Data Preprocessing:

Ensure your data is clean and structured.

Handle missing values appropriately.

Normalize or scale the data if needed.

Feature Engineering:

Consider adding relevant features like technical indicators (e.g., Moving Averages, Relative Strength Index, etc.).

Explore different time frames (daily, weekly, monthly) for historical data.

Split the Data:

Divide your dataset into training and testing sets.

Use a time-based split to mimic real-world scenarios.

Select a Model:

Choose a machine learning model suitable for time series forecasting. Options include LSTM, ARIMA, or even traditional regression models.

Model Training:

Train your selected model on the training data.

Experiment with hyperparameter tuning to improve model performance.

Model Evaluation:

Use appropriate evaluation metrics (e.g., Mean Absolute Error, Root Mean Squared Error) to assess your model's performance.

Pay attention to metrics like overfitting.

Prediction and Visualization:

Make predictions on your test dataset.

Visualize the actual vs. predicted prices to understand how well your model is performing.

Fine-Tuning:

If your model's performance is not satisfactory, consider fine-tuning hyperparameters, trying different models, or enhancing feature engineering.

Deployment:

Once you have a reliable model, you can deploy it to make real-time predictions.

Continuous Monitoring:

Regularly update your model with new data and monitor its performance over time.

Remember that stock price prediction is a complex task with many factors at play, and no model can predict with absolute certainty. It's important to approach this task with a deep understanding of the limitations and risks associated with financial forecasting.

If you have specific questions or need assistance with any of these steps, feel free to ask.