Developing an LSTM model to predict future stock prices involves several steps. These steps include data preprocessing, model building, hyperparameter tuning, and evaluation.

Below, I'll outline the steps and provide code snippets for each part.

Check for varying Timeframe (50 Years - 20 Years - 10 years)

First, we need to collect and preprocess the historical stock price data.

This typically involves normalizing the data and creating sequences for the LSTM model.

"Deep Learning" by Ian Goodfellow, Yoshua Bengio, and Aaron Courville

```python
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam

# Load data
# Added data since 1974-01-01

data = pd.read_csv('stocks_data.csv', index_col = 0)
data.head(2)
```

	Date	BA	DE	MSI	SPGI
0	1974-01-02	0.130799	1.094406	2.354811	0.191056
1	1974-01-03	0.132121	1.148318	2.440219	0.200771

```python
data['Date']
```

```
0        1974-01-02
1        1974-01-03
2        1974-01-04
3        1974-01-07
4        1974-01-08
            ...
12604    2023-12-22
12605    2023-12-26
12606    2023-12-27
12607    2023-12-28
12608    2023-12-29
Name: Date, Length: 12609, dtype: object
```

```python
# Assuming the data has a 'Date' column and 'Close' price column
data['Date'] = pd.to_datetime(data['Date'])
data.set_index('Date', inplace=True)

data.head(2)
```

```
                  BA        DE       MSI      SPGI
Date
1974-01-02  0.130799  1.094406  2.354811  0.191056
1974-01-03  0.132121  1.148318  2.440219  0.200771
```

Checking for one by one Stocks, starting with BA.

```python
# Feature scaling
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data['DE'].values.reshape(-1, 1))

scaled_data
```

```
array([[0.00107148],
       [0.00119424],
       [0.0011083 ],
       ...,
       [0.90290646],
       [0.90084999],
       [0.90222843]])
```

In time series forecasting, particularly with LSTM models, a "window" refers to a sequence of consecutive time points used as input to predict future values. A 60-day window means we are using the stock prices from the past 60 days to predict the stock price on the 61st day. This approach captures temporal dependencies and patterns in the data, which are crucial for making accurate predictions.

The choice of a 60-day window (or sequence length) in time series forecasting, particularly for stock price prediction using LSTM models, is based on several considerations:

- Historical Trends and Patterns: Stock prices often exhibit trends, cycles, and patterns over time. A 60-day window allows the model to capture these medium-term patterns, such as monthly trends, which are significant for making predictions.

- Balance Between Data Availability and Model Complexity: A longer sequence provides more historical context to the model, potentially improving its ability to learn patterns. However, too long a sequence can increase the model complexity and computational requirements, and might also lead to overfitting. A 60-day window strikes a balance by providing sufficient historical data without overwhelming the model.

- Empirical Studies and Industry Practice: Many empirical studies and industry practices in financial modeling use a range of 30 to 90 days for sequence lengths. The 60-day window is a common and practical choice within this range.
- Market Behavior: Stock markets often show significant changes within a 60-day period due to quarterly earnings reports, economic data releases, and other macroeconomic events. Capturing these dynamics can be beneficial for prediction accuracy.

```
# Create sequences
def create_sequences(data, sequence_length):
    sequences = []
    labels = []
    for i in range(len(data) - sequence_length):
        sequences.append(data[i:i+sequence_length])
        labels.append(data[i+sequence_length])
    return np.array(sequences), np.array(labels)


sequence_length = 60  # 60 days look back
X, y = create_sequences(scaled_data, sequence_length)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

len(y_train)

10039

data.shape

(12609, 4)

len(y_test)

2510

len(X_train[0])

60

len(X_train)

10039
```

Build LSTM Model

```
def build_model(units, dropout_rate, learning_rate):
    model = Sequential()
```

```
    model.add(LSTM(units=units, return_sequences=True,
input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(dropout_rate))
    model.add(LSTM(units=units))
    model.add(Dropout(dropout_rate))
    model.add(Dense(1))

    optimizer = Adam(learning_rate=learning_rate)
    model.compile(optimizer=optimizer, loss='mean_squared_error')
    return model
```

To find the best combination of hyperparameters, we can use Keras Tuner or a custom grid search.

Choosing a minimum value of 50 instead of 10 for hp_units likely reflects a balance between computational efficiency and model complexity, as well as practical considerations based on the specific problem. Here's why a minimum value of 50 might be preferred over 10:

- Sufficient Model Capacity:

A minimum value of 50 units ensures that the model has enough capacity to capture meaningful patterns in the data. In many practical scenarios, 10 units might be insufficient, leading to underfitting where the model fails to learn the underlying data distribution effectively. Avoiding Underfitting:

With only 10 units, the model might be too simplistic, especially for complex datasets. This could result in poor performance because the model cannot adequately represent the complexity of the data. Empirical Evidence:

Often, hyperparameter ranges are informed by empirical evidence and prior experiments. If past experiments or domain knowledge suggest that configurations with fewer than 50 units generally perform poorly, it makes sense to set the lower bound at 50.

- Computational Efficiency:

Exploring configurations with very low units (like 10, 20, 30) may not be an efficient use of computational resources if these configurations are likely to perform poorly. Starting at 50 helps focus the search on more promising areas of the hyperparameter space. Practical Experience:

Practical experience with similar models or datasets might indicate that starting with 50 units is a reasonable baseline that balances model complexity and training time. It avoids the pitfalls of too small networks while not being overly complex.

- Step Size Consideration:

Given a step size of 50, starting from 10 would result in a sequence of (10, 60, 110, 160, 210). This is less intuitive and potentially less useful than (50, 100, 150, 200), where each step represents a significant and meaningful increase in model capacity. Search Space Efficiency:

Hyperparameter tuning often involves a trade-off between the breadth of the search space and the granularity of the search. By starting at 50 and using a step of 50, you ensure a more focused and manageable search space, improving the likelihood of finding optimal configurations without excessive computational cost. By setting the minimum value to 50, the tuning process starts with a model complexity that is more likely to be effective, avoiding the inefficiency and potential performance issues associated with very small networks.

```
from keras_tuner import RandomSearch

def model_builder(hp):
    model = Sequential()
    hp_units = hp.Int('units', min_value=50, max_value=200, step=50)
    hp_dropout = hp.Float('dropout_rate', min_value=0.1,
max_value=0.5, step=0.1)
    hp_learning_rate = hp.Choice('learning_rate', values=[1e-2, 1e-3,
1e-4])

    model.add(LSTM(units=hp_units, return_sequences=True,
input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(hp_dropout))
    model.add(LSTM(units=hp_units))
    model.add(Dropout(hp_dropout))
    model.add(Dense(1))

    model.compile(optimizer=Adam(learning_rate=hp_learning_rate),
loss='mean_squared_error')
    return model

tuner = RandomSearch(
    model_builder,
    objective='val_loss',
    max_trials=5,
    executions_per_trial=3,
    directory='stock_price_tuning_rs_de',
    project_name='stock_price_prediction'
)

tuner.search(X_train, y_train, epochs=50, validation_split=0.2,
callbacks=[EarlyStopping(monitor='val_loss', patience=3)])
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"""
The hyperparameter search is complete. The optimal number of units in
the LSTM layer is {best_hps.get('units')}.
The optimal dropout rate is {best_hps.get('dropout_rate')}.
The optimal learning rate is {best_hps.get('learning_rate')}.
""")
```

```
Reloading Tuner from stock_price_tuning_rs_de\stock_price_prediction\
tuner0.json

The hyperparameter search is complete. The optimal number of units in
the LSTM layer is 150.
```

```
The optimal dropout rate is 0.1.
The optimal learning rate is 0.01.
```

Bayesian Optimization is a probabilistic model-based optimization method that is particularly effective for tuning hyperparameters.

```
from keras_tuner import BayesianOptimization

def model_builder(hp):
    model = Sequential()
    hp_units = hp.Int('units', min_value=50, max_value=200, step=50)
    hp_dropout = hp.Float('dropout_rate', min_value=0.1,
max_value=0.5, step=0.1)
    hp_learning_rate = hp.Choice('learning_rate', values=[1e-2, 1e-3,
1e-4])

    model.add(LSTM(units=hp_units, return_sequences=True,
input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(hp_dropout))
    model.add(LSTM(units=hp_units))
    model.add(Dropout(hp_dropout))
    model.add(Dense(1))

    model.compile(optimizer=Adam(learning_rate=hp_learning_rate),
loss='mean_squared_error')
    return model

tuner = BayesianOptimization(
    model_builder,
    objective='val_loss',
    max_trials=10,
    executions_per_trial=3,
    directory='stock_price_tuning_bayesian_de',
    project_name='stock_price_prediction'
)

tuner.search(X_train, y_train, epochs=50, validation_split=0.2,
callbacks=[EarlyStopping(monitor='val_loss', patience=3)])
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"""
The hyperparameter search is complete. The optimal number of units in
the LSTM layer is {best_hps.get('units')}.
The optimal dropout rate is {best_hps.get('dropout_rate')}.
The optimal learning rate is {best_hps.get('learning_rate')}.
""")

Trial 10 Complete [00h 08m 58s]
val_loss: 7.928437723118502e-05
```

```
Best val_loss So Far: 5.343981805102279e-05
Total elapsed time: 02h 03m 49s

The hyperparameter search is complete. The optimal number of units in
the LSTM layer is 150.
The optimal dropout rate is 0.1.
The optimal learning rate is 0.01.
```

Hyperband is an optimization algorithm that uses adaptive resource allocation and early-stopping to find the best hyperparameters quickly.

```
from keras_tuner import Hyperband

def model_builder(hp):
    model = Sequential()
    hp_units = hp.Int('units', min_value=50, max_value=200, step=50)
    hp_dropout = hp.Float('dropout_rate', min_value=0.1,
max_value=0.5, step=0.1)
    hp_learning_rate = hp.Choice('learning_rate', values=[1e-2, 1e-3,
1e-4])

    model.add(LSTM(units=hp_units, return_sequences=True,
input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(hp_dropout))
    model.add(LSTM(units=hp_units))
    model.add(Dropout(hp_dropout))
    model.add(Dense(1))

    model.compile(optimizer=Adam(learning_rate=hp_learning_rate),
loss='mean_squared_error')
    return model

tuner = Hyperband(
    model_builder,
    objective='val_loss',
    max_epochs=50,
    executions_per_trial=3,
    directory='stock_price_tuning_hyperband_de',
    project_name='stock_price_prediction'
)

tuner.search(X_train, y_train, epochs=50, validation_split=0.2,
callbacks=[EarlyStopping(monitor='val_loss', patience=3)])
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"""
The hyperparameter search is complete. The optimal number of units in
the LSTM layer is {best_hps.get('units')}.
```

```
The optimal dropout rate is {best_hps.get('dropout_rate')}.
The optimal learning rate is {best_hps.get('learning_rate')}.
""")

Trial 81 Complete [00h 12m 11s]
val_loss: 9.028100612340495e-05

Best val_loss So Far: 3.3556641331718616e-05
Total elapsed time: 20h 29m 55s

The hyperparameter search is complete. The optimal number of units in
the LSTM layer is 150.
The optimal dropout rate is 0.1.
The optimal learning rate is 0.001.
```

Grid Search is an exhaustive search method that evaluates all possible combinations of hyperparameters.

```
from keras_tuner import GridSearch

def model_builder(hp):
    model = Sequential()
    hp_units = hp.Int('units', min_value=50, max_value=200, step=50)
    hp_dropout = hp.Float('dropout_rate', min_value=0.1,
max_value=0.5, step=0.1)
    hp_learning_rate = hp.Choice('learning_rate', values=[1e-2, 1e-3,
1e-4])

    model.add(LSTM(units=hp_units, return_sequences=True,
input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(hp_dropout))
    model.add(LSTM(units=hp_units))
    model.add(Dropout(hp_dropout))
    model.add(Dense(1))

    model.compile(optimizer=Adam(learning_rate=hp_learning_rate),
loss='mean_squared_error')
    return model

tuner = GridSearch(
    model_builder,
    objective='val_loss',
    max_trials=5,
    executions_per_trial=3,
    directory='stock_price_tuning_grid_de',
    project_name='stock_price_prediction'
)

tuner.search(X_train, y_train, epochs=50, validation_split=0.2,
```

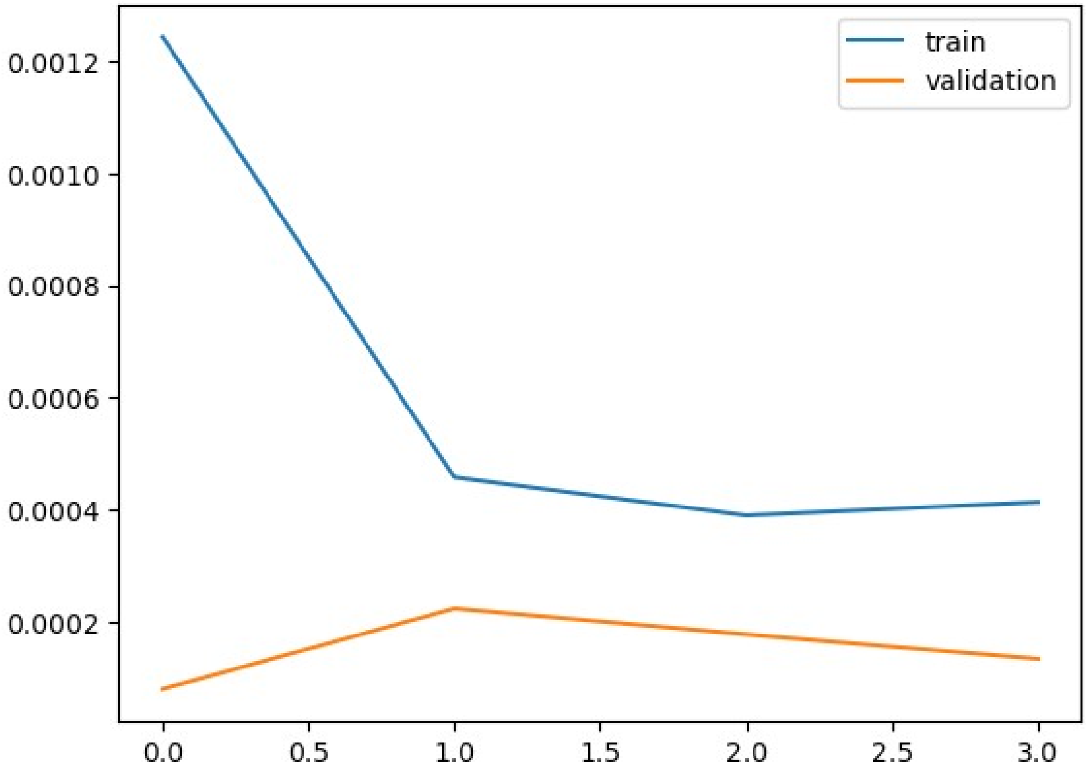
```
callbacks=[EarlyStopping(monitor='val_loss', patience=3)])
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"""
The hyperparameter search is complete. The optimal number of units in
the LSTM layer is {best_hps.get('units')}.
The optimal dropout rate is {best_hps.get('dropout_rate')}.
The optimal learning rate is {best_hps.get('learning_rate')}.
""")
```

```
Trial 5 Complete [00h 06m 34s]
val_loss: 8.718727864713098e-05

Best val_loss So Far: 5.9319852880435064e-05
Total elapsed time: 00h 42m 10s

The hyperparameter search is complete. The optimal number of units in
the LSTM layer is 50.
The optimal dropout rate is 0.1.
The optimal learning rate is 0.01.
```

```
# Build the model with the optimal hyperparameters
model = build_model(best_hps.get('units'),
best_hps.get('dropout_rate'), best_hps.get('learning_rate'))

# Train the model
history = model.fit(X_train, y_train, epochs=50, batch_size=32,
validation_split=0.2, callbacks=[EarlyStopping(monitor='val_loss',
patience=3)])

# Evaluate the model
loss = model.evaluate(X_test, y_test)
print(f'Test Loss: {loss}')

# Plot training history
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='validation')
plt.legend()
plt.show()
```

```
Epoch 1/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 27s 83ms/step - loss: 0.0031 - val_loss:
8.0522e-05
Epoch 2/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 19s 74ms/step - loss: 4.1922e-04 -
val_loss: 2.2371e-04
Epoch 3/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 19s 75ms/step - loss: 4.5007e-04 -
val_loss: 1.7784e-04
Epoch 4/50
```

```
251/251 ━━━━━━━━━━━━━━━━━━━━ 20s 80ms/step - loss: 4.8339e-04 -
val_loss: 1.3431e-04
79/79 ━━━━━━━━━━━━━━━━━━━━ 2s 22ms/step - loss: 1.2008e-04
Test Loss: 0.00012714770855382085
```



Exploring Different Sequence Lengths

While 60 days is a reasonable starting point, it's essential to experiment with different sequence lengths to determine the optimal window for your specific dataset and model. Here's how you can do that:

```
def create_sequences(data, sequence_length):
    sequences = []
    labels = []
    for i in range(len(data) - sequence_length):
        sequences.append(data[i:i+sequence_length])
        labels.append(data[i+sequence_length])
    return np.array(sequences), np.array(labels)
```

Experiment with Different Sequence Lengths You can loop through different sequence lengths to find the best performing one.

```
sequence_lengths = [30, 60, 90, 180, 360]
results = {}
```

```python
for seq_len in sequence_lengths:
    X, y = create_sequences(scaled_data, seq_len)
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

    model = build_model(best_hps.get('units'),
best_hps.get('dropout_rate'), best_hps.get('learning_rate'))
    history = model.fit(X_train, y_train, epochs=50, batch_size=32,
validation_split=0.2, callbacks=[EarlyStopping(monitor='val_loss',
patience=3)])

    loss = model.evaluate(X_test, y_test)
    results[seq_len] = loss
    print(f'Sequence Length: {seq_len}, Test Loss: {loss}')

# Find the best sequence length
best_seq_len = min(results, key=results.get)
print(f'Best Sequence Length: {best_seq_len}')
```

```
Epoch 1/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 9s 23ms/step - loss: 0.0042 - val_loss:
6.2516e-04
Epoch 2/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 7.3927e-04 -
val_loss: 1.4008e-04
Epoch 3/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 6.3101e-04 -
val_loss: 8.8061e-04
Epoch 4/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 6.9391e-04 -
val_loss: 9.5487e-05
Epoch 5/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 8.8070e-04 -
val_loss: 7.5412e-05
Epoch 6/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 7s 29ms/step - loss: 6.8378e-04 -
val_loss: 4.9860e-05
Epoch 7/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 9s 23ms/step - loss: 6.1379e-04 -
val_loss: 1.6740e-04
Epoch 8/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 6s 24ms/step - loss: 5.4029e-04 -
val_loss: 3.8615e-05
Epoch 9/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 6s 24ms/step - loss: 4.9751e-04 -
val_loss: 2.5265e-04
Epoch 10/50
252/252 ━━━━━━━━━━━━━━━━━━━━ 6s 25ms/step - loss: 6.5435e-04 -
val_loss: 1.5929e-04
Epoch 11/50
```

```
252/252 ━━━━━━━━━━━━━━━━━━━━ 6s 23ms/step - loss: 7.0685e-04 -
val_loss: 6.3622e-04
79/79 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 6.0723e-04
Sequence Length: 30, Test Loss: 0.0006633448647335172
Epoch 1/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 18s 59ms/step - loss: 0.0040 - val_loss:
0.0019
Epoch 2/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - loss: 0.0011 - val_loss:
0.0012
Epoch 3/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - loss: 6.8156e-04 -
val_loss: 2.8782e-04
Epoch 4/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - loss: 8.2427e-04 -
val_loss: 1.3902e-04
Epoch 5/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - loss: 5.2584e-04 -
val_loss: 2.6356e-04
Epoch 6/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - loss: 6.5538e-04 -
val_loss: 5.0430e-04
Epoch 7/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 10s 41ms/step - loss: 7.2441e-04 -
val_loss: 4.9363e-05
Epoch 8/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 11s 45ms/step - loss: 5.4527e-04 -
val_loss: 0.0011
Epoch 9/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 12s 50ms/step - loss: 6.6168e-04 -
val_loss: 5.2068e-05
Epoch 10/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 11s 44ms/step - loss: 6.6640e-04 -
val_loss: 5.6386e-05
79/79 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 6.3520e-05
Sequence Length: 60, Test Loss: 6.328353629214689e-05
Epoch 1/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 22s 70ms/step - loss: 0.0047 - val_loss:
3.5301e-04
Epoch 2/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 15s 62ms/step - loss: 7.2891e-04 -
val_loss: 1.2487e-04
Epoch 3/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 15s 61ms/step - loss: 6.1877e-04 -
val_loss: 2.0814e-04
Epoch 4/50
251/251 ━━━━━━━━━━━━━━━━━━━━ 16s 62ms/step - loss: 6.4969e-04 -
val_loss: 4.1115e-04
Epoch 5/50
```

```
251/251 ━━━━━━━━━━━━━━━━━━━━ 16s 62ms/step - loss: 5.7578e-04 -
val_loss: 5.7453e-04
79/79 ━━━━━━━━━━━━━━━━━━━━ 2s 19ms/step - loss: 5.4938e-04
Sequence Length: 90, Test Loss: 0.0005606361664831638
Epoch 1/50
249/249 ━━━━━━━━━━━━━━━━━━━━ 38s 141ms/step - loss: 0.0049 - val_loss:
4.3517e-04
Epoch 2/50
249/249 ━━━━━━━━━━━━━━━━━━━━ 32s 127ms/step - loss: 7.3731e-04 -
val_loss: 9.3547e-05
Epoch 3/50
249/249 ━━━━━━━━━━━━━━━━━━━━ 31s 123ms/step - loss: 6.6346e-04 -
val_loss: 3.9363e-04
Epoch 4/50
249/249 ━━━━━━━━━━━━━━━━━━━━ 33s 131ms/step - loss: 7.2056e-04 -
val_loss: 2.1407e-04
Epoch 5/50
249/249 ━━━━━━━━━━━━━━━━━━━━ 35s 138ms/step - loss: 7.6530e-04 -
val_loss: 1.3251e-04
78/78 ━━━━━━━━━━━━━━━━━━━━ 4s 53ms/step - loss: 9.2310e-05
Sequence Length: 180, Test Loss: 0.00010454434232087806
Epoch 1/50
245/245 ━━━━━━━━━━━━━━━━━━━━ 70s 273ms/step - loss: 0.0039 - val_loss:
3.3844e-04
Epoch 2/50
245/245 ━━━━━━━━━━━━━━━━━━━━ 62s 254ms/step - loss: 8.3341e-04 -
val_loss: 1.4315e-04
Epoch 3/50
245/245 ━━━━━━━━━━━━━━━━━━━━ 62s 252ms/step - loss: 6.3898e-04 -
val_loss: 1.4192e-04
Epoch 4/50
245/245 ━━━━━━━━━━━━━━━━━━━━ 62s 252ms/step - loss: 6.2009e-04 -
val_loss: 7.6711e-04
Epoch 5/50
245/245 ━━━━━━━━━━━━━━━━━━━━ 66s 267ms/step - loss: 6.1541e-04 -
val_loss: 1.9580e-04
Epoch 6/50
245/245 ━━━━━━━━━━━━━━━━━━━━ 74s 300ms/step - loss: 6.3989e-04 -
val_loss: 1.7103e-04
77/77 ━━━━━━━━━━━━━━━━━━━━ 7s 91ms/step - loss: 1.6351e-04
Sequence Length: 360, Test Loss: 0.00015127587539609522
Best Sequence Length: 60
```

Sequence Length: 90, Test Loss: 0.00033690148848108947 Best Sequence Length: 90