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Final Project - Gold Price Prediction

Introduction

Project Propose

The project aims to predict gold prices using time series data related to gold. Gold prices play an important role in the global economy, as gold is widely used in the technology field and, most importantly, is considered a store of value. We are interested in how we can use machine learning to predict its price and potentially create a trading strategy. This involves analyzing historical gold price movements and other related economic indicators to build a model that forecasts future prices.

Method

In this project, we use different machine learning algorithms to predict gold prices. We separate it into two parts: the first part involves using regression models to directly predict gold prices. In the second part, we use neural networks to predict both the price and the movement of gold prices. The following is group menbers' contribution to this project:

- Regressors (Ian Lee)
  - Random Forest Regressor
  - Linear Regressor
- Neural Networks (Eric Lee)
  - Long Short Term Memory

Data Source

Our data source is Yahoo Finance. We download, organize, and convert the data into a CSV file. We considered various factors that could influence gold prices. For example, DX-Y.NYB, which is the USD index, shows that gold often acts as a store of value. This means that when the USD loses value, gold prices typically rise. We also included major stock markets, such as those in the US, EU, Japan, and China, as they can potentially impact gold prices. Additionally, we selected gold-correlated commodities like silver and platinum. The VIX, a volatility index, is included because we believe higher volatility may drive more investors to buy gold, while lower volatility may result in fewer investors purchasing gold. Finally, we included the 10-year treasury bond as a risk-free indicator, which is an important measure of the global economy.

In [ ]:

```
import yfinance as yf
import pandas as pd

# Define the list of tickers including gold
lst = ["GOLD", "^GSPC", "^DJI", "^VIX", "^FTSE", "000001.SS", "^N225", "DX-Y.NYB", "SI=F", "PL=F", "CL=F", "^TNX"]

# Dictionary to hold data
close_price = {}

# Fetch data for all tickers
for ticker in lst:
    data = yf.download(ticker, start="2000-12-01", end="2024-05-20")
    close_price[ticker] = data['Close']

# Create DataFrame
df = pd.DataFrame(close_price)

# Filter the DataFrame to only include rows where 'GOLD' is not NaN
df = df[df['GOLD'].notna()]
# This step is actually redundant if you interpolate all missing GOLD data unless you want to remove days with no original gold data at all
df = df.dropna(subset=['GOLD'])
# Save the DataFrame to an Excel file
df.to_excel("gold_based_data_test.xlsx")
```

```
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
```

In [ ]:

```
df = pd.read_excel("gold_based_data_test.xlsx")
lst.append("Date")
temp = {}
# Fill the missing value by linear way
for ticker in lst:
    temp[ticker] = df[ticker].interpolate(method='linear')
new_df = pd.DataFrame(temp)
new_df['Date'] = pd.to_datetime(new_df['Date'], format='%Y-%m-%d')
new_df.set_index('Date', inplace=True)
# Save the filled DataFrame to both an excecl file and a csv file.
new_df.to_excel("temp.xlsx")
new_df.to_csv("temp.csv")
```

Regressors (Ian Lee)

In [ ]:

```
#Import data
import pandas as pd
data = pd.read_csv("temp.csv")
data
```

Out[ ]:

	Date	GOLD	^GSPC	^DJI	^VIX	^FTSE	000001.SS	^N225	DX-Y.NYB	SI=F	PL=F	CL=F	^TNX
0	2000-12-01	15.312500	1315.229980	10373.540039	27.480000	6170.399902	2081.843018	14835.330078	114.730003	4.640000	612.000000	32.049999	5.513
1	2000-12-04	15.690000	1324.969971	10560.950195	27.780001	6158.700195	2092.138916	14954.730469	113.709999	4.714000	622.099976	31.299999	5.522
2	2000-12-05	14.910000	1376.540039	10898.719727	24.990000	6299.000000	2091.669922	14695.049805	114.470001	4.704000	607.400024	29.549999	5.430
3	2000-12-06	15.840000	1351.459961	10664.379883	25.070000	6273.299805	2075.626953	14889.370117	113.309998	4.754000	605.400024	29.850000	5.319
4	2000-12-07	16.260000	1343.550049	10617.360352	25.340000	6231.399902	2075.043945	14720.360352	113.540001	4.724000	612.599976	29.360001	5.299
...	...	...	...	...	...	...	...	...	...	...	...	...	...
5896	2024-05-13	16.940001	5221.419922	39431.511719	13.600000	8415.000000	3148.020996	38179.460938	105.220001	28.221001	1005.299988	79.120003	4.481
5897	2024-05-14	17.150000	5246.680176	39558.109375	13.420000	8428.099609	3145.773926	38356.058594	105.010002	28.485001	1039.300049	78.019997	4.445
5898	2024-05-15	17.420000	5308.149902	39908.000000	12.450000	8445.799805	3119.902100	38385.730469	104.349998	29.514000	1063.300049	78.629997	4.356
5899	2024-05-16	17.520000	5297.100098	39869.378906	12.420000	8438.700195	3122.400879	38920.261719	104.459999	29.665001	1065.400024	79.230003	4.377
5900	2024-05-17	17.889999	5303.270020	40003.589844	11.990000	8420.299805	3154.025879	38787.378906	104.449997	31.047001	1084.599976	80.059998	4.420

5901 rows × 13 columns

Random Forest Regressor

In this part, we use the random forest regressor to evaluate if the model provides better predictions than a simple prediction method. On the test set, we compute the RMSE of a model that predicts the 1-step ahead value of $GOLD_{t+1}$ as the current value $GOLD_t$, and compare this to the best-fitting random forest model.

Method 1 - High Correlation

At the beginning, we tested the correlation to select the variables for the feature set. We found that DX-Y.NYB and PL=F have a better correlation with GOLD, so we initially selected these two variables as features for the prediction. Then, we separated the data into training, validation, and test sets to evaluate accuracy. We used the validation set to find the best hyperparameters for the random forest regressor and applied them to the model for prediction on the test set. However, as shown in the results below, although the random forest regressor performed well, its RMSE was significantly larger than that of the simple prediction method, indicating that the simple prediction was better than this model. Additionally, we observed that $GOLD_t$ has a very high influence on $GOLD_{t+1}$.

In [ ]:
```
#Guess variables to use by observing correlation
correlation_data=data.loc[:, data.columns != 'Date']
correlation_data.corr()['GOLD']
```

Out[ ]:
```
GOLD         1.000000
^GSPC       -0.392153
^DJI        -0.396197
^VIX         0.184885
^FTSE       -0.312975
000001.SS    0.073871
^N225       -0.458749
DX-Y.NYB    -0.697405
SI=F         0.433430
PL=F         0.741047
CL=F         0.492926
^TNX         0.031062
Name: GOLD, dtype: float64
```

In [ ]:
```
#Oranganize feature and target data
import numpy as np
n=len(data['GOLD'])
x=[]
y=[]
for i in range(n-5):
  x.append(list(data['GOLD'].iloc[i:i+5])+
           list(data['DX-Y.NYB'].iloc[i:i+5])+
           list(data['PL=F'].iloc[i:i+5]))
  y.append(data['GOLD'].iloc[i+5])
X=np.array(x)
y=np.array(y)
print(X[0:2])
print(y[0:2])
```

```
[[ 15.3125      15.68999958  14.90999985  15.84000015  16.26000023
  114.7300034  113.7099991  114.4700012  113.3099976  113.5400009
  612.         622.0999756  607.4000244  605.4000244  612.5999756 ]
 [ 15.68999958  14.90999985  15.84000015  16.26000023  16.31999969
  113.7099991  114.4700012  113.3099976  113.5400009  114.0500031
  622.0999756  607.4000244  605.4000244  612.5999756  607.9000244 ]]
[16.31999969 15.80000019]
```

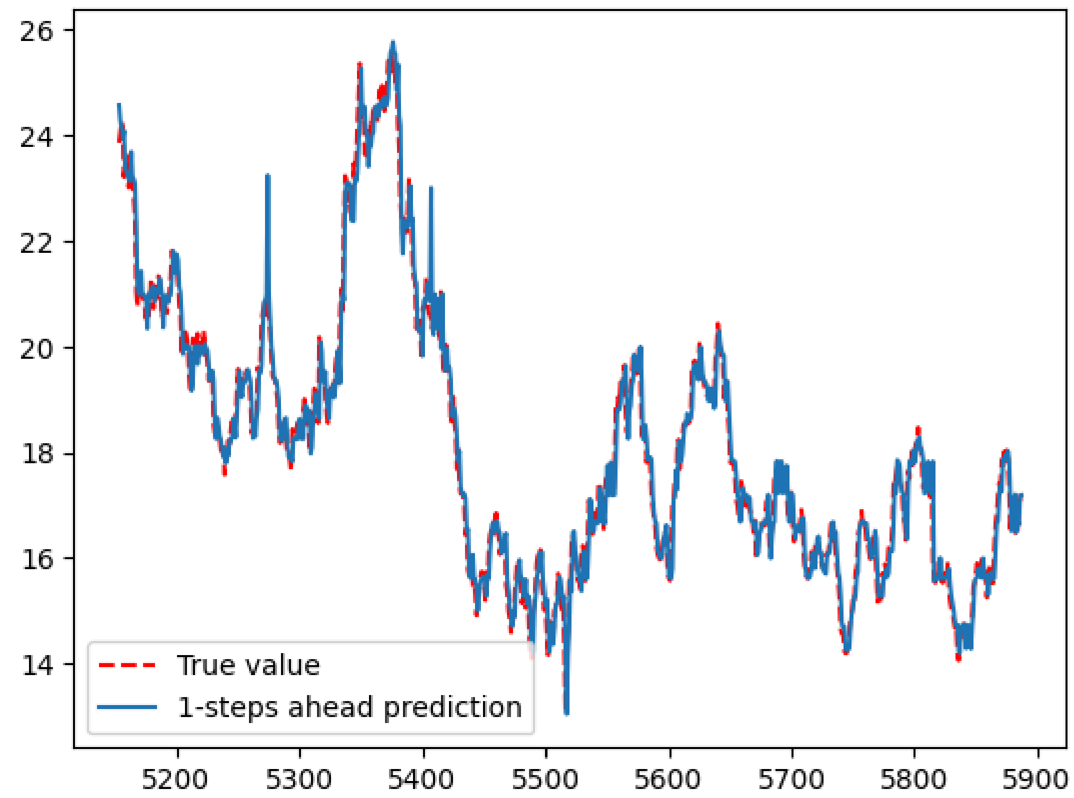
In [ ]:
```
#Create function to pick the best hyperparameters and measure the accuracy of test set
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import TimeSeriesSplit
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

series_len = data["GOLD"].size
tscv = TimeSeriesSplit(n_splits=3)

#Hyperparamter combinations
ccp_alpha_list = [10**-1, 10**-3, 10**-5, 10**-7]
n_estimators_list = [200,400,600]

def time_series_valid_test(X, y, n_split, valid_or_test, optimal_par=None):
    tscv = TimeSeriesSplit(n_splits=n_split)
    rf_rmse = []
    currentval_rmse = []
    i = 0
    for train_index, test_index in tscv.split(X):
        i += 1
        #Break test set into 50% validation set, 50% test set
        break_test_ind = int(test_index[0] + 0.5*(test_index[-1]-test_index[0]))
        valid_index = np.array(list(range(test_index[0],break_test_ind)))
        test_index = np.array(list(range(break_test_ind,test_index[-1])))

        #Split
        X_train, X_valid, X_test = X[train_index], X[valid_index], X[test_index]
        y_train, y_valid, y_test = y[train_index], y[valid_index], y[test_index]

        #Tuning
        if valid_or_test == "valid":
            X_train_red, X_train_rest, y_train_red, y_test_red = train_test_split(
                X_train, y_train, test_size=0.1, random_state=42)
            for ccp_alpha in ccp_alpha_list:
                for n_estimators in n_estimators_list:
                    model_rf = RandomForestRegressor(random_state=42, n_jobs=-1,
                               ccp_alpha=ccp_alpha, n_estimators=n_estimators)
                    model_rf.fit(X_train_red, y_train_red.ravel())
                    y_val_rf = model_rf.predict(X_valid)
                    rf_rmse.append(np.sqrt(mean_squared_error(y_valid, y_val_rf)))

        #Evalutate on test set
        if valid_or_test == "test":
            model_rf = RandomForestRegressor(random_state=42, n_jobs=-1,
                       ccp_alpha=optimal_par[0], n_estimators=optimal_par[1])
            model_rf.fit(X_train, y_train.ravel())
            y_test_rf = model_rf.predict(X_test)
            rf_rmse.append(np.sqrt(mean_squared_error(y_test, y_test_rf)))

            #Predicting as next value as the current value
            y_test_currentval = y[test_index-1]
            currentval_rmse.append(np.sqrt(mean_squared_error(y_test, y_test_currentval)))

            #Plot the prediction for the last CV fold
            if i == n_split:
                plt.plot(range(series_len-test_index.size,series_len),
                         y_test, "r--", label="True value", )
                plt.plot(range(series_len-test_index.size,series_len),
                         y_test_rf, label="1-steps ahead prediction")
                plt.legend(loc="lower left")

    #Average RMSE over CV folds
    if valid_or_test == "valid":
        rf_rmse = np.mean(np.array(rf_rmse).reshape(
            n_split, len(ccp_alpha_list)*len(n_estimators_list)), axis=0)
        return rf_rmse
    if valid_or_test == "test":
        rf_rmse = np.mean(rf_rmse)
        currentval_rmse = np.mean(currentval_rmse)

        #Returns: RF RMSE, Current value prediction RMSE, best fitted RF model
        return rf_rmse, currentval_rmse, model_rf
```

In [ ]:
```
#Pick the best hyperparameters
rf_rmse = time_series_valid_test(X, y, 3, "valid")
print(rf_rmse)
```

```
ind = 0
for ccp_alpha in ccp_alpha_list:
        for n_estimators in n_estimators_list:
            if ind == np.argmin(rf_rmse):
                optimal_par = [ccp_alpha, n_estimators]
                print(["(ccp_alpha, n_estimators):",[ccp_alpha, n_estimators]])
                print(rf_rmse[ind])
            ind += 1
```

```
[3.31507693 3.30322939 3.30429583 2.98588433 2.99765538 3.00120622
 3.04272873 3.05745577 3.06117659 3.0423724  3.05703609 3.06096275]
['(ccp_alpha, n_estimators):', [0.001, 200]]
2.9858843305757556
```

In [ ]:
```
#Results - plot
rf_rmse, currentval_rmse, model_rf = time_series_valid_test(X, y, 3, "test", optimal_par)
```



In [ ]:
```
#Results - RMSE
print("RMSE of Model 1:", rf_rmse)

print("RMSE of Simple Prediction:", currentval_rmse)
```

```
RMSE of Model 1: 5.5797629575790895
RMSE of Simple Prediction: 0.5689821043887909
```

In [ ]:
```
#Understand what feature influence the model the most
print("Importance of feature variables:", model_rf.feature_importances_)
```

```
Importance of feature variables: [1.97475574e-04 2.62029294e-04 2.86694675e-04 1.32956835e-03
 9.97043800e-01 1.11238149e-04 9.62619511e-05 9.00488170e-05
 1.00060552e-04 1.04610069e-04 8.57679863e-05 7.00292684e-05
 6.12329331e-05 7.17814793e-05 8.94013146e-05]
```

Method 2 - No GOLD

Since Model 1 shows that $GOLD_t$ has a very significant effect on gold price prediction, we wanted to check if other feature variables could achieve similar performance. Therefore, we removed $GOLD_t$ and keep DX-Y.NYB and PL=F as the feature variables. We aimed to see if we could predict gold prices using other variables without knowing the previous gold price. As shown in the results below, the prediction does not perform well at all.

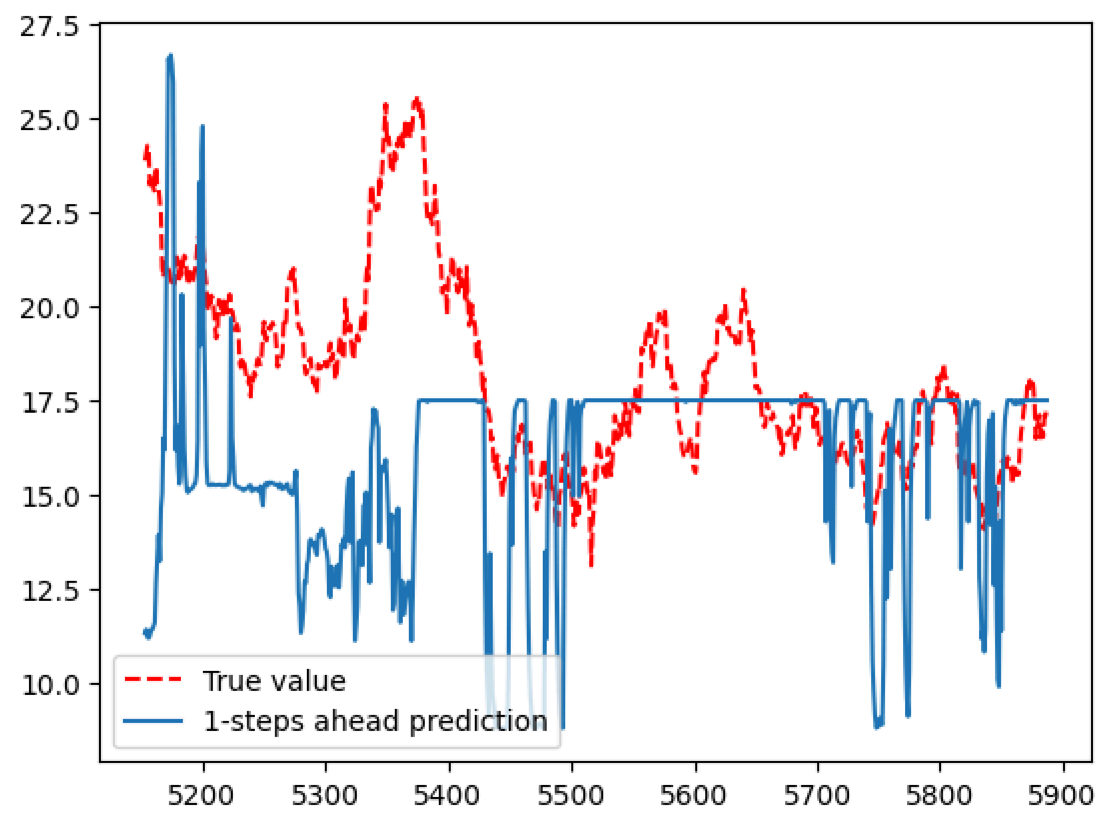
In [ ]:
```
#Pick feature variables
import numpy as np
n=len(data['GOLD'])
x=[]
y=[]
for i in range(n-5):
  x.append(list(data['DX-Y.NYB'].iloc[i:i+5])+
           list(data['PL=F'].iloc[i:i+5]))
  y.append(data['GOLD'].iloc[i+5])
X=np.array(x)
y=np.array(y)
print(X[0:2])
print(y[0:2])
```

```
[[114.7300034 113.7099991 114.4700012 113.3099976 113.5400009 612.
  622.0999756 607.4000244 605.4000244 612.5999756]
 [113.7099991 114.4700012 113.3099976 113.5400009 114.0500031 622.0999756
  607.4000244 605.4000244 612.5999756 607.9000244]]
[16.31999969 15.80000019]
```

In [ ]:
```
#Pick the best hyperparameters
rf_rmse = time_series_valid_test(X, y, 3, "valid")
print(rf_rmse)
ind = 0
for ccp_alpha in ccp_alpha_list:
        for n_estimators in n_estimators_list:
            if ind == np.argmin(rf_rmse):
                optimal_par = [ccp_alpha, n_estimators]
                print(["(ccp_alpha, n_estimators):",[ccp_alpha, n_estimators]])
                print(rf_rmse[ind])
            ind += 1
```

```
[11.49580791 11.505544   11.50250602 11.68453972 11.68584239 11.68762181
 11.67389023 11.67652124 11.67514151 11.67350061 11.67649349 11.67488969]
['(ccp_alpha, n_estimators):', [0.1, 200]]
11.495807910326471
```

In [ ]:
```
#Results - plot
rf_rmse, currentval_rmse, model_rf = time_series_valid_test(X, y, 3, "test", optimal_par)
```



In [ ]:
```
#Results - RMSE
print("RMSE of Model 2:", rf_rmse)

print("RMSE of Simple Prediction:", currentval_rmse)
```

```
RMSE of Model 2: 10.409573624139897
RMSE of Simple Prediction: 0.5689821043887909
```

In [ ]:
```
#Understand what feature influence the model the most
print("Importance of feature variables:", model_rf.feature_importances_)
```

```
Importance of feature variables: [0.02988506 0.02787451 0.02307468 0.05787958 0.17507695 0.03710006
 0.04008604 0.05552102 0.14494533 0.40855677]
```

Method 3 - only GOLD

Since the simple prediction yielded better results than the models above, we decided to see if the random forest model using only $GOLD_t$ as the feature variable could outperform the simple prediction. The results show that the random forest regressor is not suitable for gold price prediction, as it has a much larger RMSE than the simple prediction, even when using the same feature variable.

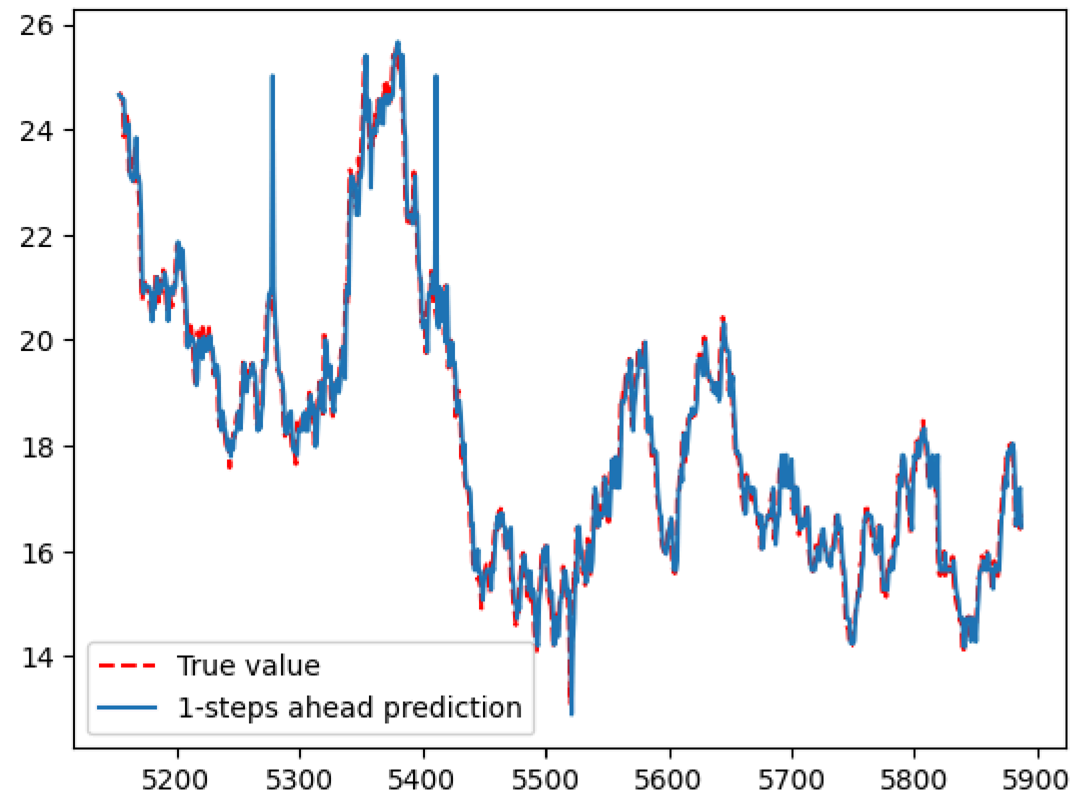
In [ ]:
```
#Pick only the previous gold price as variable
import numpy as np
n=len(data['GOLD'])
x=[]
y=[]
for i in range(n-5):
  x.append(list(data['GOLD'].iloc[i:i+1]))
  y.append(data['GOLD'].iloc[i+1])
X=np.array(x)
y=np.array(y)
print(X[0:2])
print(y[0:2])
```

```
[[15.3125    ]
 [15.68999958]]
[15.68999958 14.90999985]
```

In [ ]:
```
#Pick the best hyperparameters
rf_rmse = time_series_valid_test(X, y, 3, "valid")
print(rf_rmse)
ind = 0
for ccp_alpha in ccp_alpha_list:
        for n_estimators in n_estimators_list:
            if ind == np.argmin(rf_rmse):
                optimal_par = [ccp_alpha, n_estimators]
                print(["(ccp_alpha, n_estimators):",[ccp_alpha, n_estimators]])
                print(rf_rmse[ind])
            ind += 1
```

```
[3.24312699 3.23716537 3.24025755 2.61517558 2.61802883 2.61716214
 2.64962573 2.65234225 2.65203666 2.65005967 2.6526911  2.65228024]
['(ccp_alpha, n_estimators):', [0.001, 200]]
2.61517558353895
```

In [ ]:
```
#Results - plot
rf_rmse, currentval_rmse, model_rf = time_series_valid_test(X, y, 3, "test", optimal_par)
```



In [ ]:
```
#Results - RMSE
print("RMSE of Model 3:", rf_rmse)
print("RMSE of Simple Prediction:", currentval_rmse)
```

```
RMSE of Model 3: 5.015160989141218
RMSE of Simple Prediction: 0.5686629846293454
```

Regressors - Linear Regressor

In this part, we use the linear regressor to evaluate if the model provides better predictions than a simple prediction method. On the test set, we compute the RMSE of a model that predicts the 1-step ahead value of $GOLD_{t+1}$ as the current value $GOLD_t$, and compare this to the linear regression model.

Method 4 - Linear Model

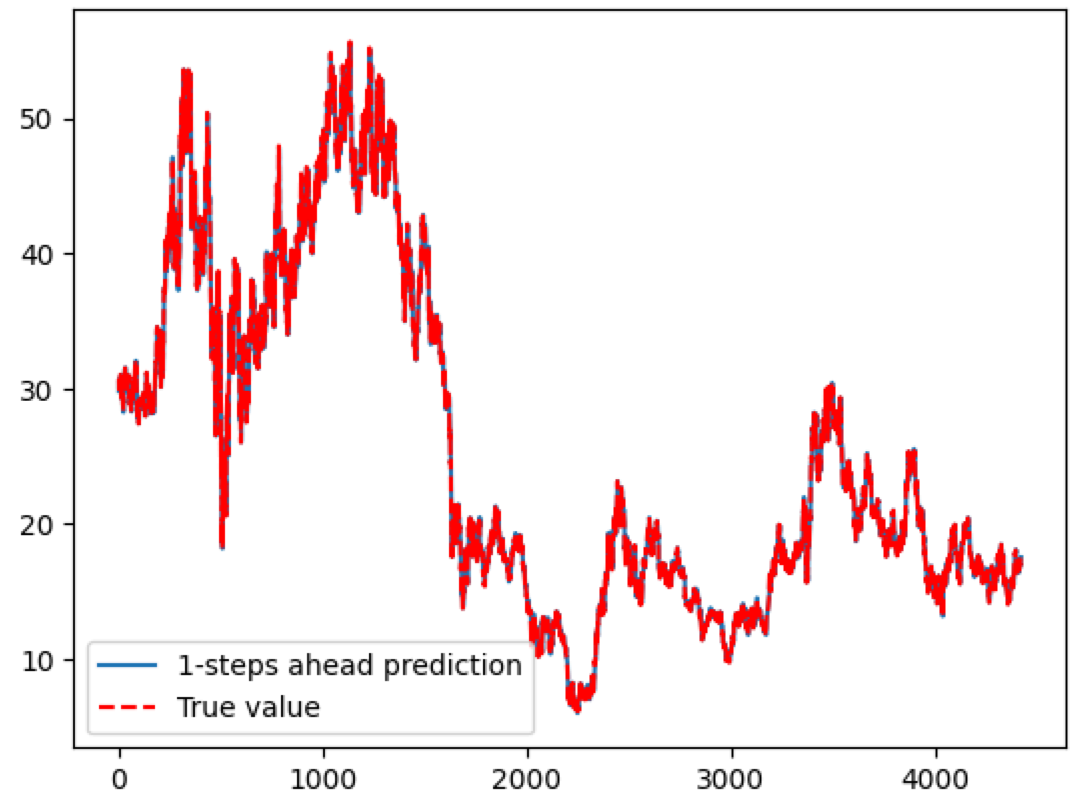
The models above suggest that simple prediction is more effective. Therefore, we considered using a linear regression model to see if it might perform better. As shown in the results below, the linear regression model performs better than the simple prediction, as it has a lower RMSE.

In [ ]:
```
#Oranganize feature and target data
import numpy as np
n=len(data['GOLD'])
x=[]
y=[]
for i in range(n-5):
  x.append(list(data['GOLD'].iloc[i:i+5]))
  y.append(data['GOLD'].iloc[i+5])
X=np.array(x)
y=np.array(y)
print(X[0:2])
print(y[0:2])
```

```
[[15.3125     15.68999958 14.90999985 15.84000015 16.26000023]
 [15.68999958 14.90999985 15.84000015 16.26000023 16.31999969]]
[16.31999969 15.80000019]
```

In [ ]:
```
from sklearn.linear_model import LinearRegression

reg = LinearRegression().fit(X[0:1472], y[0:1472])
pred=reg.predict(X[1472:])
plt.plot(pred, label="1-steps ahead prediction")
plt.plot(y[1472:], "r--", label="True value")
plt.legend(loc="lower left")
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x7d045f25a110>
```



In [ ]:
```
#Results - RMSE
print("RMSE of Model 4:", mean_squared_error(pred, y[1472:]))

print("RMSE of Simple Prediction:", currentval_rmse)
```

```
RMSE of Model 4: 0.530480346146961
RMSE of Simple Prediction: 0.5689821043887909
```

Summary - Regressors

These models aimed to predict gold prices using regressors. We began by testing correlations to select features, identifying DX-Y.NYB and PL=F as initially promising variables. Despite tuning a random forest regressor, its RMSE was significantly higher than that of a simple prediction method, highlighting the superior effectiveness of the simpler approach and the strong influence of $GOLD_t$ on future prices. Further exploration revealed that without $GOLD_t$, predictions performed poorly, and even a random forest model using only $GOLD_t$ failed to outperform the simple method. Ultimately, a linear regression model provided the best results, achieving a lower RMSE than the simple prediction, demonstrating its better capability in forecasting gold prices amoung the regressors.

Neural Networks (Eric Lee)

Long Short Term Memory (LSTM)

In this section, I create a deep Neural Network model using LSTM cells. The characteristics of LSTM cells make them particularly effective for time series prediction, as they carry significant older information to the next cell, addressing the limitations of simple RNN models.

In this project, gold price prediction is treated as a time series problem. The LSTM structure is likely to be a good fit for this task. For my Neural Network model, I will use the following structure:

- LSTM layer with 100 units and return_sequences=True
- Dropout layer with a rate of 0.2
- Another LSTM layer with 100 units and return_sequences=True
- Dropout layer with a rate of 0.2
- A final LSTM layer with 100 units
- Dropout layer with a rate of 0.2
- Dense layer with 50 units
- Dense output layer with 1 unit

Additionally, I want to evaluate how this Neural Network model performs with different types of input datasets: one with all variables, one without the gold price variable, and one with only the gold price variable. Generally, I split the input data into 80% training, 10% validation, and 10% test sets.

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
from keras.backend import clear_session
from keras.callbacks import EarlyStopping
from tensorflow.random import set_seed
from sklearn.metrics import mean_absolute_percentage_error, mean_squared_error
```

In [ ]:
```
data = pd.read_csv("temp.csv")
data['Date'] = pd.to_datetime(data['Date'])
data.sort_values(by='Date', ascending=True, inplace=True)
data.set_index('Date', inplace=True)
data
```

Out[ ]:

Date	GOLD	^GSPC	^DJI	^VIX	^FTSE	000001.SS	^N225	DX-Y.NYB	SI=F	PL=F	CL=F	^TNX
2000-12-01	15.312500	1315.229980	10373.540039	27.480000	6170.399902	2081.843018	14835.330078	114.730003	4.640000	612.000000	32.049999	5.513
2000-12-04	15.690000	1324.969971	10560.950195	27.780001	6158.700195	2092.138916	14954.730469	113.709999	4.714000	622.099976	31.299999	5.522
2000-12-05	14.910000	1376.540039	10898.719727	24.990000	6299.000000	2091.669922	14695.049805	114.470001	4.704000	607.400024	29.549999	5.430
2000-12-06	15.840000	1351.459961	10664.379883	25.070000	6273.299805	2075.626953	14889.370117	113.309998	4.754000	605.400024	29.850000	5.319
2000-12-07	16.260000	1343.550049	10617.360352	25.340000	6231.399902	2075.043945	14720.360352	113.540001	4.724000	612.599976	29.360001	5.299
...	...	...	...	...	...	...	...	...	...	...	...	...
2024-05-13	16.940001	5221.419922	39431.511719	13.600000	8415.000000	3148.020996	38179.460938	105.220001	28.221001	1005.299988	79.120003	4.481
2024-05-14	17.150000	5246.680176	39558.109375	13.420000	8428.099609	3145.773926	38356.058594	105.010002	28.485001	1039.300049	78.019997	4.445
2024-05-15	17.420000	5308.149902	39908.000000	12.450000	8445.799805	3119.902100	38385.730469	104.349998	29.514000	1063.300049	78.629997	4.356
2024-05-16	17.520000	5297.100098	39869.378906	12.420000	8438.700195	3122.400879	38920.261719	104.459999	29.665001	1065.400024	79.230003	4.377
2024-05-17	17.889999	5303.270020	40003.589844	11.990000	8420.299805	3154.025879	38787.378906	104.449997	31.047001	1084.599976	80.059998	4.420

5901 rows × 12 columns

In [ ]:
```
def train_lstm_model(X_train, y_train, X_validation, y_validation, time_step):
  model = Sequential()
  model.add(LSTM(100, return_sequences=True, input_shape=(time_step, X_train.shape[2])))
  model.add(Dropout(0.2))
  model.add(LSTM(100, return_sequences=True))
  model.add(Dropout(0.2))
  model.add(LSTM(100))
  model.add(Dropout(0.2))
  model.add(Dense(50))
  model.add(Dense(1))

  model.compile(optimizer='adam', loss='mean_squared_error')

  # Train the model

  # early_stop = EarlyStopping(monitor='val_loss', patience=20, min_delta=0.01, restore_best_weights=True)
  # early_stop = EarlyStopping(patience=10,min_delta=0.01, restore_best_weights=True, monitor="val_last_time_step_mse", mode="min")

  run = model.fit(X_train, y_train, epochs=150, batch_size=32, validation_data=(X_validation, y_validation), verbose=1)
```

```
    # model.fit(X_train, y_train, epochs=150, batch_size=32, validation_split=0.1, verbose=1, callbacks=[early_stop])

    # Make predictions
    train_predict = model.predict(X_train)
    validation_predict = model.predict(X_validation)
    test_predict = model.predict(X_test)

    # Reshape the predictions to be 2D arrays for inverse transformation
    train_predict = train_predict.reshape(-1, 1)
    validation_predict = validation_predict.reshape(-1, 1)
    test_predict = test_predict.reshape(-1, 1)

    # Create an empty array for inverse transformation
    train_predict_full = np.zeros((train_predict.shape[0], scaled_data.shape[1]))
    validation_predict_full = np.zeros((validation_predict.shape[0], scaled_data.shape[1]))
    test_predict_full = np.zeros((test_predict.shape[0], scaled_data.shape[1]))

    # Insert the predictions into the appropriate column
    train_predict_full[:, gold_index] = train_predict.flatten()
    validation_predict_full[:, gold_index] = validation_predict.flatten()
    test_predict_full[:, gold_index] = test_predict.flatten()

    # Inverse transform the predictions
    train_predict = scaler.inverse_transform(train_predict_full)[:, gold_index]
    validation_predict = scaler.inverse_transform(validation_predict_full)[:, gold_index]
    test_predict = scaler.inverse_transform(test_predict_full)[:, gold_index]

    # Inverse transform the actual target values for comparison
    y_train_actual = scaler.inverse_transform(np.concatenate((np.zeros((y_train.shape[0], gold_index)), y_train.reshape(-1, 1), np.zeros((y_train.shape[0], scaled_data.shape[1] -
    y_validation_actual = scaler.inverse_transform(np.concatenate((np.zeros((y_validation.shape[0], gold_index)), y_validation.reshape(-1, 1), np.zeros((y_validation.shape[0], sca
    y_test_actual = scaler.inverse_transform(np.concatenate((np.zeros((y_test.shape[0], gold_index)), y_test.reshape(-1, 1), np.zeros((y_test.shape[0], scaled_data.shape[1] - gold
    return train_predict, validation_predict, test_predict, y_train_actual, y_validation_actual, y_test_actual, run

def plot_predictions(y_actual, y_pred, title):
    plt.figure(figsize=(14, 7))
    plt.plot(y_actual, color='blue', label='Actual Gold Price')
    plt.plot(y_pred, color='red', linestyle='--', label='Predicted Gold Price')
    plt.title(title)
    plt.xlabel('Time')
    plt.ylabel('Gold Price')
    plt.legend()
    plt.show()

def show_results(train_predict, y_train_actual, validation_predict, y_validation_actual, test_predict, y_test_actual, history, zoom):
    # Plot the training predictions
    plot_predictions(y_train_actual, train_predict, 'Training Set: Actual vs Predicted Gold Price')

    # Plot the validation predictions
    plot_predictions(y_validation_actual, validation_predict, 'Validation Set: Actual vs Predicted Gold Price')

    # Plot the test predictions
    plot_predictions(y_test_actual, test_predict, 'Test Set: Actual vs Predicted Gold Price')

    # Plot the training and validation loss
    pd.DataFrame(history.history).plot(figsize=(8, 5))
    plt.grid(True)
    plt.gca().set_ylim(0, zoom)  # Adjust the y-axis limit to zoom in
    plt.title('Training and Validation Loss')
    plt.show()

    print("RMSE of Model:", np.sqrt(mean_squared_error(y_test_actual, test_predict)))
    MAPE = mean_absolute_percentage_error(y_test_actual, test_predict)

    Accuracy = 1 - MAPE
    print("Accuracy:", Accuracy)

def reset_session(seed=42):
    set_seed(seed)
    np.random.seed(seed)
    clear_session()
```

Method 1 - All Variables

using all variables as input data

In [ ]:
```
reset_session()
gold_index = data.columns.get_loc("GOLD")
# Feature scaling
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data)

# Define the train, validation, and test size
train_size = int(len(scaled_data) * 0.8)
validation_size = int(len(scaled_data) * 0.1)
test_size = len(scaled_data) - train_size - validation_size

# Split the data
train_data = scaled_data[:train_size]
validation_data = scaled_data[train_size:train_size + validation_size]
test_data = scaled_data[train_size + validation_size:]

# Create a function to prepare the dataset for LSTM
def create_dataset(data, time_step=1):
    X, y = [], []
    for i in range(len(data) - time_step - 1):
        a = data[i:(i + time_step), :]
        X.append(a)
        y.append(data[i + time_step, gold_index])
    return np.array(X), np.array(y)

time_step = 60  # you can choose any time step

# Create datasets
X_train, y_train = create_dataset(train_data, time_step)
X_validation, y_validation = create_dataset(validation_data, time_step)
X_test, y_test = create_dataset(test_data, time_step)
# Print shapes to verify
print(f"X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
print(f"X_validation shape: {X_validation.shape}, y_validation shape: {y_validation.shape}")
print(f"X_test shape: {X_test.shape}, y_test shape: {y_test.shape}")
```

```
X_train shape: (4659, 60, 12), y_train shape: (4659,)
X_validation shape: (529, 60, 12), y_validation shape: (529,)
X_test shape: (530, 60, 12), y_test shape: (530,)
```

In [ ]:
```
# Train the model
train_predict, validation_predict, test_predict, y_train_actual, y_validation_actual, y_test_actual, run = train_lstm_model(X_train, y_train, X_validation, y_validation, time_st
```

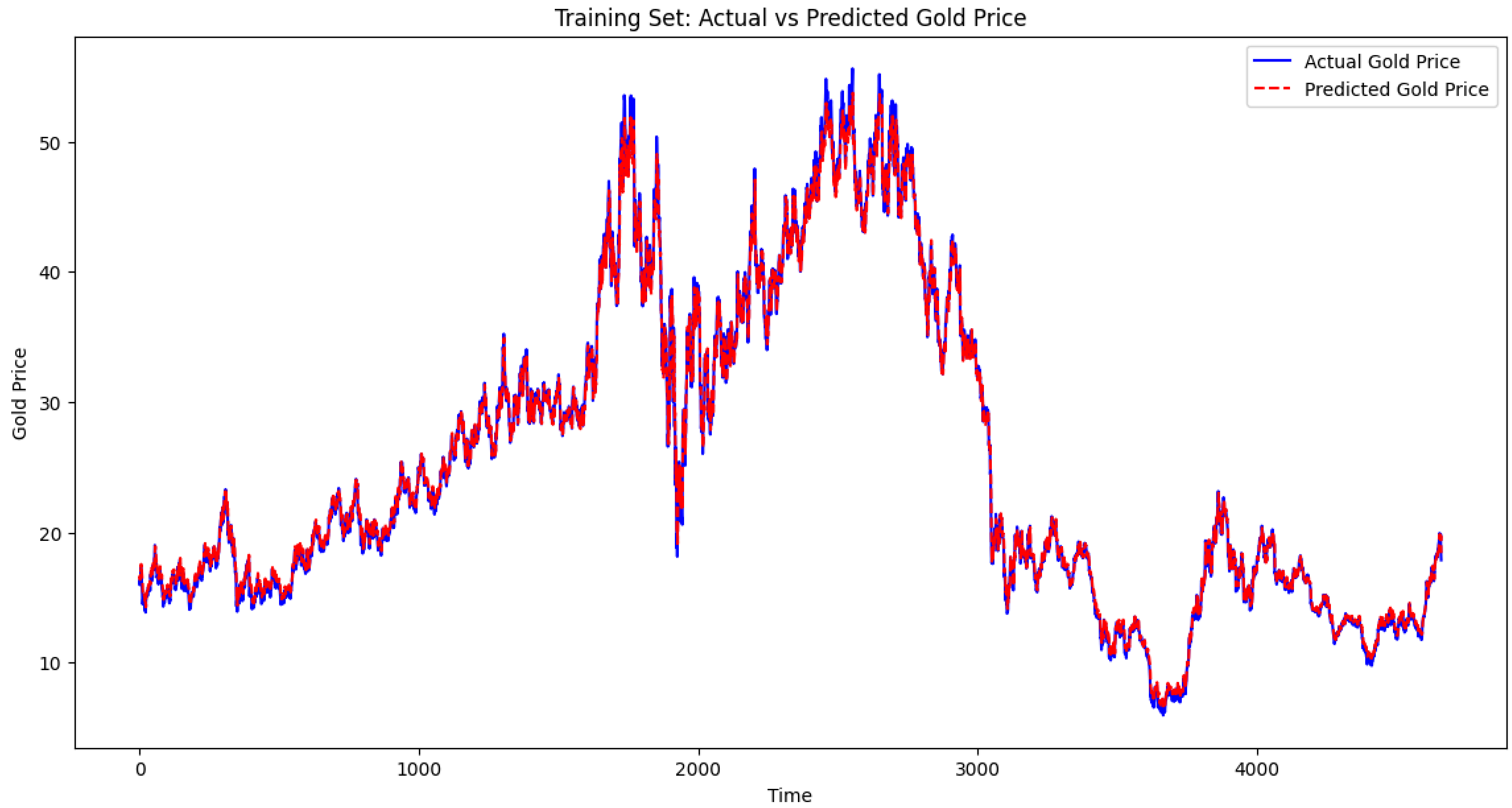
```
Epoch 1/150
146/146 [==============================] - 7s 18ms/step - loss: 0.0065 - val_loss: 0.0069
Epoch 2/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0029 - val_loss: 0.0023
Epoch 3/150
146/146 [==============================] - 2s 15ms/step - loss: 0.0024 - val_loss: 0.0057
Epoch 4/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0023 - val_loss: 0.0068
Epoch 5/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0017 - val_loss: 0.0036
Epoch 6/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0017 - val_loss: 0.0024
Epoch 7/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0016 - val_loss: 0.0024
Epoch 8/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0013 - val_loss: 0.0021
Epoch 9/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0013 - val_loss: 0.0033
Epoch 10/150
146/146 [==============================] - 2s 14ms/step - loss: 0.0012 - val_loss: 0.0021
Epoch 11/150
146/146 [==============================] - 2s 13ms/step - loss: 0.0012 - val_loss: 0.0023
Epoch 12/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0011 - val_loss: 0.0029
Epoch 13/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0010 - val_loss: 6.7689e-04
Epoch 14/150
146/146 [==============================] - 2s 12ms/step - loss: 9.9598e-04 - val_loss: 7.3565e-04
Epoch 15/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0010 - val_loss: 6.5525e-04
Epoch 16/150
146/146 [==============================] - 3s 20ms/step - loss: 0.0010 - val_loss: 9.1218e-04
Epoch 17/150
146/146 [==============================] - 4s 28ms/step - loss: 9.1898e-04 - val_loss: 5.6085e-04
Epoch 18/150
146/146 [==============================] - 3s 21ms/step - loss: 9.7991e-04 - val_loss: 3.7728e-04
Epoch 19/150
146/146 [==============================] - 3s 19ms/step - loss: 8.7421e-04 - val_loss: 0.0010
Epoch 20/150
146/146 [==============================] - 3s 21ms/step - loss: 9.6472e-04 - val_loss: 5.9110e-04
Epoch 21/150
146/146 [==============================] - 4s 30ms/step - loss: 8.6201e-04 - val_loss: 0.0015
Epoch 22/150
146/146 [==============================] - 3s 17ms/step - loss: 8.0247e-04 - val_loss: 3.6979e-04
Epoch 23/150
146/146 [==============================] - 2s 16ms/step - loss: 9.1800e-04 - val_loss: 3.7406e-04
Epoch 24/150
146/146 [==============================] - 2s 16ms/step - loss: 8.0456e-04 - val_loss: 8.1823e-04
Epoch 25/150
146/146 [==============================] - 3s 18ms/step - loss: 9.1967e-04 - val_loss: 3.6084e-04
Epoch 26/150
146/146 [==============================] - 2s 15ms/step - loss: 8.6338e-04 - val_loss: 8.1736e-04
Epoch 27/150
146/146 [==============================] - 2s 11ms/step - loss: 7.1834e-04 - val_loss: 8.2894e-04
Epoch 28/150
146/146 [==============================] - 2s 11ms/step - loss: 8.2615e-04 - val_loss: 2.6105e-04
Epoch 29/150
146/146 [==============================] - 2s 11ms/step - loss: 7.7758e-04 - val_loss: 0.0010
Epoch 30/150
146/146 [==============================] - 2s 11ms/step - loss: 7.6274e-04 - val_loss: 2.4614e-04
Epoch 31/150
146/146 [==============================] - 2s 11ms/step - loss: 7.2470e-04 - val_loss: 4.4245e-04
Epoch 32/150
146/146 [==============================] - 2s 12ms/step - loss: 6.9432e-04 - val_loss: 0.0011
Epoch 33/150
146/146 [==============================] - 2s 15ms/step - loss: 6.9851e-04 - val_loss: 7.1762e-04
Epoch 34/150
146/146 [==============================] - 2s 14ms/step - loss: 7.1619e-04 - val_loss: 1.9264e-04
Epoch 35/150
146/146 [==============================] - 2s 11ms/step - loss: 6.6847e-04 - val_loss: 2.6484e-04
Epoch 36/150
146/146 [==============================] - 2s 11ms/step - loss: 7.2710e-04 - val_loss: 2.1898e-04
Epoch 37/150
146/146 [==============================] - 2s 11ms/step - loss: 6.7562e-04 - val_loss: 6.2369e-04
Epoch 38/150
146/146 [==============================] - 2s 11ms/step - loss: 6.4214e-04 - val_loss: 4.5048e-04
Epoch 39/150
146/146 [==============================] - 2s 11ms/step - loss: 6.9637e-04 - val_loss: 2.9189e-04
Epoch 40/150
146/146 [==============================] - 2s 14ms/step - loss: 8.6353e-04 - val_loss: 0.0017
Epoch 41/150
146/146 [==============================] - 2s 15ms/step - loss: 7.2319e-04 - val_loss: 3.9925e-04
Epoch 42/150
146/146 [==============================] - 2s 12ms/step - loss: 7.1333e-04 - val_loss: 1.6178e-04
Epoch 43/150
146/146 [==============================] - 2s 12ms/step - loss: 5.9853e-04 - val_loss: 1.7312e-04
Epoch 44/150
146/146 [==============================] - 2s 12ms/step - loss: 6.1297e-04 - val_loss: 1.6840e-04
Epoch 45/150
146/146 [==============================] - 2s 12ms/step - loss: 6.4345e-04 - val_loss: 1.8204e-04
Epoch 46/150
146/146 [==============================] - 2s 12ms/step - loss: 6.9680e-04 - val_loss: 1.8877e-04
Epoch 47/150
146/146 [==============================] - 2s 14ms/step - loss: 6.5897e-04 - val_loss: 2.4608e-04
Epoch 48/150
146/146 [==============================] - 2s 16ms/step - loss: 7.4042e-04 - val_loss: 1.8844e-04
Epoch 49/150
146/146 [==============================] - 2s 13ms/step - loss: 6.7174e-04 - val_loss: 1.5704e-04
Epoch 50/150
146/146 [==============================] - 2s 12ms/step - loss: 6.8551e-04 - val_loss: 2.8866e-04
Epoch 51/150
146/146 [==============================] - 2s 12ms/step - loss: 6.3913e-04 - val_loss: 1.8906e-04
Epoch 52/150
146/146 [==============================] - 2s 12ms/step - loss: 6.3995e-04 - val_loss: 1.9109e-04
Epoch 53/150
146/146 [==============================] - 2s 12ms/step - loss: 6.0709e-04 - val_loss: 1.4122e-04
Epoch 54/150
146/146 [==============================] - 2s 13ms/step - loss: 6.3556e-04 - val_loss: 1.5953e-04
Epoch 55/150
146/146 [==============================] - 2s 15ms/step - loss: 6.5370e-04 - val_loss: 2.0374e-04
Epoch 56/150
146/146 [==============================] - 2s 11ms/step - loss: 6.4793e-04 - val_loss: 4.6880e-04
Epoch 57/150
146/146 [==============================] - 2s 11ms/step - loss: 6.6779e-04 - val_loss: 1.8877e-04
Epoch 58/150
146/146 [==============================] - 2s 11ms/step - loss: 6.0925e-04 - val_loss: 2.7470e-04
Epoch 59/150
146/146 [==============================] - 2s 11ms/step - loss: 6.4977e-04 - val_loss: 2.4048e-04
Epoch 60/150
146/146 [==============================] - 2s 11ms/step - loss: 7.1068e-04 - val_loss: 1.5690e-04
Epoch 61/150
146/146 [==============================] - 2s 11ms/step - loss: 6.0877e-04 - val_loss: 1.9585e-04
Epoch 62/150
146/146 [==============================] - 2s 15ms/step - loss: 6.3159e-04 - val_loss: 1.7736e-04
Epoch 63/150
146/146 [==============================] - 2s 13ms/step - loss: 7.7901e-04 - val_loss: 1.9056e-04
Epoch 64/150
146/146 [==============================] - 2s 11ms/step - loss: 6.1286e-04 - val_loss: 2.4578e-04
Epoch 65/150
146/146 [==============================] - 2s 11ms/step - loss: 6.0131e-04 - val_loss: 1.5094e-04
Epoch 66/150
146/146 [==============================] - 2s 11ms/step - loss: 6.2491e-04 - val_loss: 2.1860e-04
Epoch 67/150
```

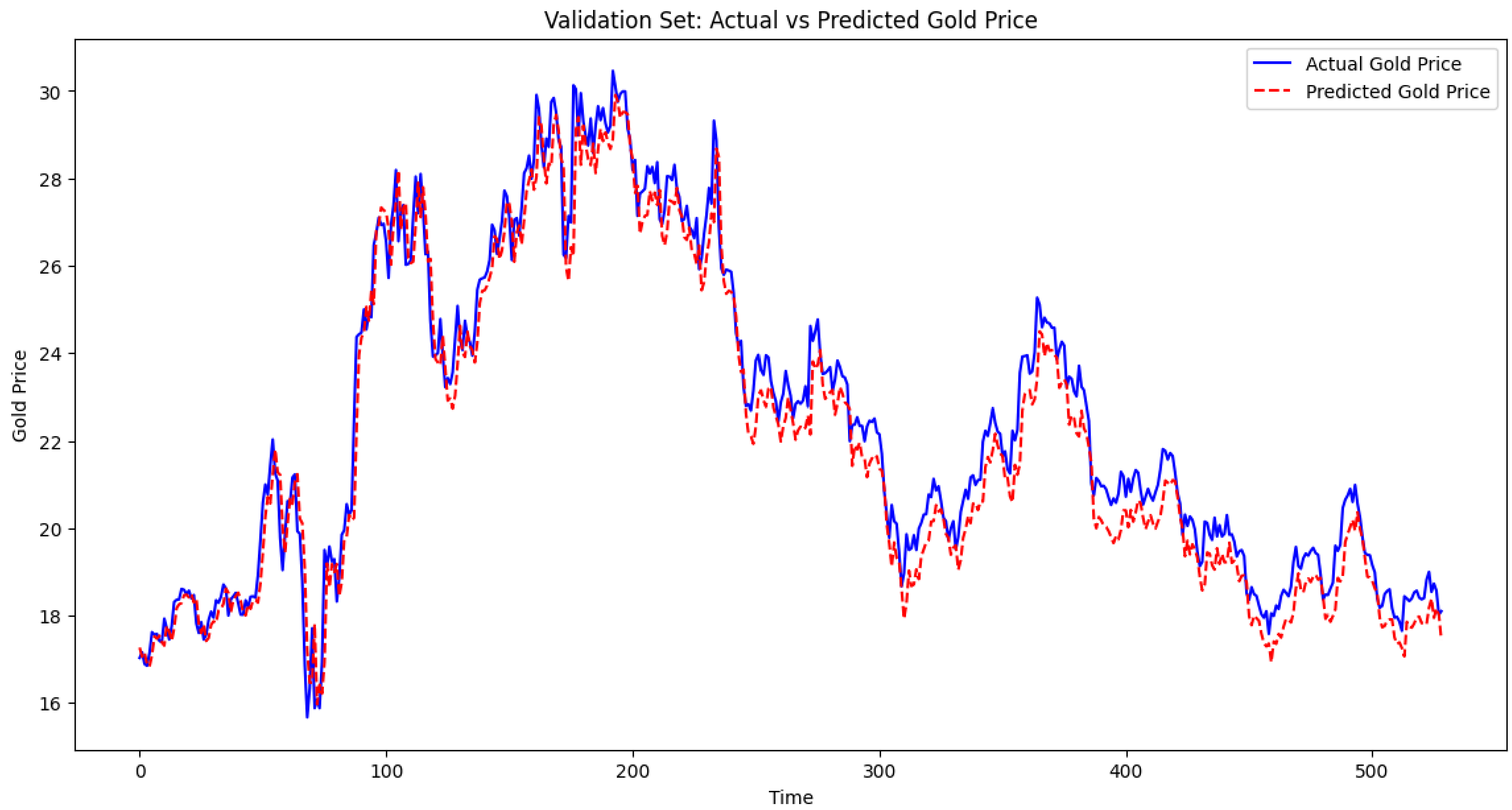
```
146/146 [==============================] - 2s 11ms/step - loss: 5.6667e-04 - val_loss: 1.3840e-04
Epoch 68/150
146/146 [==============================] - 2s 11ms/step - loss: 7.0640e-04 - val_loss: 1.9817e-04
Epoch 69/150
146/146 [==============================] - 2s 13ms/step - loss: 5.8924e-04 - val_loss: 3.5722e-04
Epoch 70/150
146/146 [==============================] - 2s 15ms/step - loss: 5.4828e-04 - val_loss: 2.0981e-04
Epoch 71/150
146/146 [==============================] - 2s 11ms/step - loss: 5.7313e-04 - val_loss: 1.5574e-04
Epoch 72/150
146/146 [==============================] - 2s 12ms/step - loss: 5.7823e-04 - val_loss: 1.9458e-04
Epoch 73/150
146/146 [==============================] - 2s 14ms/step - loss: 5.6991e-04 - val_loss: 2.5988e-04
Epoch 74/150
146/146 [==============================] - 2s 11ms/step - loss: 6.0981e-04 - val_loss: 0.0011
Epoch 75/150
146/146 [==============================] - 2s 12ms/step - loss: 6.0497e-04 - val_loss: 1.4678e-04
Epoch 76/150
146/146 [==============================] - 2s 17ms/step - loss: 5.7755e-04 - val_loss: 7.6098e-04
Epoch 77/150
146/146 [==============================] - 3s 19ms/step - loss: 6.4089e-04 - val_loss: 1.9721e-04
Epoch 78/150
146/146 [==============================] - 2s 12ms/step - loss: 5.8437e-04 - val_loss: 3.4463e-04
Epoch 79/150
146/146 [==============================] - 2s 12ms/step - loss: 5.7442e-04 - val_loss: 2.0960e-04
Epoch 80/150
146/146 [==============================] - 2s 12ms/step - loss: 6.0567e-04 - val_loss: 1.9749e-04
Epoch 81/150
146/146 [==============================] - 2s 12ms/step - loss: 5.6461e-04 - val_loss: 1.9220e-04
Epoch 82/150
146/146 [==============================] - 2s 12ms/step - loss: 5.2393e-04 - val_loss: 2.4527e-04
Epoch 83/150
146/146 [==============================] - 2s 15ms/step - loss: 6.7133e-04 - val_loss: 2.7659e-04
Epoch 84/150
146/146 [==============================] - 2s 14ms/step - loss: 5.5132e-04 - val_loss: 3.6926e-04
Epoch 85/150
146/146 [==============================] - 2s 13ms/step - loss: 5.1107e-04 - val_loss: 3.8357e-04
Epoch 86/150
146/146 [==============================] - 2s 11ms/step - loss: 6.1783e-04 - val_loss: 8.1246e-04
Epoch 87/150
146/146 [==============================] - 2s 11ms/step - loss: 5.7013e-04 - val_loss: 1.4134e-04
Epoch 88/150
146/146 [==============================] - 2s 11ms/step - loss: 5.6691e-04 - val_loss: 1.9440e-04
Epoch 89/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8322e-04 - val_loss: 4.2386e-04
Epoch 90/150
146/146 [==============================] - 3s 21ms/step - loss: 5.3050e-04 - val_loss: 1.9511e-04
Epoch 91/150
146/146 [==============================] - 2s 17ms/step - loss: 5.3144e-04 - val_loss: 2.8819e-04
Epoch 92/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8700e-04 - val_loss: 1.5844e-04
Epoch 93/150
146/146 [==============================] - 2s 12ms/step - loss: 5.4312e-04 - val_loss: 2.2852e-04
Epoch 94/150
146/146 [==============================] - 2s 12ms/step - loss: 5.5678e-04 - val_loss: 1.6083e-04
Epoch 95/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0920e-04 - val_loss: 1.7186e-04
Epoch 96/150
146/146 [==============================] - 2s 11ms/step - loss: 5.2240e-04 - val_loss: 2.7258e-04
Epoch 97/150
146/146 [==============================] - 2s 15ms/step - loss: 6.2577e-04 - val_loss: 1.8690e-04
Epoch 98/150
146/146 [==============================] - 2s 14ms/step - loss: 6.1710e-04 - val_loss: 1.6424e-04
Epoch 99/150
146/146 [==============================] - 2s 11ms/step - loss: 5.7602e-04 - val_loss: 1.6599e-04
Epoch 100/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0685e-04 - val_loss: 2.2413e-04
Epoch 101/150
146/146 [==============================] - 2s 11ms/step - loss: 5.3313e-04 - val_loss: 1.9253e-04
Epoch 102/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8575e-04 - val_loss: 2.0422e-04
Epoch 103/150
146/146 [==============================] - 2s 11ms/step - loss: 5.5720e-04 - val_loss: 1.6150e-04
Epoch 104/150
146/146 [==============================] - 2s 13ms/step - loss: 5.5738e-04 - val_loss: 2.9820e-04
Epoch 105/150
146/146 [==============================] - 2s 17ms/step - loss: 5.3945e-04 - val_loss: 1.6282e-04
Epoch 106/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8353e-04 - val_loss: 4.4522e-04
Epoch 107/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1862e-04 - val_loss: 1.5829e-04
Epoch 108/150
146/146 [==============================] - 2s 12ms/step - loss: 5.5043e-04 - val_loss: 1.7720e-04
Epoch 109/150
146/146 [==============================] - 2s 12ms/step - loss: 5.7714e-04 - val_loss: 1.5356e-04
Epoch 110/150
146/146 [==============================] - 2s 12ms/step - loss: 5.2530e-04 - val_loss: 2.3536e-04
Epoch 111/150
146/146 [==============================] - 2s 14ms/step - loss: 5.7708e-04 - val_loss: 3.0002e-04
Epoch 112/150
146/146 [==============================] - 2s 16ms/step - loss: 5.4728e-04 - val_loss: 1.9353e-04
Epoch 113/150
146/146 [==============================] - 2s 12ms/step - loss: 5.3200e-04 - val_loss: 4.2526e-04
Epoch 114/150
146/146 [==============================] - 2s 12ms/step - loss: 5.2313e-04 - val_loss: 2.3276e-04
Epoch 115/150
146/146 [==============================] - 2s 12ms/step - loss: 5.6660e-04 - val_loss: 1.8345e-04
Epoch 116/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1697e-04 - val_loss: 2.0305e-04
Epoch 117/150
146/146 [==============================] - 2s 12ms/step - loss: 5.4065e-04 - val_loss: 1.8532e-04
Epoch 118/150
146/146 [==============================] - 2s 13ms/step - loss: 5.0176e-04 - val_loss: 1.7838e-04
Epoch 119/150
146/146 [==============================] - 2s 16ms/step - loss: 5.1465e-04 - val_loss: 4.1796e-04
Epoch 120/150
146/146 [==============================] - 2s 11ms/step - loss: 5.1132e-04 - val_loss: 2.1425e-04
Epoch 121/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0931e-04 - val_loss: 1.7893e-04
Epoch 122/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0671e-04 - val_loss: 4.3381e-04
Epoch 123/150
146/146 [==============================] - 2s 11ms/step - loss: 5.5770e-04 - val_loss: 1.7705e-04
Epoch 124/150
146/146 [==============================] - 2s 11ms/step - loss: 5.2678e-04 - val_loss: 1.9673e-04
Epoch 125/150
146/146 [==============================] - 2s 12ms/step - loss: 5.7010e-04 - val_loss: 8.1253e-04
Epoch 126/150
146/146 [==============================] - 2s 15ms/step - loss: 5.4295e-04 - val_loss: 4.0229e-04
Epoch 127/150
146/146 [==============================] - 2s 12ms/step - loss: 5.4960e-04 - val_loss: 1.5071e-04
Epoch 128/150
146/146 [==============================] - 2s 11ms/step - loss: 5.1038e-04 - val_loss: 4.4330e-04
Epoch 129/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0303e-04 - val_loss: 1.8141e-04
Epoch 130/150
146/146 [==============================] - 2s 11ms/step - loss: 4.9041e-04 - val_loss: 1.8956e-04
Epoch 131/150
146/146 [==============================] - 2s 12ms/step - loss: 5.3684e-04 - val_loss: 6.3971e-04
Epoch 132/150
146/146 [==============================] - 2s 12ms/step - loss: 5.5884e-04 - val_loss: 2.0304e-04
Epoch 133/150
146/146 [==============================] - 2s 15ms/step - loss: 5.5615e-04 - val_loss: 1.5799e-04
```

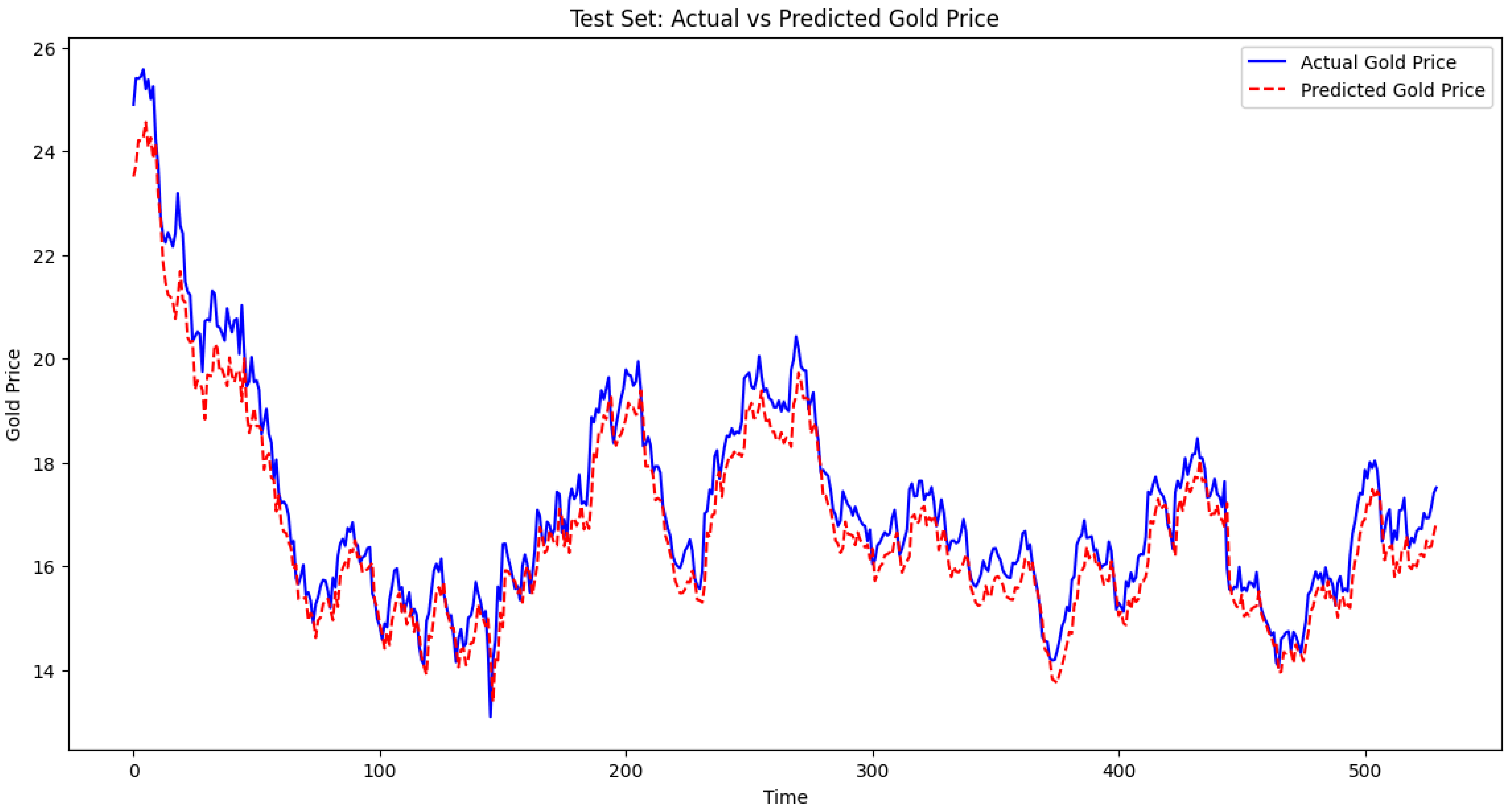
```
Epoch 134/150
146/146 [==============================] - 2s 17ms/step - loss: 5.2938e-04 - val_loss: 4.2706e-04
Epoch 135/150
146/146 [==============================] - 2s 11ms/step - loss: 4.6154e-04 - val_loss: 3.2556e-04
Epoch 136/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0736e-04 - val_loss: 1.6064e-04
Epoch 137/150
146/146 [==============================] - 2s 11ms/step - loss: 5.3480e-04 - val_loss: 1.7934e-04
Epoch 138/150
146/146 [==============================] - 2s 12ms/step - loss: 5.5586e-04 - val_loss: 1.5253e-04
Epoch 139/150
146/146 [==============================] - 2s 12ms/step - loss: 4.8357e-04 - val_loss: 2.9055e-04
Epoch 140/150
146/146 [==============================] - 2s 16ms/step - loss: 5.5416e-04 - val_loss: 2.9523e-04
Epoch 141/150
146/146 [==============================] - 2s 14ms/step - loss: 4.6647e-04 - val_loss: 2.0439e-04
Epoch 142/150
146/146 [==============================] - 2s 12ms/step - loss: 4.9373e-04 - val_loss: 2.1813e-04
Epoch 143/150
146/146 [==============================] - 2s 12ms/step - loss: 4.9642e-04 - val_loss: 2.6532e-04
Epoch 144/150
146/146 [==============================] - 2s 12ms/step - loss: 4.8822e-04 - val_loss: 1.8275e-04
Epoch 145/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1942e-04 - val_loss: 1.7230e-04
Epoch 146/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1964e-04 - val_loss: 2.4109e-04
Epoch 147/150
146/146 [==============================] - 2s 16ms/step - loss: 5.3169e-04 - val_loss: 2.0408e-04
Epoch 148/150
146/146 [==============================] - 2s 15ms/step - loss: 4.7603e-04 - val_loss: 1.4889e-04
Epoch 149/150
146/146 [==============================] - 2s 12ms/step - loss: 5.0491e-04 - val_loss: 1.7687e-04
Epoch 150/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1312e-04 - val_loss: 2.3952e-04
146/146 [==============================] - 2s 4ms/step
17/17 [==============================] - 0s 5ms/step
17/17 [==============================] - 0s 5ms/step
```

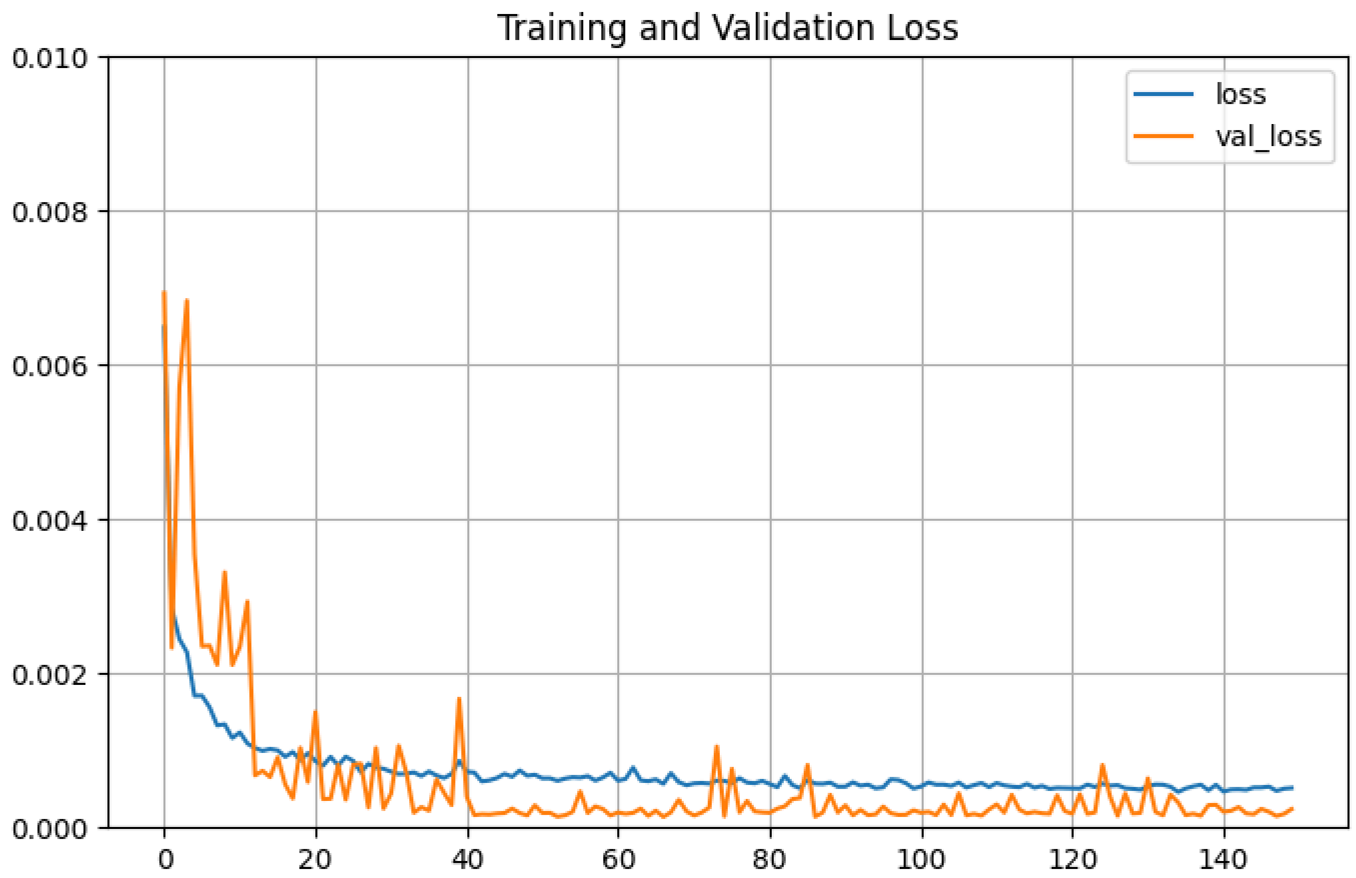
In [ ]:

```
# Plot the training predictions
show_results(train_predict, y_train_actual, validation_predict, y_validation_actual, test_predict, y_test_actual, run, 0.01)
```










```
RMSE of Model: 0.6200280078746165
Accuracy: 0.9708391645684088
```

Method 2 - No GOLD

uisng simply other variables but without gold price as input data

In [ ]:
```
reset_session()
# Feature scaling
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data)

# Define the train, validation, and test size
train_size = int(len(scaled_data) * 0.8)
validation_size = int(len(scaled_data) * 0.1)
test_size = len(scaled_data) - train_size - validation_size

# Split the data
train_data = scaled_data[:train_size]
validation_data = scaled_data[train_size:train_size + validation_size]
test_data = scaled_data[train_size + validation_size:]

# Separate the target variable (gold price) from the features
gold_index = data.columns.get_loc("GOLD")
X_train_data = np.delete(train_data, gold_index, axis=1)
y_train_data = train_data[:, gold_index]

X_validation_data = np.delete(validation_data, gold_index, axis=1)
y_validation_data = validation_data[:, gold_index]

X_test_data = np.delete(test_data, gold_index, axis=1)
y_test_data = test_data[:, gold_index]

# Create a function to prepare the dataset for LSTM
def create_dataset(X, y, time_step=1):
    Xs, ys = [], []
    for i in range(len(X) - time_step - 1):
        v = X[i:(i + time_step), :]
        Xs.append(v)
        ys.append(y[i + time_step])
    return np.array(Xs), np.array(ys)

time_step = 60 # you can choose any time step

# Create datasets
X_train, y_train = create_dataset(X_train_data, y_train_data, time_step)
X_validation, y_validation = create_dataset(X_validation_data, y_validation_data, time_step)
X_test, y_test = create_dataset(X_test_data, y_test_data, time_step)

# Print shapes to verify
print(f"X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
print(f"X_validation shape: {X_validation.shape}, y_validation shape: {y_validation.shape}")
print(f"X_test shape: {X_test.shape}, y_test shape: {y_test.shape}")
```

```
X_train shape: (4659, 60, 11), y_train shape: (4659,)
X_validation shape: (529, 60, 11), y_validation shape: (529,)
X_test shape: (530, 60, 11), y_test shape: (530,)
```

In [ ]:
```
# Train the model
train_predict, validation_predict, test_predict, y_train_actual, y_validation_actual, y_test_actual, run = train_lstm_model(X_train, y_train, X_validation, y_validation, time_st
```

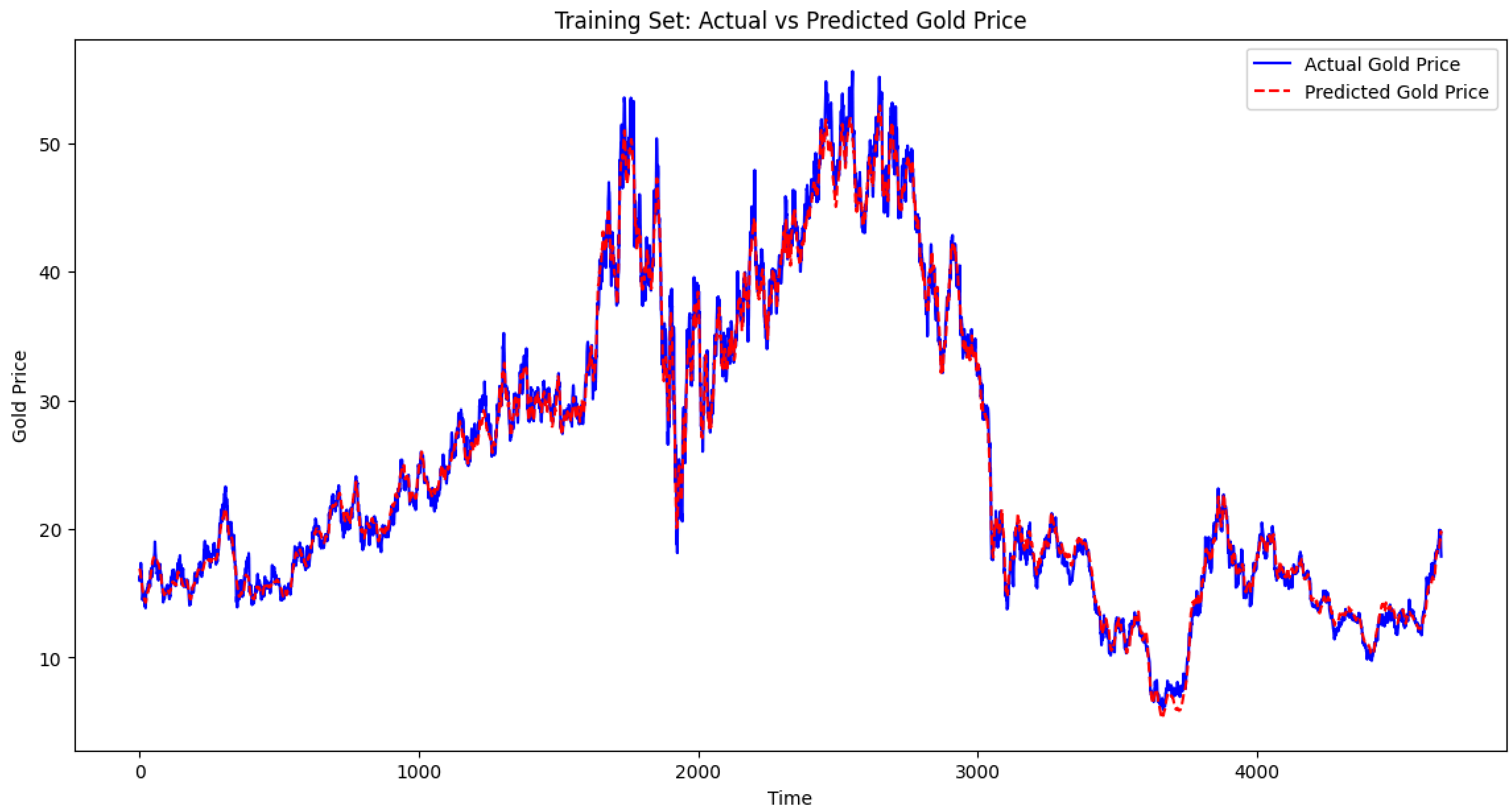
```
Epoch 1/150
146/146 [==============================] - 8s 21ms/step - loss: 0.0131 - val_loss: 0.0417
Epoch 2/150
146/146 [==============================] - 3s 17ms/step - loss: 0.0054 - val_loss: 0.0587
Epoch 3/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0038 - val_loss: 0.0384
Epoch 4/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0034 - val_loss: 0.0373
Epoch 5/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0031 - val_loss: 0.0521
Epoch 6/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0030 - val_loss: 0.0290
Epoch 7/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0026 - val_loss: 0.0213
Epoch 8/150
146/146 [==============================] - 2s 13ms/step - loss: 0.0025 - val_loss: 0.0204
Epoch 9/150
146/146 [==============================] - 2s 17ms/step - loss: 0.0024 - val_loss: 0.0197
Epoch 10/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0023 - val_loss: 0.0185
Epoch 11/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0022 - val_loss: 0.0213
Epoch 12/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0021 - val_loss: 0.0158
Epoch 13/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0018 - val_loss: 0.0129
Epoch 14/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0020 - val_loss: 0.0177
Epoch 15/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0020 - val_loss: 0.0188
Epoch 16/150
146/146 [==============================] - 2s 15ms/step - loss: 0.0018 - val_loss: 0.0157
Epoch 17/150
146/146 [==============================] - 2s 13ms/step - loss: 0.0018 - val_loss: 0.0123
Epoch 18/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0017 - val_loss: 0.0162
Epoch 19/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0018 - val_loss: 0.0093
Epoch 20/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0017 - val_loss: 0.0177
Epoch 21/150
146/146 [==============================] - 2s 14ms/step - loss: 0.0018 - val_loss: 0.0198
Epoch 22/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0017 - val_loss: 0.0184
Epoch 23/150
146/146 [==============================] - 2s 15ms/step - loss: 0.0018 - val_loss: 0.0128
Epoch 24/150
146/146 [==============================] - 2s 14ms/step - loss: 0.0016 - val_loss: 0.0157
Epoch 25/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0016 - val_loss: 0.0111
Epoch 26/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0016 - val_loss: 0.0277
Epoch 27/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0014 - val_loss: 0.0213
Epoch 28/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0014 - val_loss: 0.0147
Epoch 29/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0014 - val_loss: 0.0203
Epoch 30/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0014 - val_loss: 0.0167
Epoch 31/150
146/146 [==============================] - 2s 16ms/step - loss: 0.0013 - val_loss: 0.0161
Epoch 32/150
146/146 [==============================] - 2s 13ms/step - loss: 0.0015 - val_loss: 0.0205
Epoch 33/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0014 - val_loss: 0.0169
Epoch 34/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0013 - val_loss: 0.0123
Epoch 35/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0012 - val_loss: 0.0185
Epoch 36/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0013 - val_loss: 0.0124
Epoch 37/150
146/146 [==============================] - 2s 13ms/step - loss: 0.0013 - val_loss: 0.0097
Epoch 38/150
146/146 [==============================] - 2s 17ms/step - loss: 0.0013 - val_loss: 0.0130
Epoch 39/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0013 - val_loss: 0.0094
Epoch 40/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0013 - val_loss: 0.0179
Epoch 41/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0012 - val_loss: 0.0128
Epoch 42/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0012 - val_loss: 0.0138
Epoch 43/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0011 - val_loss: 0.0170
Epoch 44/150
146/146 [==============================] - 2s 14ms/step - loss: 0.0012 - val_loss: 0.0132
Epoch 45/150
146/146 [==============================] - 2s 16ms/step - loss: 0.0011 - val_loss: 0.0133
Epoch 46/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0012 - val_loss: 0.0129
Epoch 47/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0012 - val_loss: 0.0155
Epoch 48/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0013 - val_loss: 0.0137
Epoch 49/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0012 - val_loss: 0.0132
Epoch 50/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0011 - val_loss: 0.0133
Epoch 51/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0010 - val_loss: 0.0141
Epoch 52/150
146/146 [==============================] - 2s 15ms/step - loss: 0.0011 - val_loss: 0.0156
Epoch 53/150
146/146 [==============================] - 2s 14ms/step - loss: 0.0010 - val_loss: 0.0124
Epoch 54/150
146/146 [==============================] - 2s 12ms/step - loss: 9.9109e-04 - val_loss: 0.0115
Epoch 55/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0011 - val_loss: 0.0091
Epoch 56/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0011 - val_loss: 0.0098
Epoch 57/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0010 - val_loss: 0.0103
Epoch 58/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0011 - val_loss: 0.0145
Epoch 59/150
146/146 [==============================] - 2s 13ms/step - loss: 0.0010 - val_loss: 0.0133
Epoch 60/150
146/146 [==============================] - 2s 15ms/step - loss: 0.0010 - val_loss: 0.0078
Epoch 61/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0011 - val_loss: 0.0095
Epoch 62/150
146/146 [==============================] - 2s 11ms/step - loss: 9.3092e-04 - val_loss: 0.0132
Epoch 63/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0010 - val_loss: 0.0105
Epoch 64/150
146/146 [==============================] - 2s 11ms/step - loss: 9.6422e-04 - val_loss: 0.0111
Epoch 65/150
146/146 [==============================] - 2s 12ms/step - loss: 9.5114e-04 - val_loss: 0.0102
Epoch 66/150
146/146 [==============================] - 2s 12ms/step - loss: 9.1797e-04 - val_loss: 0.0070
Epoch 67/150
```

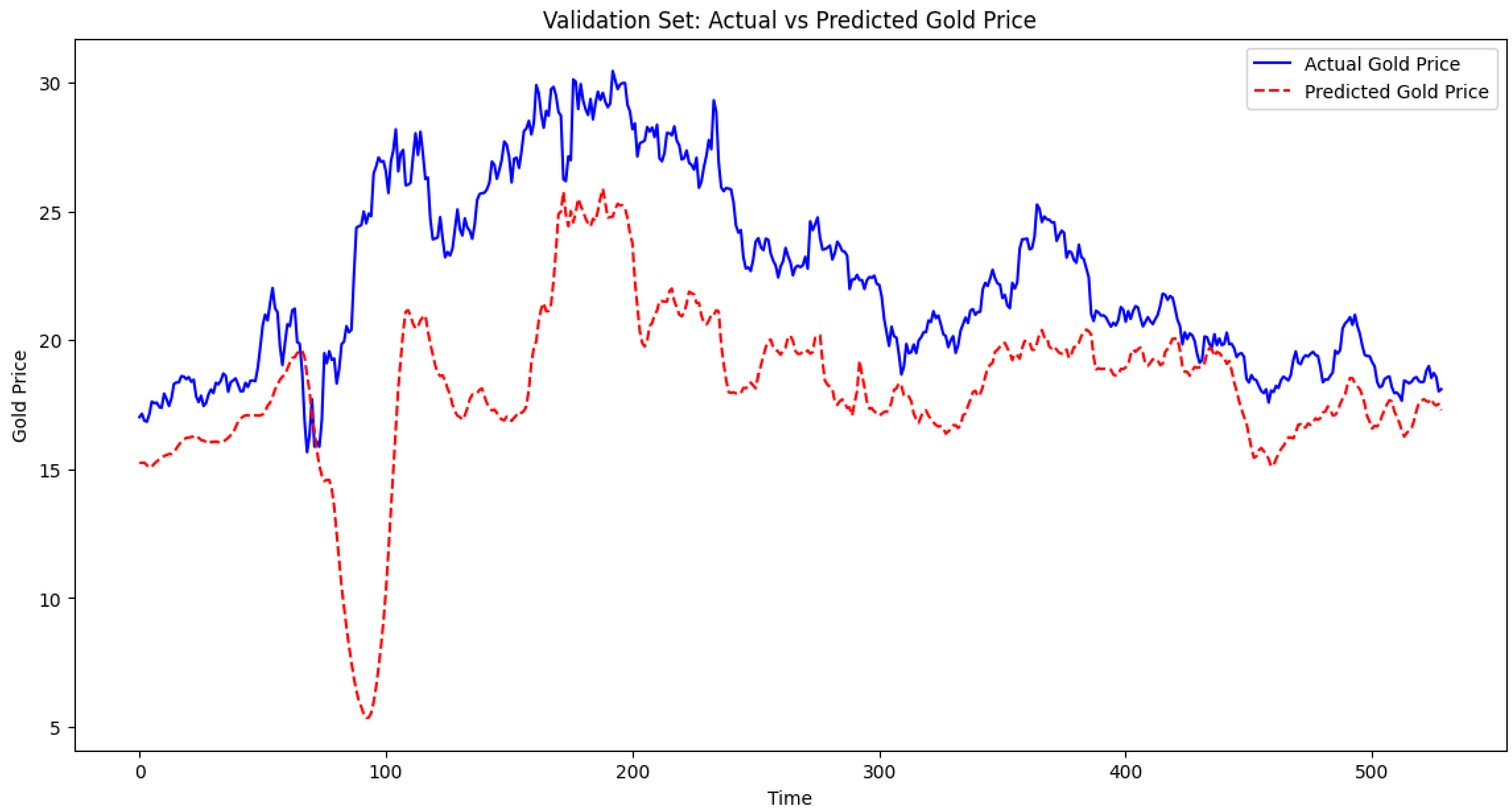
```
146/146 [==============================] - 2s 17ms/step - loss: 9.2515e-04 - val_loss: 0.0077
Epoch 68/150
146/146 [==============================] - 2s 13ms/step - loss: 9.6917e-04 - val_loss: 0.0104
Epoch 69/150
146/146 [==============================] - 2s 12ms/step - loss: 9.5509e-04 - val_loss: 0.0110
Epoch 70/150
146/146 [==============================] - 2s 12ms/step - loss: 8.4547e-04 - val_loss: 0.0128
Epoch 71/150
146/146 [==============================] - 2s 12ms/step - loss: 9.1633e-04 - val_loss: 0.0092
Epoch 72/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0011 - val_loss: 0.0070
Epoch 73/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0011 - val_loss: 0.0091
Epoch 74/150
146/146 [==============================] - 3s 18ms/step - loss: 8.2304e-04 - val_loss: 0.0139
Epoch 75/150
146/146 [==============================] - 2s 12ms/step - loss: 8.6011e-04 - val_loss: 0.0078
Epoch 76/150
146/146 [==============================] - 2s 12ms/step - loss: 8.9841e-04 - val_loss: 0.0103
Epoch 77/150
146/146 [==============================] - 2s 12ms/step - loss: 9.3106e-04 - val_loss: 0.0067
Epoch 78/150
146/146 [==============================] - 2s 11ms/step - loss: 8.1362e-04 - val_loss: 0.0074
Epoch 79/150
146/146 [==============================] - 2s 11ms/step - loss: 8.7651e-04 - val_loss: 0.0097
Epoch 80/150
146/146 [==============================] - 2s 11ms/step - loss: 8.3942e-04 - val_loss: 0.0078
Epoch 81/150
146/146 [==============================] - 2s 15ms/step - loss: 8.0785e-04 - val_loss: 0.0060
Epoch 82/150
146/146 [==============================] - 2s 13ms/step - loss: 8.8517e-04 - val_loss: 0.0084
Epoch 83/150
146/146 [==============================] - 2s 11ms/step - loss: 8.7862e-04 - val_loss: 0.0091
Epoch 84/150
146/146 [==============================] - 2s 11ms/step - loss: 7.5871e-04 - val_loss: 0.0093
Epoch 85/150
146/146 [==============================] - 2s 11ms/step - loss: 7.9489e-04 - val_loss: 0.0090
Epoch 86/150
146/146 [==============================] - 2s 11ms/step - loss: 8.0286e-04 - val_loss: 0.0095
Epoch 87/150
146/146 [==============================] - 2s 11ms/step - loss: 8.3365e-04 - val_loss: 0.0066
Epoch 88/150
146/146 [==============================] - 2s 14ms/step - loss: 7.7038e-04 - val_loss: 0.0079
Epoch 89/150
146/146 [==============================] - 2s 15ms/step - loss: 7.9604e-04 - val_loss: 0.0111
Epoch 90/150
146/146 [==============================] - 2s 11ms/step - loss: 7.7460e-04 - val_loss: 0.0080
Epoch 91/150
146/146 [==============================] - 2s 12ms/step - loss: 7.5311e-04 - val_loss: 0.0104
Epoch 92/150
146/146 [==============================] - 2s 11ms/step - loss: 7.5707e-04 - val_loss: 0.0104
Epoch 93/150
146/146 [==============================] - 2s 12ms/step - loss: 8.4576e-04 - val_loss: 0.0100
Epoch 94/150
146/146 [==============================] - 2s 11ms/step - loss: 7.8398e-04 - val_loss: 0.0083
Epoch 95/150
146/146 [==============================] - 2s 13ms/step - loss: 7.3221e-04 - val_loss: 0.0065
Epoch 96/150
146/146 [==============================] - 2s 15ms/step - loss: 7.2958e-04 - val_loss: 0.0059
Epoch 97/150
146/146 [==============================] - 2s 12ms/step - loss: 7.8533e-04 - val_loss: 0.0102
Epoch 98/150
146/146 [==============================] - 2s 12ms/step - loss: 7.9251e-04 - val_loss: 0.0074
Epoch 99/150
146/146 [==============================] - 2s 12ms/step - loss: 7.1588e-04 - val_loss: 0.0073
Epoch 100/150
146/146 [==============================] - 2s 12ms/step - loss: 7.2951e-04 - val_loss: 0.0080
Epoch 101/150
146/146 [==============================] - 2s 12ms/step - loss: 9.3439e-04 - val_loss: 0.0102
Epoch 102/150
146/146 [==============================] - 2s 13ms/step - loss: 7.0923e-04 - val_loss: 0.0108
Epoch 103/150
146/146 [==============================] - 2s 16ms/step - loss: 7.3237e-04 - val_loss: 0.0085
Epoch 104/150
146/146 [==============================] - 2s 13ms/step - loss: 6.9937e-04 - val_loss: 0.0095
Epoch 105/150
146/146 [==============================] - 2s 12ms/step - loss: 7.2207e-04 - val_loss: 0.0102
Epoch 106/150
146/146 [==============================] - 2s 12ms/step - loss: 7.7186e-04 - val_loss: 0.0105
Epoch 107/150
146/146 [==============================] - 2s 12ms/step - loss: 6.5759e-04 - val_loss: 0.0089
Epoch 108/150
146/146 [==============================] - 2s 12ms/step - loss: 7.3110e-04 - val_loss: 0.0064
Epoch 109/150
146/146 [==============================] - 2s 13ms/step - loss: 7.9205e-04 - val_loss: 0.0139
Epoch 110/150
146/146 [==============================] - 3s 17ms/step - loss: 6.9098e-04 - val_loss: 0.0087
Epoch 111/150
146/146 [==============================] - 2s 12ms/step - loss: 6.6618e-04 - val_loss: 0.0111
Epoch 112/150
146/146 [==============================] - 2s 11ms/step - loss: 6.6715e-04 - val_loss: 0.0076
Epoch 113/150
146/146 [==============================] - 2s 11ms/step - loss: 6.7107e-04 - val_loss: 0.0106
Epoch 114/150
146/146 [==============================] - 2s 11ms/step - loss: 6.6467e-04 - val_loss: 0.0108
Epoch 115/150
146/146 [==============================] - 2s 11ms/step - loss: 6.9156e-04 - val_loss: 0.0075
Epoch 116/150
146/146 [==============================] - 2s 11ms/step - loss: 6.9575e-04 - val_loss: 0.0090
Epoch 117/150
146/146 [==============================] - 2s 15ms/step - loss: 6.8732e-04 - val_loss: 0.0092
Epoch 118/150
146/146 [==============================] - 2s 14ms/step - loss: 6.6026e-04 - val_loss: 0.0109
Epoch 119/150
146/146 [==============================] - 2s 11ms/step - loss: 5.9826e-04 - val_loss: 0.0079
Epoch 120/150
146/146 [==============================] - 2s 11ms/step - loss: 6.8994e-04 - val_loss: 0.0102
Epoch 121/150
146/146 [==============================] - 2s 11ms/step - loss: 7.0777e-04 - val_loss: 0.0103
Epoch 122/150
146/146 [==============================] - 2s 11ms/step - loss: 6.7112e-04 - val_loss: 0.0084
Epoch 123/150
146/146 [==============================] - 2s 11ms/step - loss: 7.0769e-04 - val_loss: 0.0094
Epoch 124/150
146/146 [==============================] - 2s 13ms/step - loss: 6.3448e-04 - val_loss: 0.0074
Epoch 125/150
146/146 [==============================] - 2s 15ms/step - loss: 6.1825e-04 - val_loss: 0.0117
Epoch 126/150
146/146 [==============================] - 2s 12ms/step - loss: 6.8352e-04 - val_loss: 0.0101
Epoch 127/150
146/146 [==============================] - 2s 11ms/step - loss: 6.1657e-04 - val_loss: 0.0086
Epoch 128/150
146/146 [==============================] - 2s 11ms/step - loss: 6.7473e-04 - val_loss: 0.0076
Epoch 129/150
146/146 [==============================] - 2s 11ms/step - loss: 6.4833e-04 - val_loss: 0.0096
Epoch 130/150
146/146 [==============================] - 2s 11ms/step - loss: 6.4663e-04 - val_loss: 0.0061
Epoch 131/150
146/146 [==============================] - 2s 13ms/step - loss: 6.4885e-04 - val_loss: 0.0098
Epoch 132/150
146/146 [==============================] - 2s 16ms/step - loss: 7.2346e-04 - val_loss: 0.0083
Epoch 133/150
146/146 [==============================] - 2s 13ms/step - loss: 7.1654e-04 - val_loss: 0.0086
```

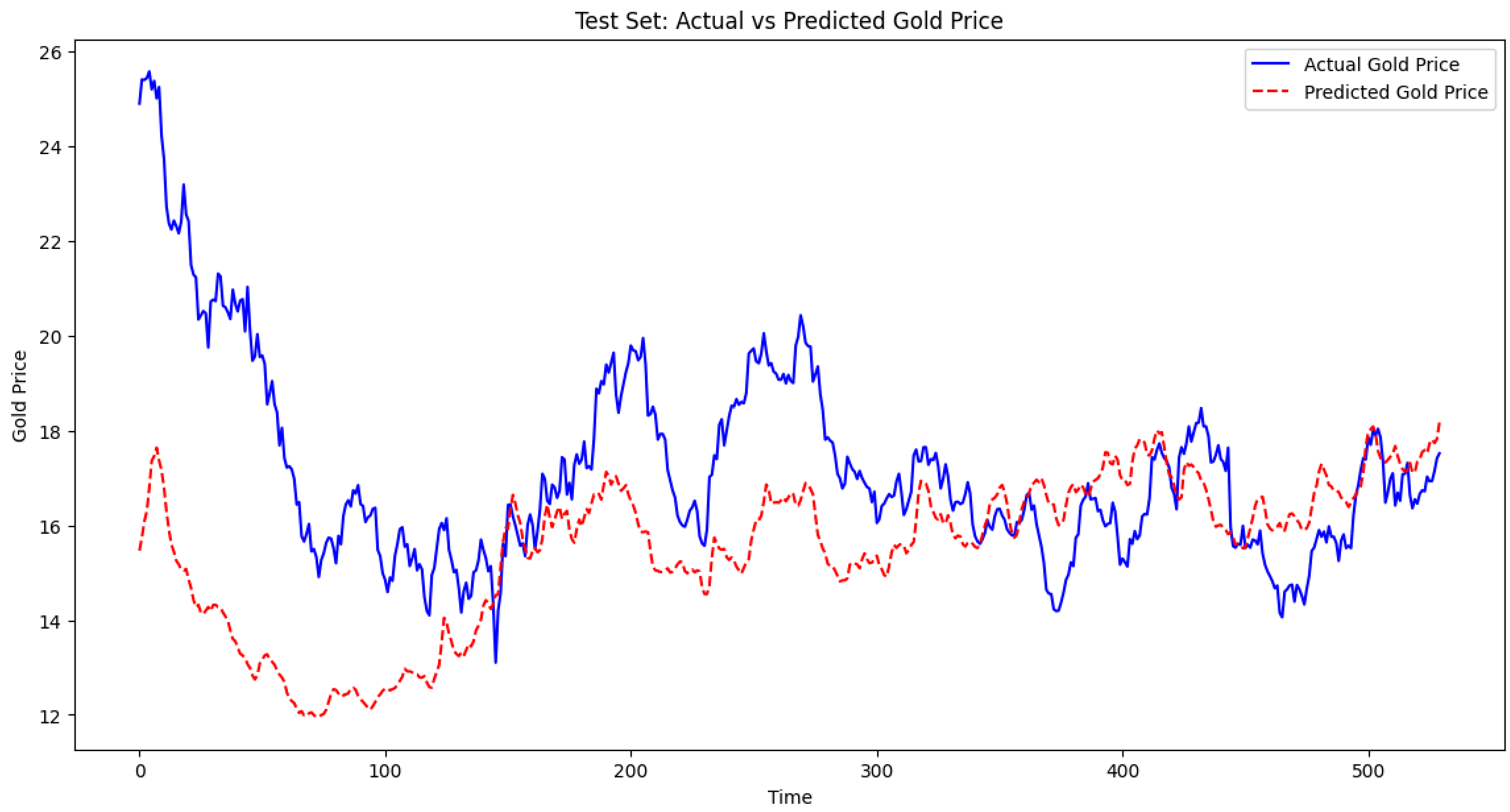
```
Epoch 134/150
146/146 [==============================] - 2s 12ms/step - loss: 6.6258e-04 - val_loss: 0.0073
Epoch 135/150
146/146 [==============================] - 2s 12ms/step - loss: 5.7630e-04 - val_loss: 0.0091
Epoch 136/150
146/146 [==============================] - 2s 12ms/step - loss: 6.0675e-04 - val_loss: 0.0083
Epoch 137/150
146/146 [==============================] - 2s 12ms/step - loss: 6.4895e-04 - val_loss: 0.0095
Epoch 138/150
146/146 [==============================] - 2s 12ms/step - loss: 6.1582e-04 - val_loss: 0.0076
Epoch 139/150
146/146 [==============================] - 2s 17ms/step - loss: 5.8252e-04 - val_loss: 0.0094
Epoch 140/150
146/146 [==============================] - 2s 13ms/step - loss: 5.9919e-04 - val_loss: 0.0118
Epoch 141/150
146/146 [==============================] - 2s 12ms/step - loss: 6.2021e-04 - val_loss: 0.0122
Epoch 142/150
146/146 [==============================] - 2s 12ms/step - loss: 6.1025e-04 - val_loss: 0.0091
Epoch 143/150
146/146 [==============================] - 2s 13ms/step - loss: 5.9600e-04 - val_loss: 0.0107
Epoch 144/150
146/146 [==============================] - 2s 12ms/step - loss: 6.9891e-04 - val_loss: 0.0089
Epoch 145/150
146/146 [==============================] - 2s 12ms/step - loss: 6.0514e-04 - val_loss: 0.0092
Epoch 146/150
146/146 [==============================] - 2s 16ms/step - loss: 6.5998e-04 - val_loss: 0.0077
Epoch 147/150
146/146 [==============================] - 2s 12ms/step - loss: 5.7998e-04 - val_loss: 0.0099
Epoch 148/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8703e-04 - val_loss: 0.0098
Epoch 149/150
146/146 [==============================] - 2s 11ms/step - loss: 6.5725e-04 - val_loss: 0.0093
Epoch 150/150
146/146 [==============================] - 2s 11ms/step - loss: 5.6967e-04 - val_loss: 0.0122
146/146 [==============================] - 2s 5ms/step
17/17 [==============================] - 0s 5ms/step
17/17 [==============================] - 0s 4ms/step
```

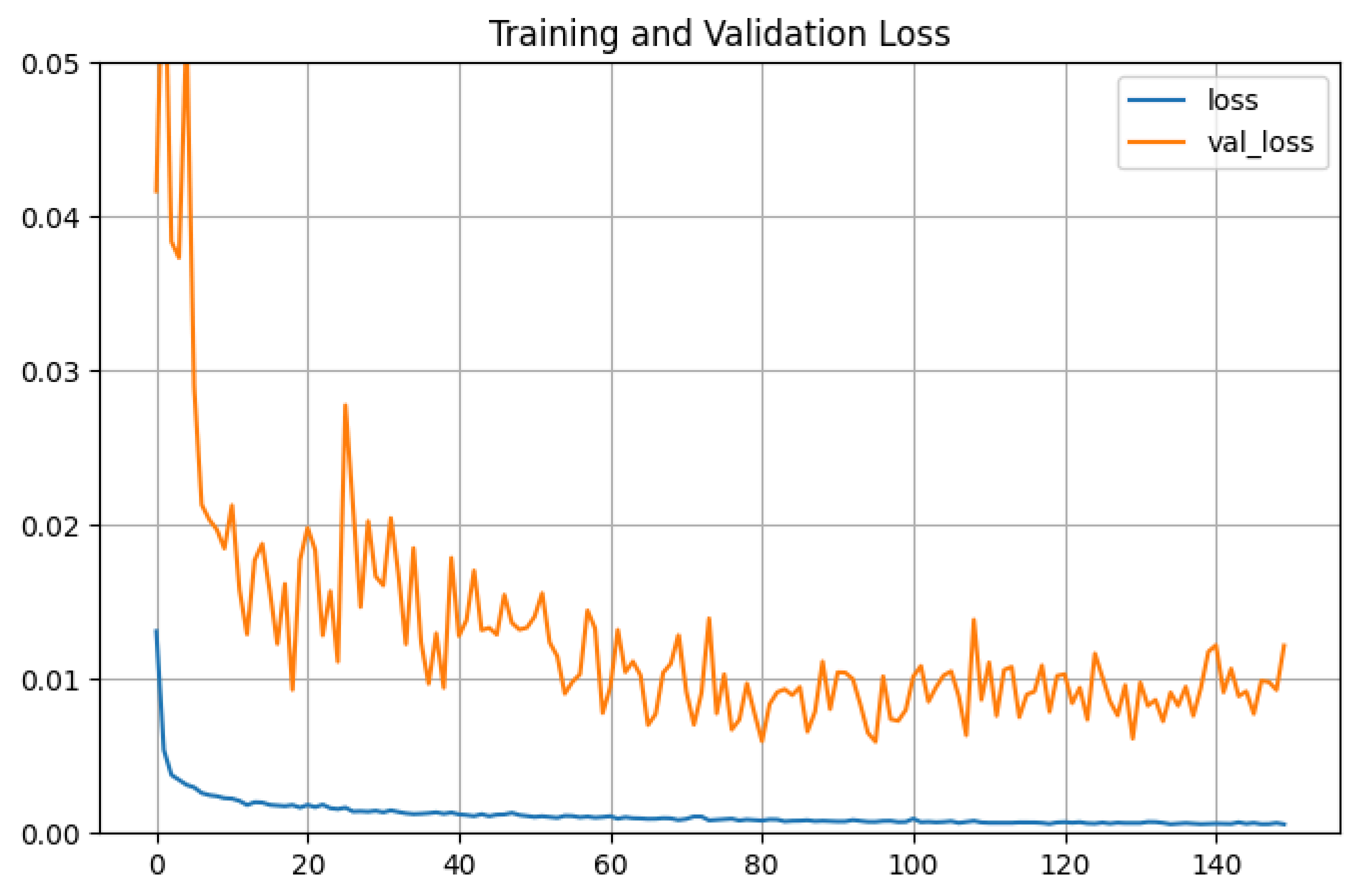
In [ ]:

```
# Plot the training predictions
show_results(train_predict, y_train_actual, validation_predict, y_validation_actual, test_predict, y_test_actual, run, 0.05)
```










```
RMSE of Model: 2.993252445473248
Accuracy: 0.8790734335920092
```

Method 3 - Only GOLD

uisng simply gold price but without other variables as input data

In [ ]:
```
reset_session()
# Feature scaling
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data)

# Define the train, validation, and test size
train_size = int(len(scaled_data) * 0.8)
validation_size = int(len(scaled_data) * 0.1)
test_size = len(scaled_data) - train_size - validation_size

# Split the data
train_data = scaled_data[:train_size]
validation_data = scaled_data[train_size:train_size + validation_size]
test_data = scaled_data[train_size + validation_size:]

# Create a function to prepare the dataset for LSTM
def create_dataset(data, time_step=1):
    X, y = [], []
    for i in range(len(data) - time_step - 1):
        a = data[i:(i + time_step), 0]  # Only gold price
        X.append(a)
        y.append(data[i + time_step, 0])  # Predict the future gold price
    return np.array(X), np.array(y)

time_step = 60  # you can choose any time step

# Create datasets
X_train, y_train = create_dataset(train_data, time_step)
X_validation, y_validation = create_dataset(validation_data, time_step)
X_test, y_test = create_dataset(test_data, time_step)

# Reshape the data to be [samples, time steps, features]
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_validation = X_validation.reshape(X_validation.shape[0], X_validation.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

# Print shapes to verify
print(f"X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
print(f"X_validation shape: {X_validation.shape}, y_validation shape: {y_validation.shape}")
print(f"X_test shape: {X_test.shape}, y_test shape: {y_test.shape}")
```

```
X_train shape: (4659, 60, 1), y_train shape: (4659,)
X_validation shape: (529, 60, 1), y_validation shape: (529,)
X_test shape: (530, 60, 1), y_test shape: (530,)
```

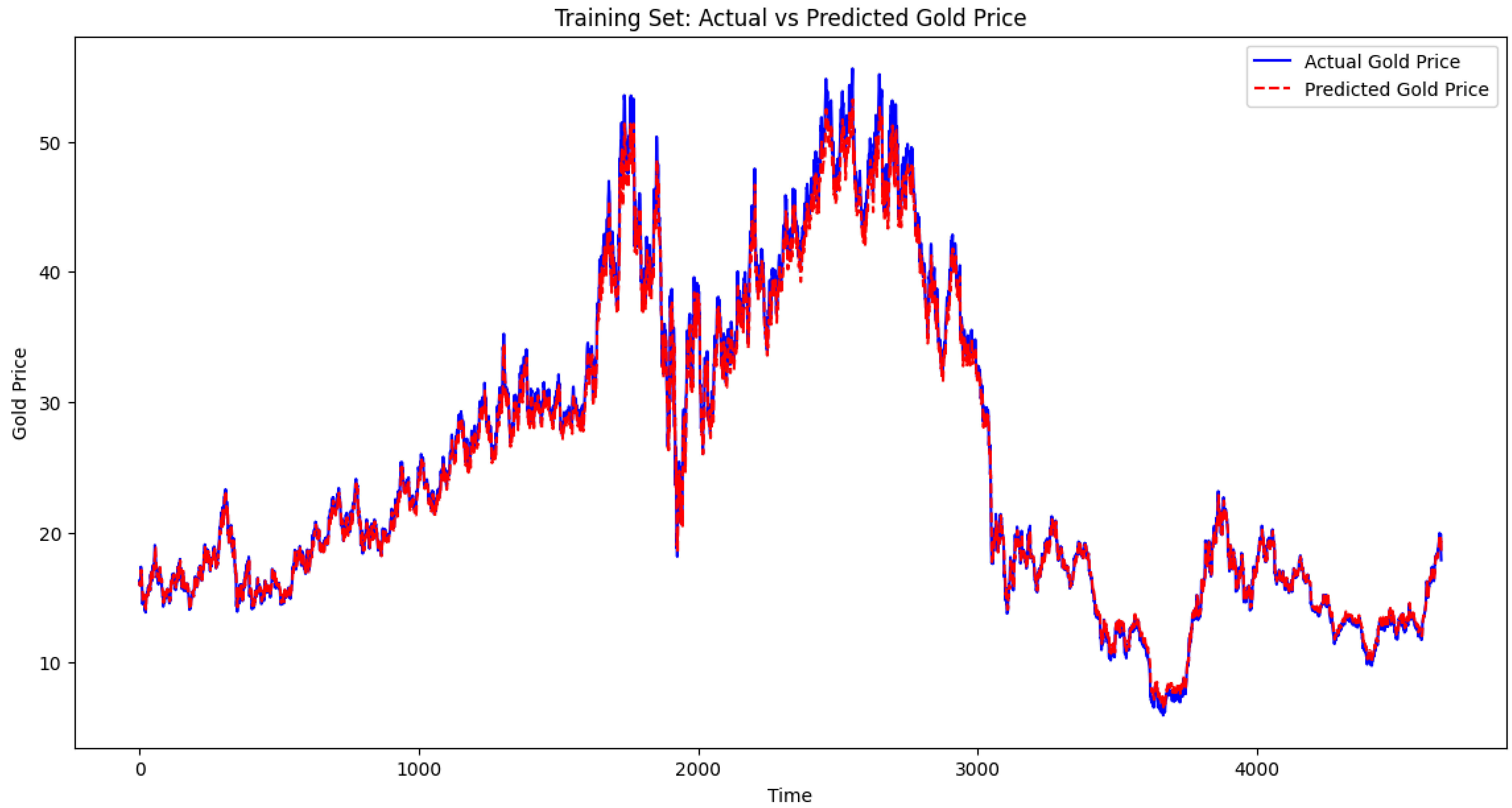
In [ ]:
```
# Train the model
train_predict, validation_predict, test_predict, y_train_actual, y_validation_actual, y_test_actual, run = train_lstm_model(X_train, y_train, X_validation, y_validation, time_st
```

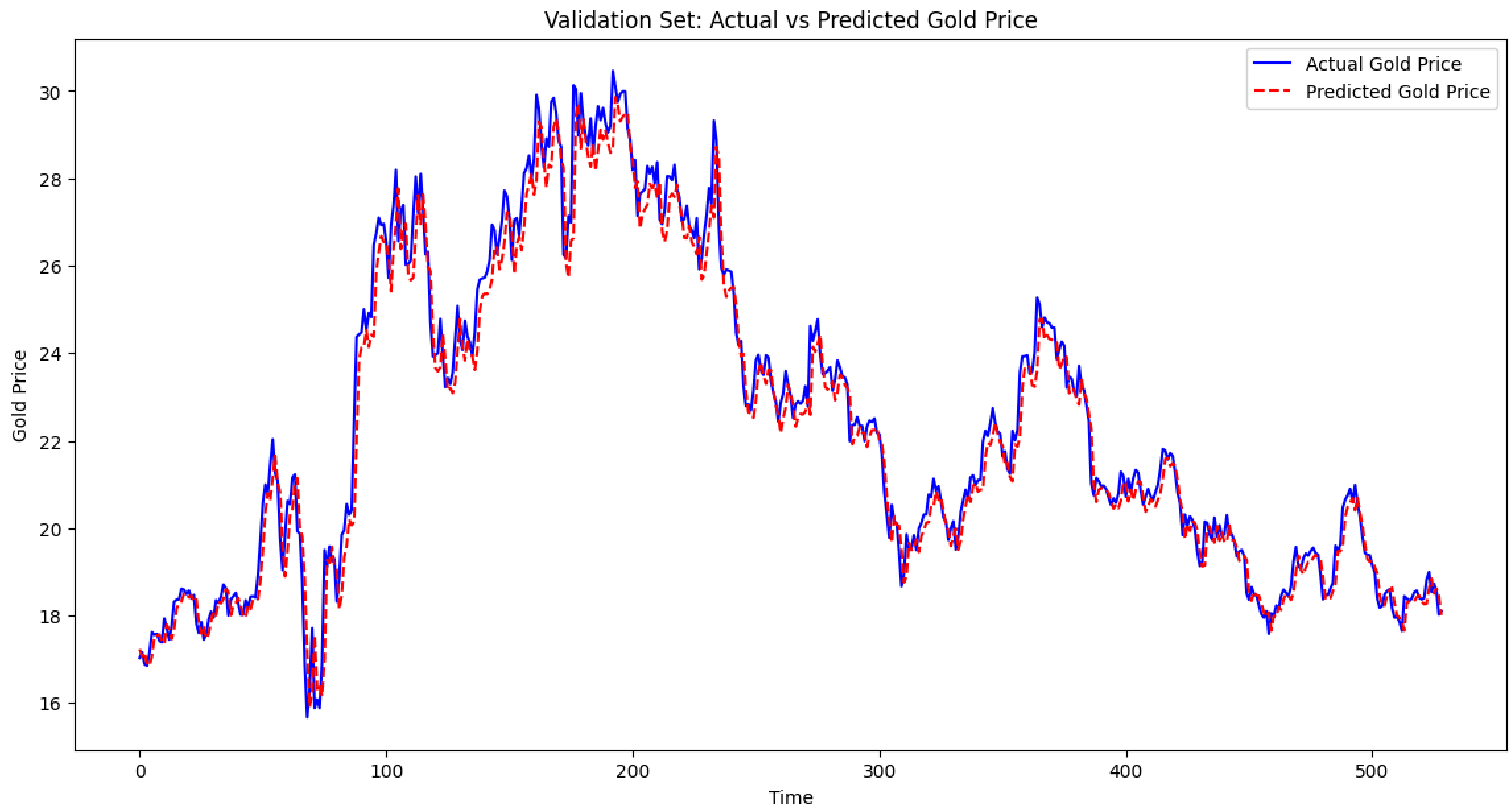
```
Epoch 1/150
146/146 [==============================] - 8s 18ms/step - loss: 0.0063 - val_loss: 0.0011
Epoch 2/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0021 - val_loss: 7.7744e-04
Epoch 3/150
146/146 [==============================] - 2s 15ms/step - loss: 0.0019 - val_loss: 5.4283e-04
Epoch 4/150
146/146 [==============================] - 2s 13ms/step - loss: 0.0016 - val_loss: 4.7910e-04
Epoch 5/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0014 - val_loss: 4.1311e-04
Epoch 6/150
146/146 [==============================] - 2s 11ms/step - loss: 0.0012 - val_loss: 5.1625e-04
Epoch 7/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0011 - val_loss: 5.0285e-04
Epoch 8/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0010 - val_loss: 4.7939e-04
Epoch 9/150
146/146 [==============================] - 2s 12ms/step - loss: 0.0010 - val_loss: 3.4634e-04
Epoch 10/150
146/146 [==============================] - 2s 15ms/step - loss: 8.4061e-04 - val_loss: 3.8686e-04
Epoch 11/150
146/146 [==============================] - 2s 14ms/step - loss: 8.6276e-04 - val_loss: 5.1987e-04
Epoch 12/150
146/146 [==============================] - 2s 11ms/step - loss: 8.0464e-04 - val_loss: 2.8344e-04
Epoch 13/150
146/146 [==============================] - 2s 12ms/step - loss: 8.0059e-04 - val_loss: 3.3526e-04
Epoch 14/150
146/146 [==============================] - 2s 12ms/step - loss: 7.5931e-04 - val_loss: 2.6482e-04
Epoch 15/150
146/146 [==============================] - 2s 12ms/step - loss: 8.1576e-04 - val_loss: 2.3791e-04
Epoch 16/150
146/146 [==============================] - 2s 12ms/step - loss: 7.9007e-04 - val_loss: 2.4298e-04
Epoch 17/150
146/146 [==============================] - 2s 16ms/step - loss: 7.7624e-04 - val_loss: 4.1594e-04
Epoch 18/150
146/146 [==============================] - 2s 14ms/step - loss: 7.6678e-04 - val_loss: 2.0637e-04
Epoch 19/150
146/146 [==============================] - 2s 12ms/step - loss: 6.7074e-04 - val_loss: 2.7077e-04
Epoch 20/150
146/146 [==============================] - 2s 12ms/step - loss: 6.6311e-04 - val_loss: 2.0184e-04
Epoch 21/150
146/146 [==============================] - 2s 12ms/step - loss: 6.9438e-04 - val_loss: 2.0415e-04
Epoch 22/150
146/146 [==============================] - 2s 12ms/step - loss: 6.4721e-04 - val_loss: 2.6508e-04
Epoch 23/150
146/146 [==============================] - 2s 11ms/step - loss: 7.4451e-04 - val_loss: 1.8137e-04
Epoch 24/150
146/146 [==============================] - 2s 13ms/step - loss: 6.2900e-04 - val_loss: 2.5183e-04
Epoch 25/150
146/146 [==============================] - 2s 14ms/step - loss: 7.4160e-04 - val_loss: 2.3207e-04
Epoch 26/150
146/146 [==============================] - 2s 11ms/step - loss: 6.7339e-04 - val_loss: 1.9189e-04
Epoch 27/150
146/146 [==============================] - 2s 11ms/step - loss: 6.2324e-04 - val_loss: 1.6905e-04
Epoch 28/150
146/146 [==============================] - 2s 11ms/step - loss: 7.0042e-04 - val_loss: 2.2347e-04
Epoch 29/150
146/146 [==============================] - 2s 11ms/step - loss: 6.4246e-04 - val_loss: 1.8392e-04
Epoch 30/150
146/146 [==============================] - 2s 11ms/step - loss: 6.5832e-04 - val_loss: 1.6657e-04
Epoch 31/150
146/146 [==============================] - 2s 11ms/step - loss: 5.9685e-04 - val_loss: 1.8352e-04
Epoch 32/150
146/146 [==============================] - 2s 15ms/step - loss: 6.4429e-04 - val_loss: 2.1615e-04
Epoch 33/150
146/146 [==============================] - 2s 13ms/step - loss: 6.7520e-04 - val_loss: 1.9029e-04
Epoch 34/150
146/146 [==============================] - 2s 11ms/step - loss: 5.9917e-04 - val_loss: 1.7014e-04
Epoch 35/150
146/146 [==============================] - 2s 11ms/step - loss: 5.7051e-04 - val_loss: 1.5524e-04
Epoch 36/150
146/146 [==============================] - 2s 11ms/step - loss: 6.6352e-04 - val_loss: 1.5934e-04
Epoch 37/150
146/146 [==============================] - 2s 11ms/step - loss: 6.4522e-04 - val_loss: 1.8201e-04
Epoch 38/150
146/146 [==============================] - 2s 11ms/step - loss: 5.9984e-04 - val_loss: 1.8394e-04
Epoch 39/150
146/146 [==============================] - 2s 13ms/step - loss: 6.6736e-04 - val_loss: 3.9271e-04
Epoch 40/150
146/146 [==============================] - 2s 15ms/step - loss: 7.3027e-04 - val_loss: 2.5433e-04
Epoch 41/150
146/146 [==============================] - 2s 12ms/step - loss: 7.1279e-04 - val_loss: 1.4411e-04
Epoch 42/150
146/146 [==============================] - 2s 12ms/step - loss: 6.8727e-04 - val_loss: 2.0623e-04
Epoch 43/150
146/146 [==============================] - 2s 12ms/step - loss: 5.6742e-04 - val_loss: 1.5723e-04
Epoch 44/150
146/146 [==============================] - 2s 12ms/step - loss: 5.6982e-04 - val_loss: 1.5579e-04
Epoch 45/150
146/146 [==============================] - 2s 12ms/step - loss: 6.3145e-04 - val_loss: 1.6546e-04
Epoch 46/150
146/146 [==============================] - 2s 13ms/step - loss: 6.1478e-04 - val_loss: 1.7269e-04
Epoch 47/150
146/146 [==============================] - 2s 17ms/step - loss: 6.3072e-04 - val_loss: 1.6961e-04
Epoch 48/150
146/146 [==============================] - 2s 12ms/step - loss: 6.6495e-04 - val_loss: 1.7309e-04
Epoch 49/150
146/146 [==============================] - 2s 12ms/step - loss: 6.0878e-04 - val_loss: 2.1681e-04
Epoch 50/150
146/146 [==============================] - 2s 12ms/step - loss: 6.3906e-04 - val_loss: 1.6969e-04
Epoch 51/150
146/146 [==============================] - 2s 15ms/step - loss: 5.7273e-04 - val_loss: 1.7815e-04
Epoch 52/150
146/146 [==============================] - 2s 15ms/step - loss: 5.6946e-04 - val_loss: 1.6177e-04
Epoch 53/150
146/146 [==============================] - 2s 17ms/step - loss: 5.8221e-04 - val_loss: 1.4236e-04
Epoch 54/150
146/146 [==============================] - 2s 13ms/step - loss: 6.3082e-04 - val_loss: 1.3631e-04
Epoch 55/150
146/146 [==============================] - 2s 11ms/step - loss: 6.3501e-04 - val_loss: 1.9383e-04
Epoch 56/150
146/146 [==============================] - 2s 11ms/step - loss: 6.0679e-04 - val_loss: 1.4834e-04
Epoch 57/150
146/146 [==============================] - 2s 11ms/step - loss: 6.0212e-04 - val_loss: 1.3864e-04
Epoch 58/150
146/146 [==============================] - 2s 11ms/step - loss: 5.7328e-04 - val_loss: 1.6019e-04
Epoch 59/150
146/146 [==============================] - 2s 11ms/step - loss: 6.2477e-04 - val_loss: 1.3929e-04
Epoch 60/150
146/146 [==============================] - 2s 13ms/step - loss: 6.2729e-04 - val_loss: 1.5002e-04
Epoch 61/150
146/146 [==============================] - 2s 15ms/step - loss: 5.8021e-04 - val_loss: 1.4254e-04
Epoch 62/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8762e-04 - val_loss: 1.5117e-04
Epoch 63/150
146/146 [==============================] - 2s 11ms/step - loss: 6.8387e-04 - val_loss: 1.4005e-04
Epoch 64/150
146/146 [==============================] - 2s 11ms/step - loss: 5.9927e-04 - val_loss: 1.4204e-04
Epoch 65/150
146/146 [==============================] - 2s 11ms/step - loss: 5.5396e-04 - val_loss: 1.3997e-04
Epoch 66/150
146/146 [==============================] - 2s 11ms/step - loss: 6.8261e-04 - val_loss: 1.4443e-04
Epoch 67/150
```

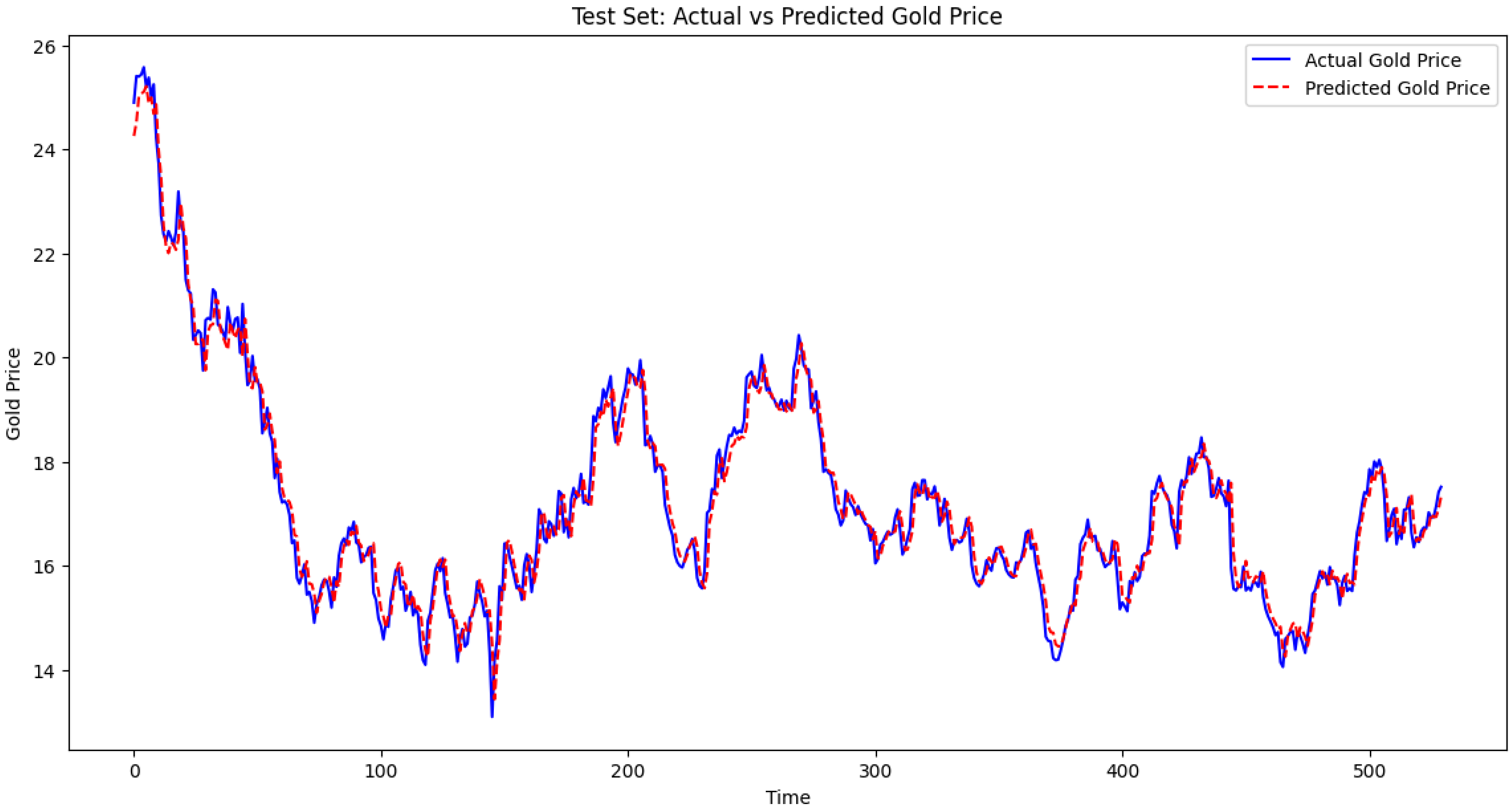
```
146/146 [==============================] - 2s 12ms/step - loss: 5.7147e-04 - val_loss: 1.3611e-04
Epoch 68/150
146/146 [==============================] - 2s 15ms/step - loss: 6.1645e-04 - val_loss: 1.4509e-04
Epoch 69/150
146/146 [==============================] - 2s 12ms/step - loss: 5.9892e-04 - val_loss: 1.5528e-04
Epoch 70/150
146/146 [==============================] - 2s 11ms/step - loss: 5.3416e-04 - val_loss: 1.6985e-04
Epoch 71/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8029e-04 - val_loss: 1.4606e-04
Epoch 72/150
146/146 [==============================] - 2s 11ms/step - loss: 5.5691e-04 - val_loss: 1.3930e-04
Epoch 73/150
146/146 [==============================] - 2s 11ms/step - loss: 5.3592e-04 - val_loss: 1.3849e-04
Epoch 74/150
146/146 [==============================] - 2s 12ms/step - loss: 6.2632e-04 - val_loss: 1.5473e-04
Epoch 75/150
146/146 [==============================] - 2s 14ms/step - loss: 5.9844e-04 - val_loss: 1.5106e-04
Epoch 76/150
146/146 [==============================] - 2s 15ms/step - loss: 5.4162e-04 - val_loss: 1.9392e-04
Epoch 77/150
146/146 [==============================] - 2s 12ms/step - loss: 5.9822e-04 - val_loss: 1.8010e-04
Epoch 78/150
146/146 [==============================] - 2s 11ms/step - loss: 5.4193e-04 - val_loss: 1.6602e-04
Epoch 79/150
146/146 [==============================] - 2s 12ms/step - loss: 5.3830e-04 - val_loss: 3.3158e-04
Epoch 80/150
146/146 [==============================] - 2s 12ms/step - loss: 5.7237e-04 - val_loss: 1.6857e-04
Epoch 81/150
146/146 [==============================] - 2s 12ms/step - loss: 5.6010e-04 - val_loss: 1.3905e-04
Epoch 82/150
146/146 [==============================] - 2s 14ms/step - loss: 5.2637e-04 - val_loss: 1.7504e-04
Epoch 83/150
146/146 [==============================] - 2s 16ms/step - loss: 6.1461e-04 - val_loss: 2.1204e-04
Epoch 84/150
146/146 [==============================] - 2s 12ms/step - loss: 5.3407e-04 - val_loss: 1.6669e-04
Epoch 85/150
146/146 [==============================] - 2s 12ms/step - loss: 5.0482e-04 - val_loss: 1.5133e-04
Epoch 86/150
146/146 [==============================] - 2s 12ms/step - loss: 5.8515e-04 - val_loss: 1.6424e-04
Epoch 87/150
146/146 [==============================] - 2s 12ms/step - loss: 5.3010e-04 - val_loss: 1.3731e-04
Epoch 88/150
146/146 [==============================] - 2s 11ms/step - loss: 5.4189e-04 - val_loss: 1.5792e-04
Epoch 89/150
146/146 [==============================] - 2s 13ms/step - loss: 5.6214e-04 - val_loss: 2.3122e-04
Epoch 90/150
146/146 [==============================] - 2s 16ms/step - loss: 5.1882e-04 - val_loss: 1.5815e-04
Epoch 91/150
146/146 [==============================] - 2s 12ms/step - loss: 5.5286e-04 - val_loss: 1.4192e-04
Epoch 92/150
146/146 [==============================] - 2s 11ms/step - loss: 5.9253e-04 - val_loss: 1.6028e-04
Epoch 93/150
146/146 [==============================] - 2s 11ms/step - loss: 5.4038e-04 - val_loss: 1.3933e-04
Epoch 94/150
146/146 [==============================] - 2s 11ms/step - loss: 5.2704e-04 - val_loss: 1.3482e-04
Epoch 95/150
146/146 [==============================] - 2s 11ms/step - loss: 5.1485e-04 - val_loss: 3.2693e-04
Epoch 96/150
146/146 [==============================] - 2s 11ms/step - loss: 5.3047e-04 - val_loss: 2.0152e-04
Epoch 97/150
146/146 [==============================] - 3s 19ms/step - loss: 5.9400e-04 - val_loss: 1.6731e-04
Epoch 98/150
146/146 [==============================] - 2s 14ms/step - loss: 6.0982e-04 - val_loss: 1.8146e-04
Epoch 99/150
146/146 [==============================] - 2s 11ms/step - loss: 5.6691e-04 - val_loss: 1.3753e-04
Epoch 100/150
146/146 [==============================] - 2s 11ms/step - loss: 5.1462e-04 - val_loss: 2.3826e-04
Epoch 101/150
146/146 [==============================] - 2s 11ms/step - loss: 5.2273e-04 - val_loss: 1.3968e-04
Epoch 102/150
146/146 [==============================] - 2s 11ms/step - loss: 5.6103e-04 - val_loss: 1.7008e-04
Epoch 103/150
146/146 [==============================] - 2s 11ms/step - loss: 5.4604e-04 - val_loss: 2.0392e-04
Epoch 104/150
146/146 [==============================] - 2s 13ms/step - loss: 5.4910e-04 - val_loss: 2.6541e-04
Epoch 105/150
146/146 [==============================] - 2s 15ms/step - loss: 5.4491e-04 - val_loss: 1.3616e-04
Epoch 106/150
146/146 [==============================] - 2s 12ms/step - loss: 5.8193e-04 - val_loss: 1.3532e-04
Epoch 107/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1875e-04 - val_loss: 1.3969e-04
Epoch 108/150
146/146 [==============================] - 2s 12ms/step - loss: 5.4678e-04 - val_loss: 1.7086e-04
Epoch 109/150
146/146 [==============================] - 2s 15ms/step - loss: 5.6784e-04 - val_loss: 1.3170e-04
Epoch 110/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1655e-04 - val_loss: 2.1026e-04
Epoch 111/150
146/146 [==============================] - 2s 15ms/step - loss: 5.3403e-04 - val_loss: 2.4921e-04
Epoch 112/150
146/146 [==============================] - 2s 15ms/step - loss: 5.4960e-04 - val_loss: 1.9086e-04
Epoch 113/150
146/146 [==============================] - 2s 12ms/step - loss: 5.4644e-04 - val_loss: 1.4611e-04
Epoch 114/150
146/146 [==============================] - 2s 15ms/step - loss: 4.9320e-04 - val_loss: 1.4054e-04
Epoch 115/150
146/146 [==============================] - 2s 12ms/step - loss: 5.6335e-04 - val_loss: 1.4045e-04
Epoch 116/150
146/146 [==============================] - 2s 12ms/step - loss: 5.3753e-04 - val_loss: 1.5368e-04
Epoch 117/150
146/146 [==============================] - 2s 12ms/step - loss: 5.5421e-04 - val_loss: 2.0731e-04
Epoch 118/150
146/146 [==============================] - 2s 16ms/step - loss: 5.2153e-04 - val_loss: 1.3359e-04
Epoch 119/150
146/146 [==============================] - 2s 14ms/step - loss: 4.9710e-04 - val_loss: 1.4702e-04
Epoch 120/150
146/146 [==============================] - 2s 11ms/step - loss: 4.9505e-04 - val_loss: 1.4615e-04
Epoch 121/150
146/146 [==============================] - 2s 11ms/step - loss: 4.9874e-04 - val_loss: 1.3723e-04
Epoch 122/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1014e-04 - val_loss: 1.4108e-04
Epoch 123/150
146/146 [==============================] - 2s 11ms/step - loss: 5.2077e-04 - val_loss: 1.4821e-04
Epoch 124/150
146/146 [==============================] - 2s 11ms/step - loss: 5.1713e-04 - val_loss: 1.7749e-04
Epoch 125/150
146/146 [==============================] - 2s 13ms/step - loss: 5.2492e-04 - val_loss: 2.2866e-04
Epoch 126/150
146/146 [==============================] - 2s 15ms/step - loss: 5.5155e-04 - val_loss: 1.3977e-04
Epoch 127/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1552e-04 - val_loss: 1.4104e-04
Epoch 128/150
146/146 [==============================] - 2s 11ms/step - loss: 5.2032e-04 - val_loss: 1.4049e-04
Epoch 129/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0867e-04 - val_loss: 1.4418e-04
Epoch 130/150
146/146 [==============================] - 2s 11ms/step - loss: 5.0549e-04 - val_loss: 1.6167e-04
Epoch 131/150
146/146 [==============================] - 2s 12ms/step - loss: 5.5076e-04 - val_loss: 1.7980e-04
Epoch 132/150
146/146 [==============================] - 2s 11ms/step - loss: 5.4383e-04 - val_loss: 2.7054e-04
Epoch 133/150
146/146 [==============================] - 2s 15ms/step - loss: 5.6941e-04 - val_loss: 1.5832e-04
```

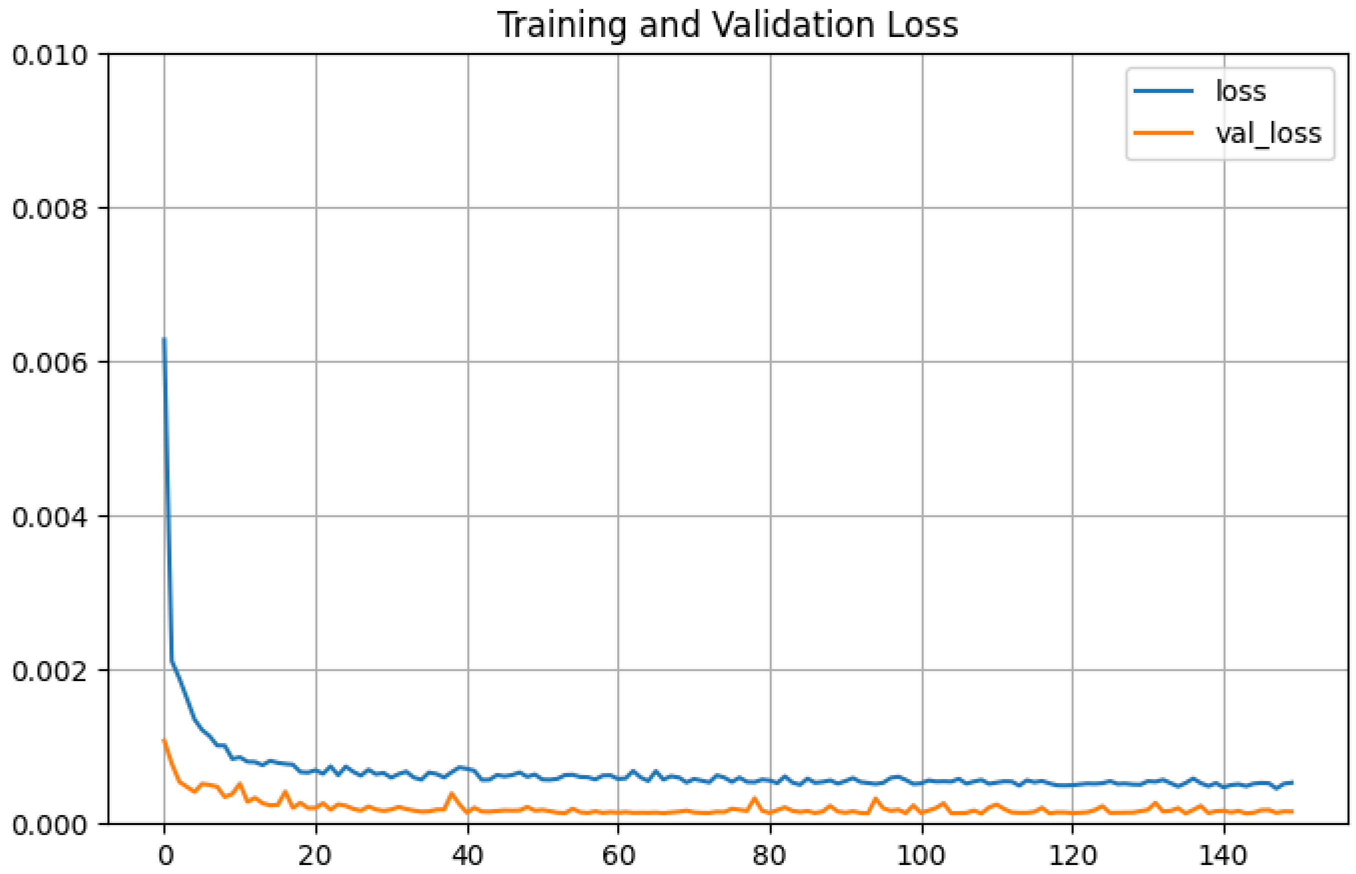
```
Epoch 134/150
146/146 [==============================] - 2s 13ms/step - loss: 5.2452e-04 - val_loss: 1.6675e-04
Epoch 135/150
146/146 [==============================] - 2s 11ms/step - loss: 4.8274e-04 - val_loss: 2.0263e-04
Epoch 136/150
146/146 [==============================] - 2s 11ms/step - loss: 5.2771e-04 - val_loss: 1.3287e-04
Epoch 137/150
146/146 [==============================] - 2s 11ms/step - loss: 5.8624e-04 - val_loss: 1.7857e-04
Epoch 138/150
146/146 [==============================] - 2s 12ms/step - loss: 5.2555e-04 - val_loss: 2.3157e-04
Epoch 139/150
146/146 [==============================] - 2s 12ms/step - loss: 4.8671e-04 - val_loss: 1.3773e-04
Epoch 140/150
146/146 [==============================] - 2s 15ms/step - loss: 5.2649e-04 - val_loss: 1.6223e-04
Epoch 141/150
146/146 [==============================] - 2s 15ms/step - loss: 4.7124e-04 - val_loss: 1.6758e-04
Epoch 142/150
146/146 [==============================] - 2s 12ms/step - loss: 5.0143e-04 - val_loss: 1.4675e-04
Epoch 143/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1086e-04 - val_loss: 1.6571e-04
Epoch 144/150
146/146 [==============================] - 2s 12ms/step - loss: 4.8682e-04 - val_loss: 1.3289e-04
Epoch 145/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1904e-04 - val_loss: 1.4249e-04
Epoch 146/150
146/146 [==============================] - 2s 12ms/step - loss: 5.2863e-04 - val_loss: 1.7578e-04
Epoch 147/150
146/146 [==============================] - 2s 15ms/step - loss: 5.2355e-04 - val_loss: 1.7861e-04
Epoch 148/150
146/146 [==============================] - 2s 16ms/step - loss: 4.5540e-04 - val_loss: 1.4056e-04
Epoch 149/150
146/146 [==============================] - 2s 12ms/step - loss: 5.1865e-04 - val_loss: 1.5931e-04
Epoch 150/150
146/146 [==============================] - 2s 12ms/step - loss: 5.3115e-04 - val_loss: 1.5655e-04
146/146 [==============================] - 2s 5ms/step
17/17 [==============================] - 0s 5ms/step
17/17 [==============================] - 0s 5ms/step
```

In [ ]:
```
# Plot the training predictions
show_results(train_predict, y_train_actual, validation_predict, y_validation_actual, test_predict, y_test_actual, run, 0.01)
```










```
RMSE of Model: 0.36847706573055033
Accuracy: 0.9836855437365676
```

Summary - LSTM

Based on the results and plots above, we can conclude that the dataset containing only gold prices (method 3) performs the best under this neural network. Its predictions are the closest to the real-world prices, and its learning curve is the most effective among the three methods. The dataset with all variables (method 1) shows similar prediction accuracy to the method 3 dataset, but its learning curve is more erratic compared to method 3. On the other hand, the dataset without gold prices (method 2) shows a significant difference compared to the other two datasets. Although its accuracy is close to 90%, there is a large gap between its predictions and the real-world prices in the gold price plot. In general, the LSTM model indicates that gold prices heavily rely on their own historical values. Nevertheless, the LSTM model using the dataset that only includes other variables still demonstrates good capability in predicting trends.

Conclusion

In conclusion, this project demonstrated the application of various machine learning techniques to predict gold prices. The analysis included both traditional regression models and advanced neural networks, specifically LSTM models, to capture the complex time series dynamics of gold prices. The performance of the regression models varied significantly, highlighting the importance of model selection and tuning.

Among the regression models, the Random Forest Regressor and Linear Regressor were employed. The Random Forest Regressor, despite its complexity, did not outperform a simple prediction method, indicating that it may not be well-suited for this specific task. The Linear Regressor, on the other hand, showed better performance, achieving a lower RMSE compared to the simple prediction method, suggesting it can capture some underlying trends in the data.

The LSTM model showed promise in leveraging historical data to improve prediction accuracy. The evaluation across different datasets and model structures highlighted the importance of feature selection and model tuning. Despite the challenges, the results underscore the potential of machine learning in financial forecasting, offering valuable insights for future research and practical applications in trading strategies and risk management. The comparison of model performance emphasizes that while neural networks like LSTM can provide advanced capabilities, simpler models can also be effective with the right features and tuning.