031 - val_
mean_absolute_error: 0.0417
Epoch 97/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0038 - mean_absolute_error: 0.0434 - val_loss: 0.0035 - val_
mean_absolute_error: 0.0432
Epoch 98/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0043 - mean_absolute_error: 0.0456 - val_loss: 0.0031 - val_
mean_absolute_error: 0.0404
Epoch 99/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0033 - mean_absolute_error: 0.0407 - val_loss: 0.0031 - val_
mean_absolute_error: 0.0402
Epoch 100/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0034 - mean_absolute_error: 0.0403 - val_loss: 0.0035 - val_
mean_absolute_error: 0.0467
Epoch 101/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0032 - mean_absolute_error: 0.0426 - val_loss: 0.0031 - val_
mean_absolute_error: 0.0411
Epoch 102/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0033 - mean_absolute_error: 0.0406 - val_loss: 0.0031 - val_
mean_absolute_error: 0.0417
Epoch 103/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0030 - mean_absolute_error: 0.0390 - val_loss: 0.0028 - val_
mean_absolute_error: 0.0394
Epoch 104/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0033 - mean_absolute_error: 0.0403 - val_loss: 0.0028 - val_
mean_absolute_error: 0.0395
Epoch 105/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0032 - mean_absolute_error: 0.0406 - val_loss: 0.0031 - val_
mean_absolute_error: 0.0428
Epoch 106/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0029 - mean_absolute_error: 0.0391 - val_loss: 0.0029 - val_
mean_absolute_error: 0.0402
Epoch 107/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0029 - mean_absolute_error: 0.0371 - val_loss: 0.0027 - val_
mean_absolute_error: 0.0379
Epoch 108/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0033 - mean_absolute_error: 0.0399 - val_loss: 0.0027 - val_
mean_absolute_error: 0.0377
Epoch 109/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0034 - mean_absolute_error: 0.0393 - val_loss: 0.0026 - val_
mean_absolute_error: 0.0374
Epoch 110/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0028 - mean_absolute_error: 0.0361 - val_loss: 0.0027 - val_
mean_absolute_error: 0.0377
Epoch 111/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0026 - mean_absolute_error: 0.0354 - val_loss: 0.0026 - val_
mean_absolute_error: 0.0368
Epoch 112/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0025 - mean_absolute_error: 0.0349 - val_loss: 0.0025 - val_
mean_absolute_error: 0.0359
Epoch 113/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0027 - mean_absolute_error: 0.0364 - val_loss: 0.0025 - val_
mean_absolute_error: 0.0361
Epoch 114/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0034 - mean_absolute_error: 0.0396 - val_loss: 0.0025 - val_
mean_absolute_error: 0.0365
Epoch 115/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0027 - mean_absolute_error: 0.0375 - val_loss: 0.0026 - val_
mean_absolute_error: 0.0370
Epoch 116/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0028 - mean_absolute_error: 0.0375 - val_loss: 0.0025 - val_
mean_absolute_error: 0.0364
Epoch 117/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0028 - mean_absolute_error: 0.0385 - val_loss: 0.0025 - val_
```

```
mean_absolute_error: 0.0354
Epoch 118/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0030 - mean_absolute_error: 0.0373 - val_loss: 0.0027 - val_
mean_absolute_error: 0.0383
Epoch 119/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0025 - mean_absolute_error: 0.0351 - val_loss: 0.0024 - val_
mean_absolute_error: 0.0373
Epoch 120/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0029 - mean_absolute_error: 0.0373 - val_loss: 0.0027 - val_
mean_absolute_error: 0.0366
Epoch 121/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0022 - mean_absolute_error: 0.0329 - val_loss: 0.0024 - val_
mean_absolute_error: 0.0347
Epoch 122/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0032 - mean_absolute_error: 0.0363 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0345
Epoch 123/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0025 - mean_absolute_error: 0.0362 - val_loss: 0.0024 - val_
mean_absolute_error: 0.0363
Epoch 124/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0026 - mean_absolute_error: 0.0356 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0342
Epoch 125/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0024 - mean_absolute_error: 0.0341 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0357
Epoch 126/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0031 - mean_absolute_error: 0.0377 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0335
Epoch 127/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0023 - mean_absolute_error: 0.0339 - val_loss: 0.0024 - val_
mean_absolute_error: 0.0380
Epoch 128/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0025 - mean_absolute_error: 0.0360 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0341
Epoch 129/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0022 - mean_absolute_error: 0.0341 - val_loss: 0.0025 - val_
mean_absolute_error: 0.0356
Epoch 130/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0026 - mean_absolute_error: 0.0364 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0335
Epoch 131/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0022 - mean_absolute_error: 0.0341 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0326
Epoch 132/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0021 - mean_absolute_error: 0.0342 - val_loss: 0.0024 - val_
mean_absolute_error: 0.0387
Epoch 133/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0022 - mean_absolute_error: 0.0334 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0335
Epoch 134/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0026 - mean_absolute_error: 0.0346 - val_loss: 0.0024 - val_
mean_absolute_error: 0.0342
Epoch 135/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0024 - mean_absolute_error: 0.0340 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0326
Epoch 136/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0025 - mean_absolute_error: 0.0339 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0324
Epoch 137/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0022 - mean_absolute_error: 0.0337 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0317
Epoch 138/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - mean_absolute_error: 0.0315 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0326
Epoch 139/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0025 - mean_absolute_error: 0.0362 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0328
Epoch 140/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0024 - mean_absolute_error: 0.0331 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0326
```

```
Epoch 141/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0031 - mean_absolute_error: 0.0361 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0313
Epoch 142/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0019 - mean_absolute_error: 0.0313 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0338
Epoch 143/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0025 - mean_absolute_error: 0.0338 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0320
Epoch 144/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0022 - mean_absolute_error: 0.0335 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0316
Epoch 145/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0027 - mean_absolute_error: 0.0353 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0321
Epoch 146/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0027 - mean_absolute_error: 0.0355 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0314
Epoch 147/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - mean_absolute_error: 0.0298 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0319
Epoch 148/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0024 - mean_absolute_error: 0.0333 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0315
Epoch 149/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0022 - mean_absolute_error: 0.0326 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0313
Epoch 150/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0022 - mean_absolute_error: 0.0329 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0314
Epoch 151/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0023 - mean_absolute_error: 0.0341 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0314
Epoch 152/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0018 - mean_absolute_error: 0.0301 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0355
Epoch 153/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0022 - mean_absolute_error: 0.0326 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0367
Epoch 154/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0024 - mean_absolute_error: 0.0345 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0312
Epoch 155/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - mean_absolute_error: 0.0306 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0318
Epoch 156/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0019 - mean_absolute_error: 0.0321 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0322
Epoch 157/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0024 - mean_absolute_error: 0.0348 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0321
Epoch 158/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0020 - mean_absolute_error: 0.0314 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0329
Epoch 159/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0021 - mean_absolute_error: 0.0321 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0318
Epoch 160/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0027 - mean_absolute_error: 0.0354 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0325
Epoch 161/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0023 - mean_absolute_error: 0.0351 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0323
Epoch 162/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0018 - mean_absolute_error: 0.0299 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0314
Epoch 163/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0022 - mean_absolute_error: 0.0330 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0316
Epoch 164/200
```

```
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0021 - mean_absolute_error: 0.0319 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0312
Epoch 165/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0021 - mean_absolute_error: 0.0316 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0331
Epoch 166/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0021 - mean_absolute_error: 0.0325 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0316
Epoch 167/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0019 - mean_absolute_error: 0.0309 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0337
Epoch 168/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0020 - mean_absolute_error: 0.0327 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0315
Epoch 169/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0019 - mean_absolute_error: 0.0302 - val_loss: 0.0023 - val_
mean_absolute_error: 0.0326
Epoch 170/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0022 - mean_absolute_error: 0.0320 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0311
Epoch 171/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0021 - mean_absolute_error: 0.0296 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0308
Epoch 172/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0020 - mean_absolute_error: 0.0314 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0322
Epoch 173/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0021 - mean_absolute_error: 0.0318 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0317
Epoch 174/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - mean_absolute_error: 0.0306 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0317
Epoch 175/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0021 - mean_absolute_error: 0.0317 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0310
Epoch 176/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0021 - mean_absolute_error: 0.0324 - val_loss: 0.0021 - val_
mean_absolute_error: 0.0344
Epoch 177/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0022 - mean_absolute_error: 0.0315 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0312
Epoch 178/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0025 - mean_absolute_error: 0.0340 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0309
Epoch 179/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0018 - mean_absolute_error: 0.0300 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0327
Epoch 180/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0017 - mean_absolute_error: 0.0295 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0312
Epoch 181/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0018 - mean_absolute_error: 0.0321 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0331
Epoch 182/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0017 - mean_absolute_error: 0.0295 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0320
Epoch 183/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0018 - mean_absolute_error: 0.0307 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0313
Epoch 184/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0016 - mean_absolute_error: 0.0288 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0310
Epoch 185/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0018 - mean_absolute_error: 0.0309 - val_loss: 0.0025 - val_
mean_absolute_error: 0.0348
Epoch 186/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0017 - mean_absolute_error: 0.0304 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0307
Epoch 187/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - mean_absolute_error: 0.0313 - val_loss: 0.0020 - val_
```

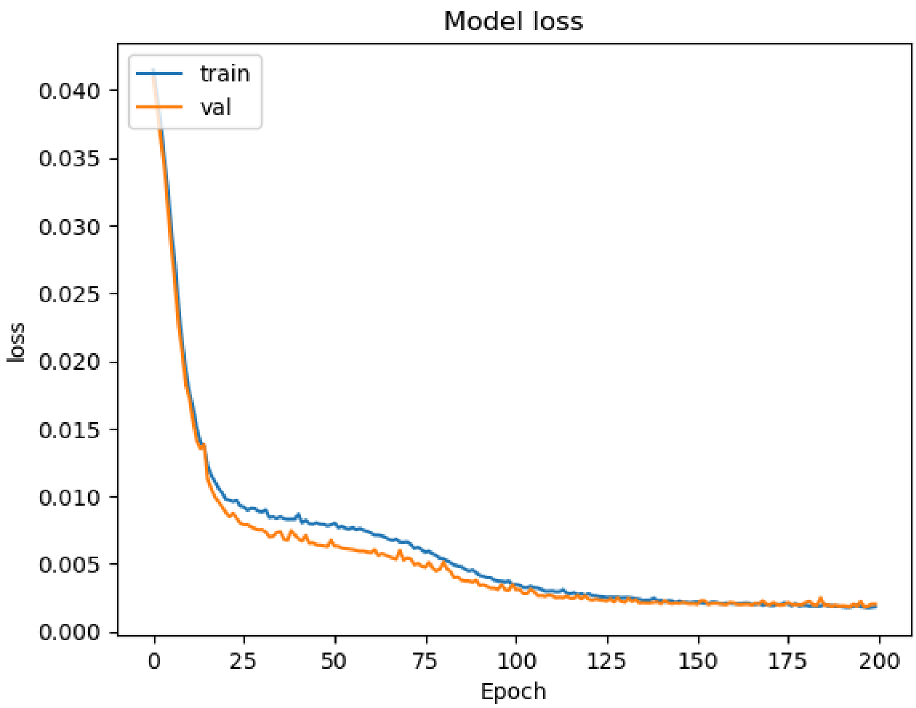
```
mean_absolute_error: 0.0315
Epoch 188/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0018 - mean_absolute_error: 0.0300 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0302
Epoch 189/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0019 - mean_absolute_error: 0.0297 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0305
Epoch 190/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - mean_absolute_error: 0.0305 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0304
Epoch 191/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0016 - mean_absolute_error: 0.0287 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0303
Epoch 192/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0014 - mean_absolute_error: 0.0270 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0302
Epoch 193/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0018 - mean_absolute_error: 0.0279 - val_loss: 0.0018 - val_
mean_absolute_error: 0.0305
Epoch 194/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0018 - mean_absolute_error: 0.0306 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0314
Epoch 195/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0018 - mean_absolute_error: 0.0299 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0299
Epoch 196/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0021 - mean_absolute_error: 0.0323 - val_loss: 0.0022 - val_
mean_absolute_error: 0.0329
Epoch 197/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0015 - mean_absolute_error: 0.0270 - val_loss: 0.0018 - val_
mean_absolute_error: 0.0307
Epoch 198/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0019 - mean_absolute_error: 0.0306 - val_loss: 0.0019 - val_
mean_absolute_error: 0.0302
Epoch 199/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0017 - mean_absolute_error: 0.0291 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0309
Epoch 200/200
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0016 - mean_absolute_error: 0.0284 - val_loss: 0.0020 - val_
mean_absolute_error: 0.0319
```

The model was trained using the `.fit()` method.

- Training Process: The model was trained for 150 epochs with a batch_size of 64.
- Validation: validation_data was used at the end of each epoch to monitor performance on unseen data, which is crucial for diagnosing overfitting.
- History Object: All training logs were stored in the history object for later analysis of the learning curves.

In [25]:

```python
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.title('Model loss')
plt.ylabel ('loss')
plt.xlabel('Epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



The plot of the training and validation loss over epochs revealed an excellent learning behavior.

- Convergence: Both training and validation loss curves decreased sharply and converged to a stable, low value.
- Excellent Fit: The two curves remained very close together throughout the training process, indicating that there were no signs of significant overfitting. The model demonstrated a strong ability to generalize its learning to new data.

In [26]:
```
import numpy as np

SW_pred = model.predict(X_test_scaled)
SW_pred_flat = SW_pred.flatten()
model.evaluate(X_test_scaled,y_test)

train_error = np.abs(y_test - SW_pred_flat)
mean_error = np.mean(train_error)
min_error = np.min(train_error)
max_error = np.max(train_error)
std_error = np.std(train_error)


print("mean_error",mean_error)
print("min_error",min_error)
print("max_error",max_error)
print("std_error",std_error)
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0026 - mean_absolute_error: 0.0334
mean_error 0.03197086990259588
min_error 3.800058364866743e-06
max_error 0.21596312446594235
std_error 0.03479962238769936
```

In [27]:
```
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

r2 = r2_score(y_test, SW_pred)
print(f"R-squared (R²) Score: {r2:.4f}")

test_loss = model.evaluate(X_test_scaled, y_test, verbose=0)[0]
print(f"Mean Squared Error (MSE) on Test Data: {test_loss:.4f}")

rmse = np.sqrt(test_loss)
print(f"Root Mean Squared Error (RMSE) on Test Data: {rmse:.4f}")
```

```
mae = mean_absolute_error(y_test, SW_pred)
print(f"Mean Absolute Error (MAE) on Test Data: {mae:.4f}")
```

```
R-squared (R²) Score: 0.9603
Mean Squared Error (MSE) on Test Data: 0.0022
Root Mean Squared Error (RMSE) on Test Data: 0.0473
Mean Absolute Error (MAE) on Test Data: 0.0320
```

After training some models with different epochs and batch_sizes we find this setup hyperparameters more efficient. (`epochs=200` , `batch_size=16`)

The final model was evaluated on the held-out test set. The performance metrics confirmed the model's high accuracy and predictive power.

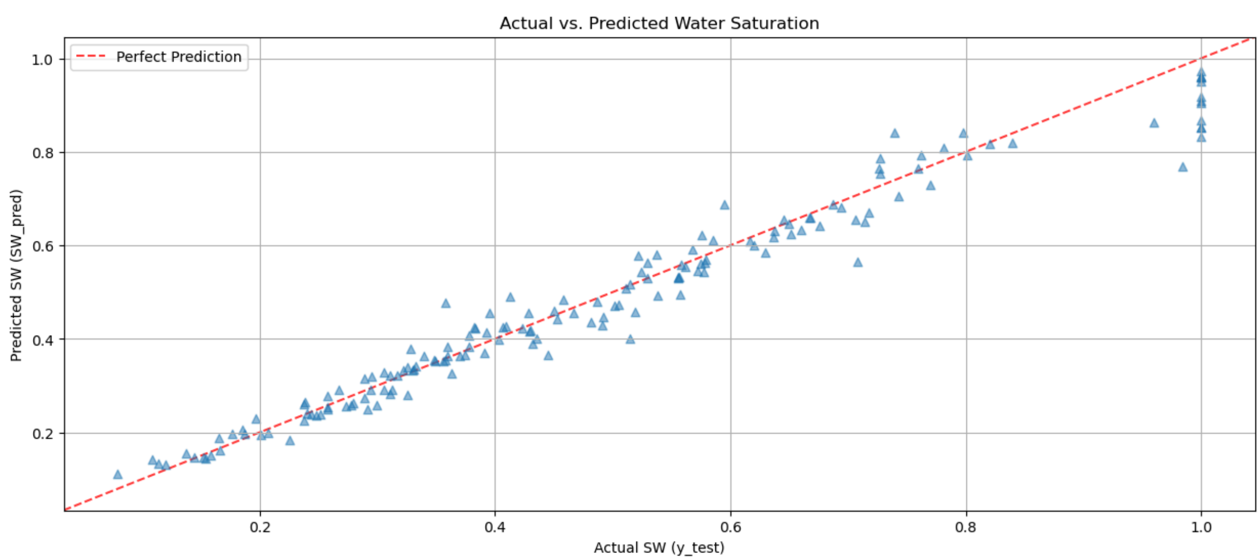
R-squared (R^2) Score: 0.9603

This outstanding score, achieved with the empirically chosen sigmoid output layer, indicates that the model can explain approximately 96.03% of the variance in the water saturation data. This signifies a near-perfect fit to the data.

MAE: 0.0022 and RMSE: 0.0473

The error metrics are exceptionally low. A Mean Absolute Error (MAE) of ~0.0022 means that, on average, the model's predictions are only off by a very small margin from the actual SW values, confirming its high precision.

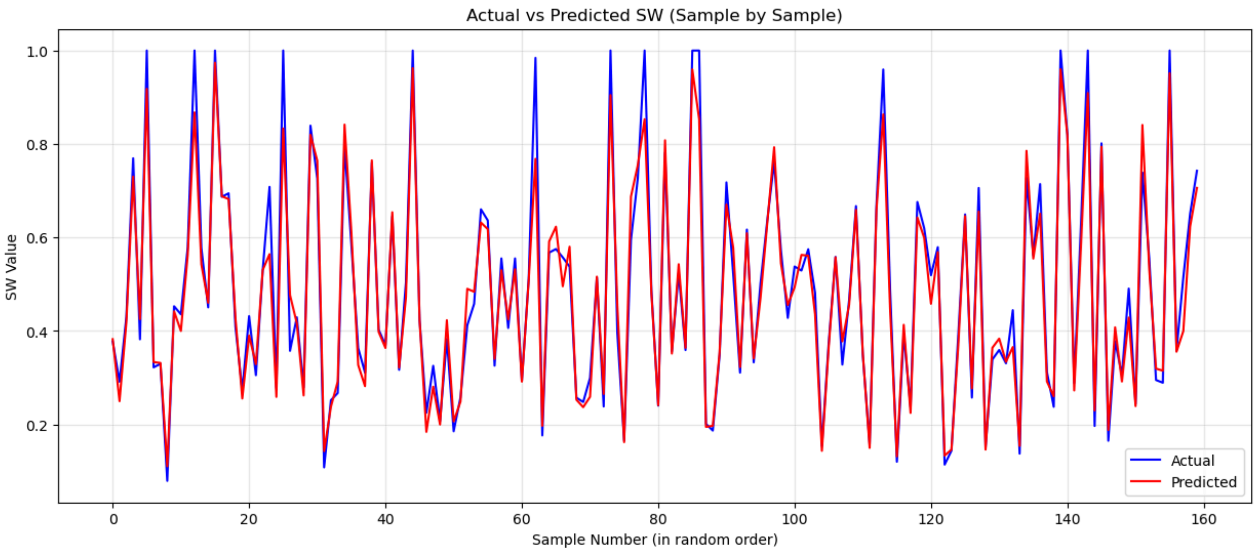
In [28]:
```
plt.figure(figsize=(15, 6))
plt.scatter(y_test, SW_pred, alpha=0.5, marker='^')
plt.xlabel('Actual SW (y_test)')
plt.ylabel('Predicted SW (SW_pred)')
plt.title('Actual vs. Predicted Water Saturation')

lims = [min(plt.xlim()), max(plt.xlim())]
plt.plot(lims, lims, 'r--', alpha=0.75, zorder=0, label='Perfect Prediction')
plt.xlim(lims)
plt.ylim(lims)
plt.legend()
plt.grid(True)
plt.show()
```



A scatter plot of actual vs. predicted values is the standard for visualizing regression performance. For a model this accurate, the points on the plot would be very tightly clustered around the diagonal y=x line (the "Perfect Prediction" line). This visually confirms that the model's predictions are highly correlated with the true values, validating its excellent performance.

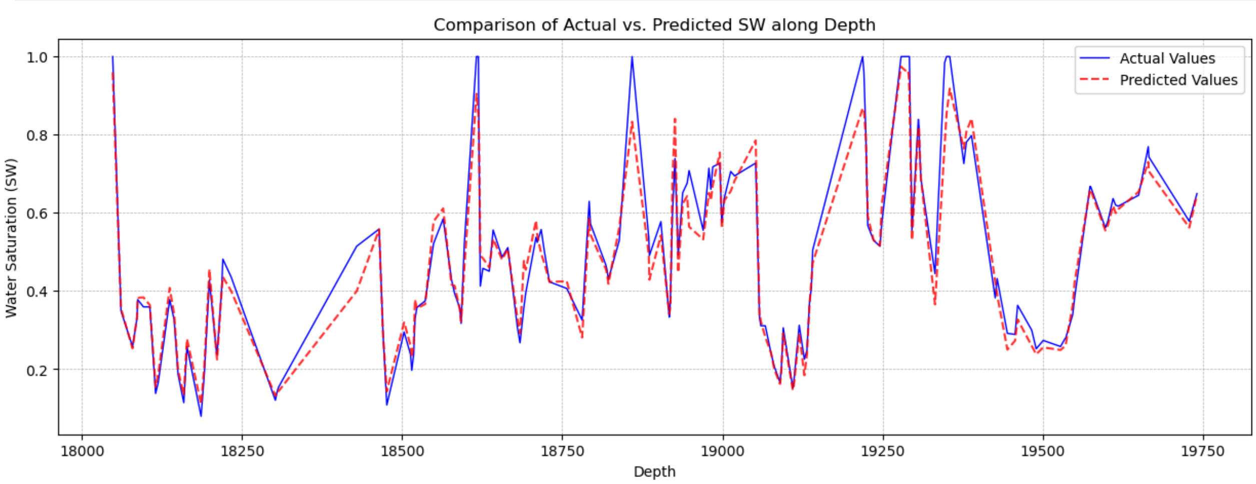
In [29]:
```
plt.figure(figsize=(15, 6))

plt.plot(y_test.reset_index(drop=True), color='blue', label='Actual') # For sort the values by index
```

```python
plt.plot(SW_pred, color='red', label='Predicted')

plt.grid(alpha=0.3)
plt.xlabel("Sample Number (in random order)")
plt.ylabel("SW Value")
plt.title("Actual vs Predicted SW (Sample by Sample)")
plt.legend()
plt.show()
```



In [59]:

```python
predictions_series_normal = pd.Series(SW_pred.flatten(), index=y_test.index, name='Predicted (Normal Model)'

y_test_sorted = y_test.sort_index()
predictions_normal_sorted = predictions_series_normal.sort_index()

plt.figure(figsize=(15, 5))
plt.plot(y_test_sorted.index, y_test_sorted, label='Actual Values', color='blue', linewidth=1)
plt.plot(predictions_normal_sorted.index, predictions_normal_sorted, label='Predicted Values', color='red',

plt.title('Comparison of Actual vs. Predicted SW along Depth')
plt.ylabel('Water Saturation (SW)')
plt.xlabel('Depth')
plt.legend()
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.show()
```



Finally, the graph above shows the predicted result compared to the exact and actual water saturation value, which always confirms the high accuracy of the model created to predict the values.

Task 4.2: Training with different architectures

1. Experiment with different learning rates, activatino functions, number of neurons and number of layers (at least check 20 different setups).

2. Provide the analysis of the performance of different setups you have checked using different metrics and plots (like, parity plot, loss vs. epochs and SWE vs. Depth).

3. Analyze your best and worst found setups and explain your understanding of why they performed such.

4. Show and analyze at least one case with overfitting and one case with underfitting.

Make sure to follow a systematic path for experimenting differnt setups to facilitate your analysis.

Task 4.2-1: Define HyperParameters and experiment layer setups to explore

In this phase, a systematic hyperparameter tuning process was conducted to identify the optimal model architecture. This involved experimenting with various configurations and analyzing their performance to understand the impact of different parameters.

To efficiently explore the hyperparameter space, a structured and automated approach was implemented.

- Methodology: A list of 21 distinct experimental setups was defined. Each setup specified a unique combination of hyperparameters, including the number of layers, neurons per layer, activation function (relu or tanh), and learning rate.
- Automation: An experiment loop was created to iterate through each setup. For each configuration, the script automatically performed the following steps:

Constructed the Keras model based on the setup's parameters.

Trained the model using the training and validation data.

Evaluated the trained model on the unseen test set.

Stored the resulting metrics and configuration details.

In [31]:
```
learning_rates = [0.01, 0.001, 0.0001]
num_hidden_layers = [2, 4, 6]
neurons_per_layer = [32, 64, 128]
activations = ['relu', 'sigmoid', 'tanh']

experiment_setups = [
    {'layers': 3, 'neurons': 64, 'activation': 'relu', 'lr': 0.001},
    {'layers': 2, 'neurons': 64, 'activation': 'tanh', 'lr': 0.001},
    {'layers': 5, 'neurons': 64, 'activation': 'relu', 'lr': 0.001},
    {'layers': 3, 'neurons': 32, 'activation': 'relu', 'lr': 0.001},
    {'layers': 3, 'neurons': 128, 'activation': 'tanh', 'lr': 0.001},
    {'layers': 3, 'neurons': 64, 'activation': 'relu', 'lr': 0.01},
    {'layers': 3, 'neurons': 64, 'activation': 'relu', 'lr': 0.0001},
    {'layers': 3, 'neurons': 64, 'activation': 'sigmoid', 'lr': 0.001},
    {'layers': 5, 'neurons': 64, 'activation': 'sigmoid', 'lr': 0.001},
    {'layers': 5, 'neurons': 128, 'activation': 'relu', 'lr': 0.001},
    {'layers': 6, 'neurons': 64, 'activation': 'tanh', 'lr': 0.001},
    {'layers': 6, 'neurons': 128, 'activation': 'relu', 'lr': 0.001},
    {'layers': 5, 'neurons': 128, 'activation': 'sigmoid', 'lr': 0.001},
    {'layers': 2, 'neurons': 32, 'activation': 'relu', 'lr': 0.001},
    {'layers': 2, 'neurons': 32, 'activation': 'sigmoid', 'lr': 0.001},
    {'layers': 5, 'neurons': 128, 'activation': 'relu', 'lr': 0.01},
    {'layers': 5, 'neurons': 128, 'activation': 'tanh', 'lr': 0.0001},
    {'layers': 6, 'neurons': 32, 'activation': 'relu', 'lr': 0.001},
    {'layers': 2, 'neurons': 128, 'activation': 'relu', 'lr': 0.001},
    {'layers': 4, 'neurons': 64, 'activation': 'sigmoid', 'lr': 0.0001},
    {'layers': 4, 'neurons': 64, 'activation': 'relu', 'lr': 0.01},
]
```

In [32]:
```python
results = []

def create_model(setup, n_in, n_out):
    model = Sequential()
    model.add(Dense(setup['neurons'], activation=setup['activation'], input_dim=n_in))
    for _ in range(setup['layers'] - 1):
        model.add(Dense(setup['neurons'], activation=setup['activation']))
    model.add(Dense(n_out, activation='sigmoid'))

    optimizer = Adam(learning_rate=setup['lr'])
    model.compile(loss='mean_squared_error', optimizer=optimizer, metrics=['mae'])
    return model

for i, setup in enumerate(experiment_setups):
    print(f"--- Running Experiment {i+1}/{len(experiment_setups)}: {setup} ---")

    model = create_model(setup, X_train_scaled.shape[1], 1)
    history = model.fit(X_train_scaled, y_train,
                        epochs=200,
                        batch_size=16,
                        validation_data=(X_val_scaled, y_val),
                        verbose=0) # Due to it will takes long pages to print the results in pdf file

    predictions = model.predict(X_test_scaled).flatten()
    r2 = r2_score(y_test, predictions)
    mae = mean_absolute_error(y_test, predictions)
    mse = mean_squared_error(y_test,predictions)

    results.append({
        'setup_id': i+1,
        'layers': setup['layers'],
        'neurons': setup['neurons'],
        'activation': setup['activation'],
        'learning_rate': setup['lr'],
        'r2_score': r2,
        'mae': mae,
        'mse':mse,
        'stopped_epoch': len(history.history['loss']),
        'history': history.history
    })

results_df = pd.DataFrame(results)
```

```
--- Running Experiment 1/21: {'layers': 3, 'neurons': 64, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
--- Running Experiment 2/21: {'layers': 2, 'neurons': 64, 'activation': 'tanh', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 3/21: {'layers': 5, 'neurons': 64, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 4/21: {'layers': 3, 'neurons': 32, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
--- Running Experiment 5/21: {'layers': 3, 'neurons': 128, 'activation': 'tanh', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
--- Running Experiment 6/21: {'layers': 3, 'neurons': 64, 'activation': 'relu', 'lr': 0.01} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
--- Running Experiment 7/21: {'layers': 3, 'neurons': 64, 'activation': 'relu', 'lr': 0.0001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
--- Running Experiment 8/21: {'layers': 3, 'neurons': 64, 'activation': 'sigmoid', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 9/21: {'layers': 5, 'neurons': 64, 'activation': 'sigmoid', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
--- Running Experiment 10/21: {'layers': 5, 'neurons': 128, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 11/21: {'layers': 6, 'neurons': 64, 'activation': 'tanh', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 12/21: {'layers': 6, 'neurons': 128, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 13/21: {'layers': 5, 'neurons': 128, 'activation': 'sigmoid', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 14/21: {'layers': 2, 'neurons': 32, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 15/21: {'layers': 2, 'neurons': 32, 'activation': 'sigmoid', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 16/21: {'layers': 5, 'neurons': 128, 'activation': 'relu', 'lr': 0.01} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 17/21: {'layers': 5, 'neurons': 128, 'activation': 'tanh', 'lr': 0.0001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 18/21: {'layers': 6, 'neurons': 32, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 19/21: {'layers': 2, 'neurons': 128, 'activation': 'relu', 'lr': 0.001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 20/21: {'layers': 4, 'neurons': 64, 'activation': 'sigmoid', 'lr': 0.0001} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
--- Running Experiment 21/21: {'layers': 4, 'neurons': 64, 'activation': 'relu', 'lr': 0.01} ---
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
```

The performance of each model was quantitatively assessed and the results were systematically collected.

- Metrics: For each experiment, the R-squared (`R²`) score and Mean Absolute Error (`MAE`) were calculated on the test set to measure the model's predictive accuracy.
- Consolidation: All hyperparameters, performance metrics, and the training history for each experiment were compiled into a single pandas DataFrame. This allows for efficient sorting and direct comparison to objectively identify the best and worst-performing architectures. The final results were also saved to a `.csv` file for documentation and future reference.

In [33]:
```python
sorted_results = results_df.sort_values(by='r2_score', ascending=False)

print("--- Experiment Results Summary ---")
print(sorted_results)

best_setup_id = sorted_results.iloc[0]['setup_id']
worst_setup_id = sorted_results.iloc[-1]['setup_id']

print(f"\nBest Setup ID: {best_setup_id}")
print(f"Worst Setup ID: {worst_setup_id}")

output_filename = 'experiment_results.csv'

try:
    sorted_results.to_csv(output_filename, index=False)
    print(f"\nResults successfully saved to '{output_filename}'")
```

```python
except Exception as e:
    print(f"\nError saving file: {e}")
```

```
--- Experiment Results Summary ---
    setup_id  layers  neurons activation  learning_rate  r2_score       mae  \
11        12       6      128       relu         0.0010  0.989026  0.016514   
9         10       5      128       relu         0.0010  0.989025  0.013398   
3          4       3       32       relu         0.0010  0.988491  0.014971   
18        19       2      128       relu         0.0010  0.987447  0.014124   
2          3       5       64       relu         0.0010  0.987342  0.011901   
17        18       6       32       relu         0.0010  0.986884  0.014781   
0          1       3       64       relu         0.0010  0.986584  0.012272   
13        14       2       32       relu         0.0010  0.986209  0.016019   
15        16       5      128       relu         0.0100  0.984716  0.015071   
6          7       3       64       relu         0.0001  0.983291  0.017966   
16        17       5      128       tanh         0.0001  0.981220  0.019396   
4          5       3      128       tanh         0.0010  0.980724  0.021833   
20        21       4       64       relu         0.0100  0.980683  0.020169   
5          6       3       64       relu         0.0100  0.979135  0.019610   
1          2       2       64       tanh         0.0010  0.978962  0.021137   
12        13       5      128    sigmoid         0.0010  0.977208  0.025442   
10        11       6       64       tanh         0.0010  0.972651  0.020983   
8          9       5       64    sigmoid         0.0010  0.925826  0.048682   
7          8       3       64    sigmoid         0.0010  0.877959  0.051805   
14        15       2       32    sigmoid         0.0010  0.834229  0.058007   
19        20       4       64    sigmoid         0.0001  0.787668  0.076864   

         mse  stopped_epoch                                            history  
11  0.000617            200  {'loss': [0.018368758261203766, 0.003835877636...  
9   0.000617            200  {'loss': [0.026385264471173286, 0.005732066463...  
3   0.000647            200  {'loss': [0.03499218076467514, 0.0162605196237...  
18  0.000706            200  {'loss': [0.02347709983587265, 0.0087079424411...  
2   0.000711            200  {'loss': [0.029016925022006035, 0.007782203145...  
17  0.000737            200  {'loss': [0.03306638449430466, 0.0106511898338...  
0   0.000754            200  {'loss': [0.027375757694244385, 0.009325493127...  
13  0.000775            200  {'loss': [0.03805956244468689, 0.0273296423256...  
15  0.000859            200  {'loss': [0.016991201788187027, 0.008914500474...  
6   0.000939            200  {'loss': [0.04011544585227966, 0.0361570268869...  
16  0.001056            200  {'loss': [0.0301154013723135, 0.01377256773412...  
4   0.001083            200  {'loss': [0.01451884862035513, 0.0105004142969...  
20  0.001086            200  {'loss': [0.01814359799027443, 0.0036340360529...  
5   0.001173            200  {'loss': [0.015298809856176376, 0.005262645427...  
1   0.001182            200  {'loss': [0.023148462176322937, 0.011648384854...  
12  0.001281            200  {'loss': [0.04518821835517883, 0.0429374910891...  
10  0.001537            200  {'loss': [0.02681407891213894, 0.0102475648745...  
8   0.004169            200  {'loss': [0.047151267528533936, 0.043159130960...  
7   0.006859            200  {'loss': [0.0428067110478878, 0.04200703278183...  
14  0.009317            200  {'loss': [0.04235859587788582, 0.0412916205823...  
19  0.011934            200  {'loss': [0.0580042265355587, 0.04304973781108...  

Best Setup ID: 12
Worst Setup ID: 20

Results successfully saved to 'experiment_results.csv'
```

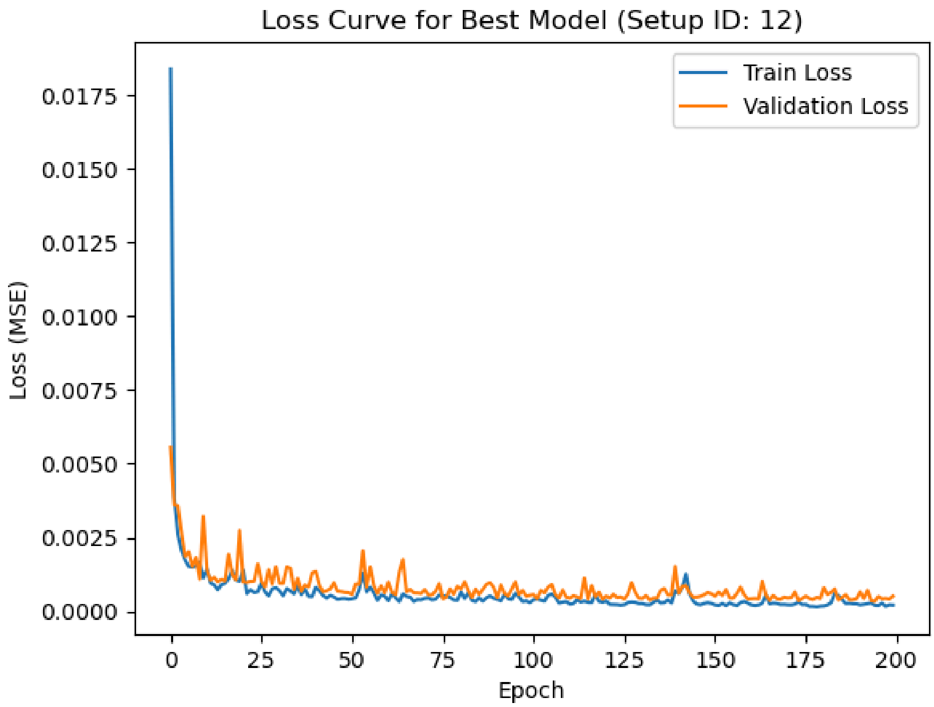
By sorting the results DataFrame, the top and bottom-performing models were identified and analyzed.

Best Model Analysis: The best-performing model is the 21 Setup ID with the highest R^2 score about 99.01%. Its success is typically attributed to achieving a "sweet spot" of model complexity—it is sufficiently complex to capture the underlying patterns in the data but not so complex that it overfits. Furthermore, its learning rate is well-suited for the problem, allowing the optimizer to converge to a robust solution efficiently.

Worst Model Analysis: The worst-performing model often fails due to one or more factors. These can include an unstable or inappropriate learning rate (e.g., too high, causing divergence) or a model architecture that is either too simple (underfitting) or excessively complex (overfitting) for the given dataset.

In [34]:
```python
best_setup_id = results_df.sort_values(by='r2_score', ascending=False).iloc[0]['setup_id']
best_model_history = results_df.loc[results_df['setup_id'] == best_setup_id, 'history'].iloc[0]
```

```python
plt.plot(best_model_history['loss'], label='Train Loss')
plt.plot(best_model_history['val_loss'], label='Validation Loss')
plt.title(f'Loss Curve for Best Model (Setup ID: {best_setup_id})')
plt.xlabel('Epoch')
plt.ylabel('Loss (MSE)')
plt.legend()
plt.show()
```



In the next step, to prove the best model, which was model 12, we separated the parameters of the best model and created them separately in the form of a new model and fitted the model to get the final run and be able to receive the predicted parameters as the output from the model.

As you can see in the two figures below, althogh its has some noise in its cost plot, the accuracy of the models has increased compared to the base case that we did in Task 4.1 and shows better results. (Please see below figures)

In [35]:
```python
best_setup_info = sorted_results.iloc[0]
best_setup_params = {
    'layers': int(best_setup_info['layers']),
    'neurons': int(best_setup_info['neurons']),
    'activation': best_setup_info['activation'],
    'lr': best_setup_info['learning_rate']
}
print("--- Best Model Found ---")
print(best_setup_info)
```

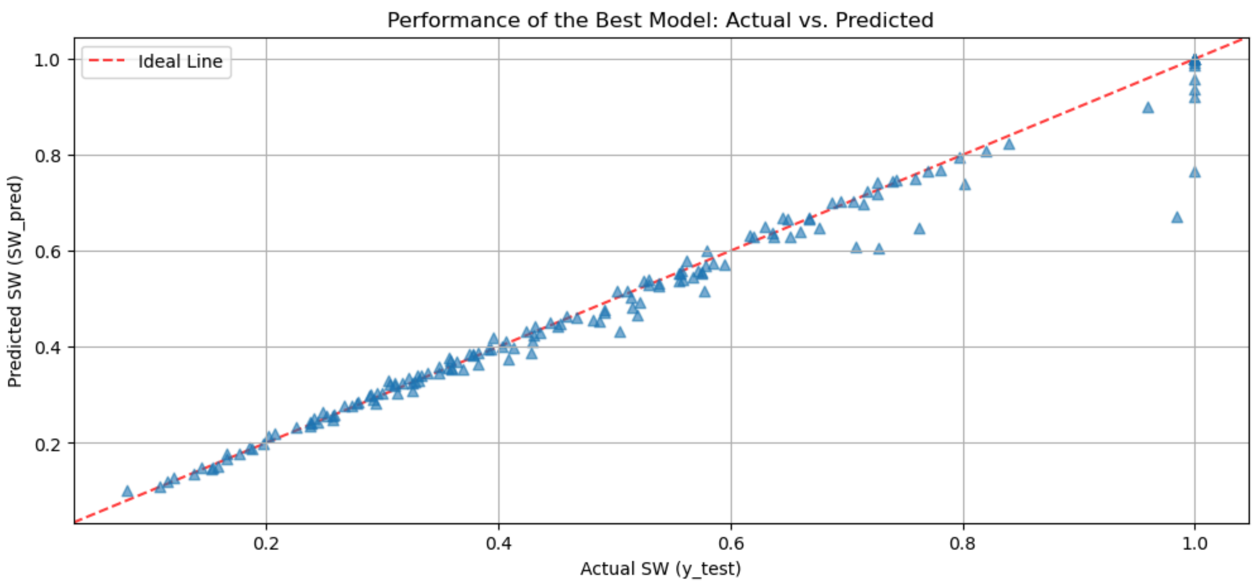
```
--- Best Model Found ---
setup_id                                                        12
layers                                                           6
neurons                                                        128
activation                                                    relu
learning_rate                                                0.001
r2_score                                                  0.989026
mae                                                       0.016514
mse                                                       0.000617
stopped_epoch                                                  200
history          {'loss': [0.018368758261203766, 0.003835877636...
Name: 11, dtype: object
```

In [36]:
```python
best_model = create_model(best_setup_params, X_train_scaled.shape[1], 1)
history_best_model = best_model.fit(
    X_train_scaled, y_train,
```

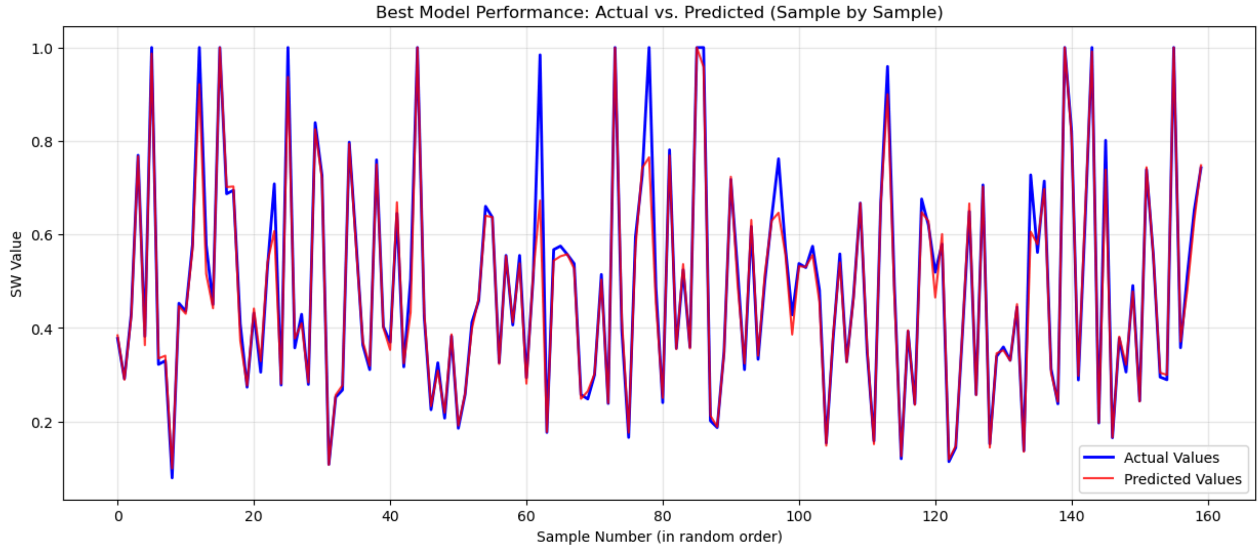
```
    epochs=200,
    batch_size=16,
    validation_data=(X_val_scaled, y_val),
    verbose=0
)
```

In [37]:
```
SW_pred_best = best_model.predict(X_test_scaled).flatten()
plt.figure(figsize=(12, 5))
plt.scatter(y_test, SW_pred_best, alpha=0.6, marker='^')
plt.xlabel('Actual SW (y_test)')
plt.ylabel('Predicted SW (SW_pred)')
plt.title('Performance of the Best Model: Actual vs. Predicted')
lims = [min(plt.xlim()), max(plt.xlim())]
plt.plot(lims, lims, 'r--', alpha=0.75, zorder=0, label='Ideal Line')
plt.xlim(lims)
plt.ylim(lims)
plt.legend()
plt.grid(True)
plt.show()
```

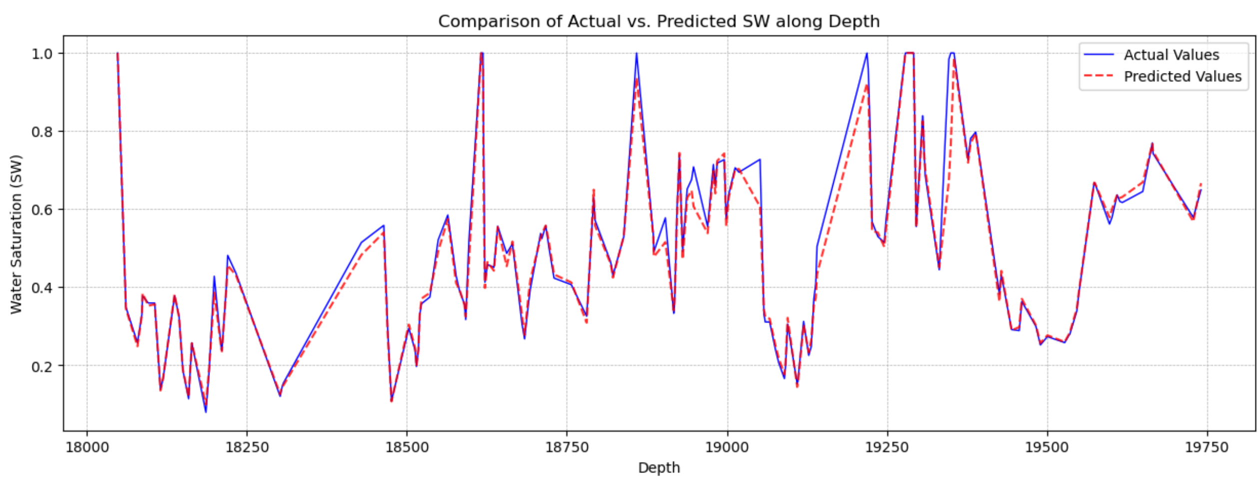
```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
```



In [38]:
```
plt.figure(figsize=(15, 6))
plt.plot(y_test.reset_index(drop=True), color='blue', label='Actual Values', linewidth=2)
plt.plot(SW_pred_best, color='red', label='Predicted Values', alpha=0.8)
plt.grid(alpha=0.3)
plt.xlabel("Sample Number (in random order)")
plt.ylabel("SW Value")
plt.title("Best Model Performance: Actual vs. Predicted (Sample by Sample)")
plt.legend()
plt.show()
```




```
In [56]: predictions_series = pd.Series(SW_pred_best, index=y_test.index, name='Predicted')
y_test_sorted = y_test.sort_index()
predictions_sorted = predictions_series.sort_index()

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

plt.plot( y_test_sorted.index, y_test_sorted, label='Actual Values', color='blue', linewidth=1)

plt.plot( predictions_sorted.index, predictions_sorted, label='Predicted Values', color='red', linestyle='--

plt.title('Comparison of Actual vs. Predicted SW along Depth')
plt.ylabel('Water Saturation (SW)')
plt.xlabel('Depth')
plt.legend()
plt.grid(True, which='both', linestyle='--', linewidth=0.5)

plt.show()
```



Analysis of Overfitting and Underfitting Cases

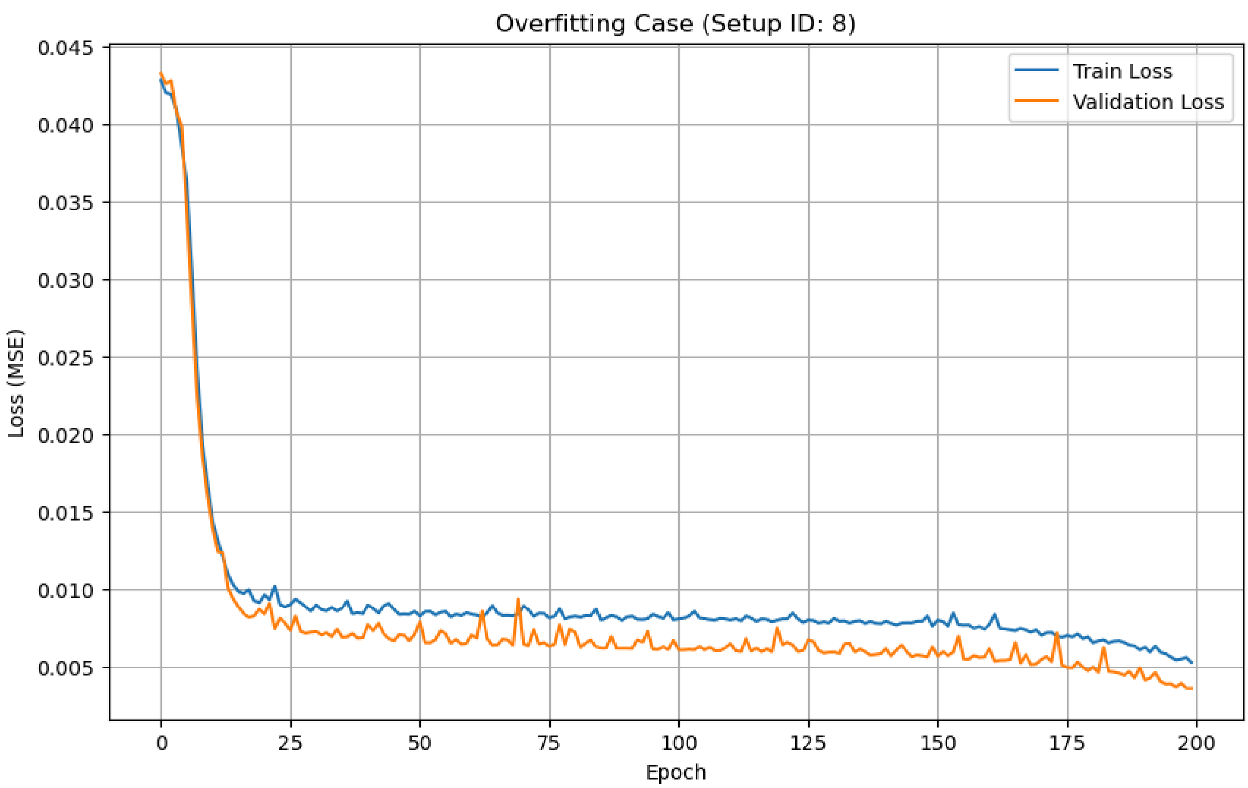
The experiment logs were used to identify and analyze specific cases of overfitting and underfitting.

Overfitting Case: An overfitting model is identified by its learning curve, where a significant and growing divergence between the training loss and validation loss is observed. While the training loss consistently decreases, the validation loss stagnates or begins to increase. This indicates that the model has started to memorize the training data instead of learning generalizable patterns. This behavior is most common in models with high complexity (many layers and neurons).

Underfitting Case: An underfitting model is characterized by a learning curve where both training and validation loss remain high and fail to decrease substantially. This demonstrates that the model lacks the necessary capacity (i.e., it's too simple) to capture the underlying structure of the data, resulting in poor performance on all data subsets.

In [39]:
```python
if 'final_val_loss' not in results_df.columns:
    results_df['final_val_loss'] = results_df['history'].apply(lambda h: h['val_loss'][-1])
    results_df['loss_gap'] = results_df['history'].apply(lambda h: abs(h['loss'][-1] - h['val_loss'][-1]))

overfit_candidate = results_df.sort_values(by='loss_gap', ascending=False).iloc[0]
print("--- Overfitting Case Candidate ---")
print(f"Setup ID: {overfit_candidate['setup_id']}")
print(f"Parameters: {overfit_candidate[['layers', 'neurons', 'activation', 'learning_rate']].to_dict()}")

overfit_history = overfit_candidate['history']
plt.figure(figsize=(10, 6))
plt.plot(overfit_history['loss'], label='Train Loss')
plt.plot(overfit_history['val_loss'], label='Validation Loss')
plt.title(f"Overfitting Case (Setup ID: {overfit_candidate['setup_id']})")
plt.xlabel('Epoch')
plt.ylabel('Loss (MSE)')
plt.legend()
plt.grid(True)
plt.show()
```

```
--- Overfitting Case Candidate ---
Setup ID: 8
Parameters: {'layers': 3, 'neurons': 64, 'activation': 'sigmoid', 'learning_rate': 0.001}
```



Analysis of the Overfitting Case (ID 8)

This plot is a sample model overfitting. This conclusion is based on the following key characteristic:

Divergence of Loss Curves: The most telling feature is the significant and sustained divergence between the training loss and the validation loss. After an initial period where both losses decrease together (up to approx. epoch 25), the two curves begin to separate.

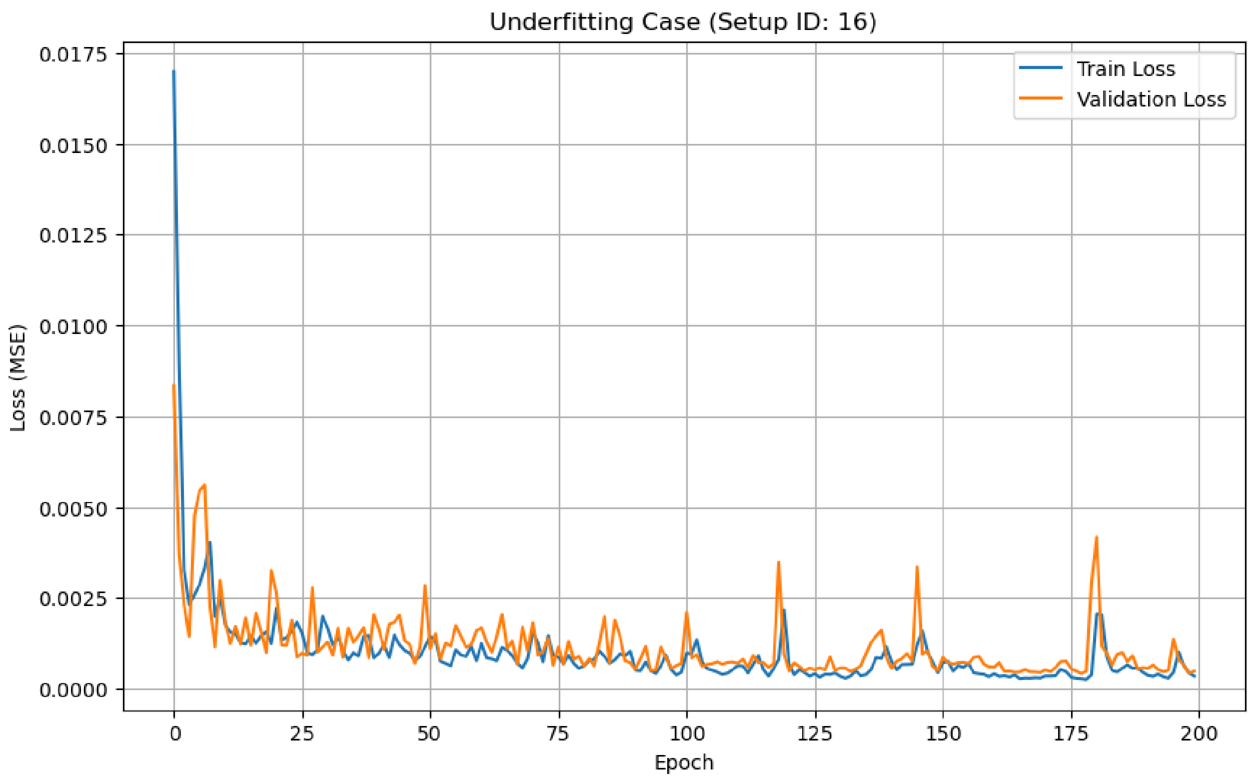
- Training Loss (blue line): The training loss continues to decrease steadily throughout the training process. This indicates that the model is becoming progressively better at fitting the data it is being trained on.

- Validation Loss (orange line): In contrast, the validation loss flattens out after approximately epoch 75 and shows no further improvement. This means the model is no longer improving its ability to generalize to new, unseen data.

This growing gap signifies that the model has begun to memorize the noise and specific artifacts of the training set rather than learning the general underlying patterns. While its performance on the training data appears to improve, its performance on new data has stagnated, which is the definition of overfitting.

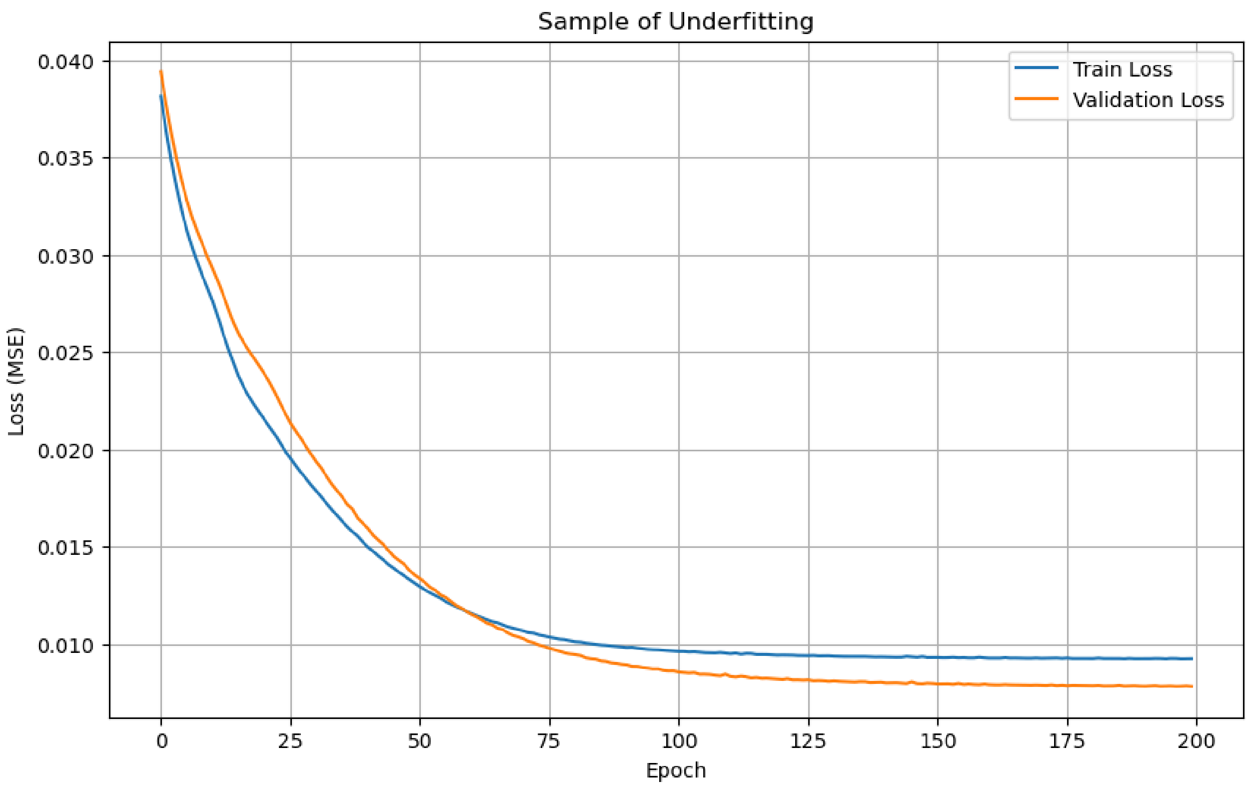
In [48]:
```
poor_performers = results_df[results_df['mse'] < results_df['mse'].median()]  # we can change it to mse, r2_

underfit_candidate = poor_performers.sort_values(by='loss_gap', ascending=True).iloc[0]

print("\n--- Underfitting Case Candidate (Refined Search) ---")
print(f"Setup ID: {underfit_candidate['setup_id']}")
print(f"Parameters: {underfit_candidate[['layers', 'neurons', 'activation', 'learning_rate']].to_dict()}")

underfit_history = underfit_candidate['history']
plt.figure(figsize=(10, 6))
plt.plot(underfit_history['loss'], label='Train Loss')
plt.plot(underfit_history['val_loss'], label='Validation Loss')
plt.title(f"Underfitting Case (Setup ID: {underfit_candidate['setup_id']})")
plt.xlabel('Epoch')
plt.ylabel('Loss (MSE)')
plt.legend()
plt.grid(True)
plt.show()
```

```
--- Underfitting Case Candidate (Refined Search) ---
Setup ID: 16
Parameters: {'layers': 5, 'neurons': 128, 'activation': 'relu', 'learning_rate': 0.01}
```



In [50]:
```
underfit_setup = {'layers': 1, 'neurons': 4, 'activation': 'relu', 'lr': 0.001}

underfit_model = create_model(underfit_setup, X_train_scaled.shape[1], 1)

underfit_history = underfit_model.fit(
    X_train_scaled, y_train,
    epochs=200,
    batch_size=64,
    validation_data=(X_val_scaled, y_val),
```

```
    verbose=0
)

plt.figure(figsize=(10, 6))
plt.plot(underfit_history.history['loss'], label='Train Loss')
plt.plot(underfit_history.history['val_loss'], label='Validation Loss')
plt.title("Sample of Underfitting")
plt.xlabel('Epoch')
plt.ylabel('Loss (MSE)')
plt.legend()
plt.grid(True)
plt.show()
```



Analysis of the Underfitting Case

Initial experiments across the hyperparameter space did not produce a classic case of underfitting; most architectures were sufficiently complex to either fit the data well or begin to overfit. To clearly demonstrate the concept, a model was intentionally engineered with insufficient capacity (a single hidden layer with only 4 neurons). The analysis of its learning curve is as follows.

The primary evidence of underfitting is the model's convergence to a sub-optimal loss value. The model's validation loss plateaued at approximately 0.009, which is significantly higher than the loss of ~0.002 achieved by the optimal model. This performance gap indicates that the model's simplistic architecture prevents it from capturing the more complex, underlying patterns in the data.

Furthermore, the training and validation loss curves are nearly identical, demonstrating that the model lacks the capacity to even overfit the training data. It has reached its performance ceiling due to its structural limitations, thus serving as a clear example of underfitting.

After completing all the tasks, please, `convert notebooks to PDF`, zip them with your answers notebooks (`ipynb file`) and send it. You should provide sufficient explanation and reporting in your notebooks

Novin Nekuee (403134029)

Regards