Pytorch_Capstone_Project_Rajgowthaman_Rajendran_Minutely_Model

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1 Predicting Bitcoin Price Movements and Volatility Using Transformer-Based Deep Learning Models.

1.0.1 Rajgowthaman Rajendran

Bitcoin's price is highly volatile, making accurate short-term price and volatility predictions crucial for traders and investors. This project aims to develop a Transformer-based deep learning model to forecast Bitcoin's short-term price movements and volatility based on historical price data. Unlike traditional methods, Transformers efficiently capture long-range dependencies in time-series data, making them well-suited for this task. The model will leverage self-attention mechanisms to identify complex temporal patterns in Bitcoin price fluctuations. It will predict short-term price trends (e.g., next-minute, next-hour, next-day) and volatility levels to help traders make informed decisions. Key features include opening, closing, highest, and lowest prices, volume data, and volatility indicators to enhance forecasting accuracy.

Implementation

- Data Preprocessing: Clean and preprocess the dataset, handle missing values, and scale the features (e.g., normalization of price data).
- Feature Engineering: Create new features, such as moving averages, relative strength index (RSI), and other technical indicators, to improve predictions.
- Model Development: Use Transformer models (e.g., Time Series Transformer or Informer) to capture long-range dependencies.
- Training & Optimization: Train the model in PyTorch using mean squared error (MSE) loss and optimize using Adam optimizer.
- Evaluation & Fine-Tuning: Evaluate the model using metrics like RMSE (Root Mean Squared Error), accuracy, and mean absolute error (MAE), and directional accuracy; fine-tune hyper-parameters.

1.0.2 Data Collection

The dataset used for this project is a comprehensive, minute-level Bitcoin (BTC) price and volume dataset covering the period from 2012 to 2025. The data was compiled from two sources:

1. Historical BTC Data (2012–March 2021)

Source: Kaggle Dataset by mczielinski

This dataset provided historical daily Bitcoin price data including Open, High, Low, Close, and Volume.

2. Minute-Level BTC Data (Post March 31, 2021)

To ensure up-to-date granularity, we implemented a custom Python scraper using the Binance API to collect minute-level candlestick data from April 1, 2021, to present. The script iteratively paginates through 1-minute intervals, fetches 1000 rows per API call, and merges the results into a single DataFrame.

Minutely Model

[17]:
```
import pandas as pd
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
from torch.utils.data import DataLoader, Dataset, random_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sns

# Load the cleaned dataset (Timestamp is already the index)
df = pd.read_csv("btc_base_cleaned_2012_to_2025.csv", index_col=0,␣
 ↪parse_dates=True)

# Quick preview
print("Data loaded successfully!")
print(f"Rows: {len(df):,} | Columns: {df.shape[1]}")
df.head()
```

```
Data loaded successfully!
Rows: 6,976,871 | Columns: 5
```

[17]:

	Open	High	Low	Close	Volume
2012-01-01 10:01:00	4.58	4.58	4.58	4.58	0.0
2012-01-01 10:02:00	4.58	4.58	4.58	4.58	0.0
2012-01-01 10:03:00	4.58	4.58	4.58	4.58	0.0
2012-01-01 10:04:00	4.58	4.58	4.58	4.58	0.0
2012-01-01 10:05:00	4.58	4.58	4.58	4.58	0.0

2. Exploratory Data Analysis

- 2.1. Dataset Summary

[21]:
```
# Basic info
#Only keep last 30 days
df = df.last("30D")
print("Date Range:")
```

```python
print(f"Start: {df.index.min()}")
print(f"End:   {df.index.max()}")

print("\nColumns:")
print(df.columns.tolist())

print("\nMissing values per column:")
print(df.isna().sum())
```

```
Date Range:
Start: 2025-03-08 11:12:00
End:   2025-04-07 11:11:00

Columns:
['Open', 'High', 'Low', 'Close', 'Volume']

Missing values per column:
Open      0
High      0
Low       0
Close     0
Volume    0
dtype: int64
```

```
<ipython-input-21-2ab68e444bdf>:3: FutureWarning:

last is deprecated and will be removed in a future version. Please create a mask
and filter using `.loc` instead
```

3: Feature Engineering and Informer Sequence Preparation

This section derives key technical indicators to enhance the model's predictive ability by capturing market patterns and dynamics:

- **Log Returns**
  Computed as the natural logarithm of consecutive closing prices. This stabilizes variance and better models relative price changes.
- **Moving Averages (MA)**
  - `MA_20`: 20-period simple moving average to capture short-term trends.
  - `MA_50`: 50-period simple moving average for medium-term trends.
- **Exponential Moving Average (EMA)**
  - `EMA_20`: Weighted average that reacts more significantly to recent price changes.
- **Bollinger Bands**
  Defined as:

  - Upper Band = `MA_20` + 2 × rolling standard deviation
  - Lower Band = `MA_20` - 2 × rolling standard deviation
    Helps identify periods of high or low volatility.

- **Relative Strength Index (RSI)**
  Measures the strength and speed of price movements over a 14-period window. Values above 70 indicate overbought conditions, while below 30 indicate oversold.
- **Rolling Volatility**
  Calculated as the standard deviation of log returns over a 60-period window, indicating how much the price fluctuates over time.

Finally, we drop any rows with `NaN` values that result from rolling calculations to ensure data consistency.

[26]:
```
# Feature Engineering
df['Log_Returns'] = np.log(df['Close'] / df['Close'].shift(1))

# Moving Averages
df['MA_20'] = df['Close'].rolling(window=20).mean()
df['MA_50'] = df['Close'].rolling(window=50).mean()

# Exponential Moving Average
df['EMA_20'] = df['Close'].ewm(span=20, adjust=False).mean()

# Bollinger Bands
rolling_std = df['Close'].rolling(window=20).std()
df['BB_upper'] = df['MA_20'] + 2 * rolling_std
df['BB_lower'] = df['MA_20'] - 2 * rolling_std

# RSI (Relative Strength Index)
delta = df['Close'].diff()
gain = delta.where(delta > 0, 0)
loss = -delta.where(delta < 0, 0)
avg_gain = gain.rolling(window=14).mean()
avg_loss = loss.rolling(window=14).mean()
rs = avg_gain / avg_loss
df['RSI'] = 100 - (100 / (1 + rs))

# Volatility (rolling std of log returns)
df['Volatility'] = df['Log_Returns'].rolling(window=60).std()

# Lag features
df['Close_lag_1'] = df['Close'].shift(1)
df['Close_lag_2'] = df['Close'].shift(2)

# Directional target (1 = up, 0 = down)
df['Direction'] = (df['Close'].shift(-1) > df['Close']).astype(int)
```

```python
# Drop rows with NaNs from rolling/lags
df.dropna(inplace=True)

# Preview
df[['Close', 'Log_Returns', 'RSI', 'Volatility', 'Direction']].head()
```

[26]:

	Close	Log_Returns	RSI	Volatility	Direction
2025-03-08 12:12:00	85896.0	0.000501	46.990741	0.000573	1
2025-03-08 12:13:00	85930.0	0.000396	50.858369	0.000565	1
2025-03-08 12:14:00	85952.0	0.000256	52.977413	0.000566	1
2025-03-08 12:15:00	85968.0	0.000186	52.880658	0.000566	0
2025-03-08 12:16:00	85958.0	-0.000116	44.418605	0.000559	1

- 3.2. Feature Selection

[27]:
```python
features = [
    'Close', 'Volume', 'MA_20', 'MA_50', 'EMA_20',
    'BB_upper', 'BB_lower', 'RSI', 'Volatility',
    'Close_lag_1', 'Close_lag_2'
]

target_cols = ['Close', 'Volatility', 'Direction']
```

- 3.3. Scaling

  We will normalize features and targets using MinMaxScaler.

[28]:
```python
from sklearn.preprocessing import MinMaxScaler

# Scale inputs
feature_scaler = MinMaxScaler()
X_scaled_h = feature_scaler.fit_transform(df[features])

# Scale targets
target_scaler = MinMaxScaler()
y_scaled_h = target_scaler.fit_transform(df[target_cols])
```

PyTorch-Style Dataset That Reads From X_scaled Directly

[29]:
```python
from torch.utils.data import Dataset

class BitcoinMultiTaskDataset(Dataset):
    def __init__(self, X_scaled, df_targets, window_size):
        self.X = X_scaled
        self.close = df_targets['Close'].values
        self.volatility = df_targets['Volatility'].values
        self.direction = df_targets['Direction'].values
        self.window_size = window_size
```

```
    def __len__(self):
        return len(self.X) - self.window_size

    def __getitem__(self, idx):
        x_seq = self.X[idx:idx + self.window_size]
        y_close = self.close[idx + self.window_size]
        y_vol = self.volatility[idx + self.window_size]
        y_dir = self.direction[idx + self.window_size]
        return (
            torch.tensor(x_seq, dtype=torch.float32),
            torch.tensor([y_close, y_vol, y_dir], dtype=torch.float32)
        )
```

Split Chronologically

[30]:
```
from torch.utils.data import DataLoader, random_split

# Set window size
window_size = 60

# Build dataset
multi_dataset = BitcoinMultiTaskDataset(X_scaled_h, df[['Close', 'Volatility',␣
 ↪'Direction']], window_size=window_size)

# Train/Test split (80/20)
train_size = int(len(multi_dataset) * 0.8)
test_size = len(multi_dataset) - train_size

train_dataset, test_dataset = random_split(multi_dataset, [train_size,␣
 ↪test_size])

# DataLoaders
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)

print(f"Train Samples: {len(train_dataset)} | Test Samples:␣
 ↪{len(test_dataset)}")
```

```
Train Samples: 34464 | Test Samples: 8616
```

2 Daily Transformer model to forecast Minute-wise BTC price and volatility.

Define Time Series Transformer

[31]:
```
import torch.nn as nn

class MultiTaskTransformer(nn.Module):
    def __init__(self, input_size, d_model=64, nhead=4, num_layers=2, dropout=0.
 ↪1):
        super(MultiTaskTransformer, self).__init__()
        self.input_proj = nn.Linear(input_size, d_model)

        encoder_layer = nn.TransformerEncoderLayer(
            d_model=d_model, nhead=nhead, dropout=dropout, batch_first=True
        )
        self.encoder = nn.TransformerEncoder(encoder_layer,␣
 ↪num_layers=num_layers)

        # Output: [Close, Volatility, Direction]
        self.output_layer = nn.Linear(d_model, 3)

    def forward(self, x):
        x = self.input_proj(x)
        x = self.encoder(x)
        return self.output_layer(x[:, -1, :])  # Use last time step's output
```

2.0.1 Define Mixed Loss Function for Multi-Task Output

Since we're predicting 3 outputs:

- Close (regression)
- Volatility (regression)
- Direction (binary classification)

We'll use a composite loss combining:

- SmoothL1Loss for Close & Volatility
- BCEWithLogitsLoss for Direction (no sigmoid needed in model)

[40]:
```
# Define loss functions
regression_loss = nn.SmoothL1Loss()
classification_loss = nn.BCEWithLogitsLoss()

def multi_task_loss(preds, targets, alpha=10):
    """
    preds: tensor of shape (batch_size, 3)
    targets: tensor of shape (batch_size, 3)
    alpha: weight for classification loss
    """
    pred_close = preds[:, 0]
    pred_vol = preds[:, 1]
```

```
    pred_dir = preds[:, 2]

    target_close = targets[:, 0]
    target_vol = targets[:, 1]
    target_dir = targets[:, 2]

    loss_close = regression_loss(pred_close, target_close)
    loss_vol = regression_loss(pred_vol, target_vol)
    loss_direction = classification_loss(pred_dir, target_dir)

    return loss_close + loss_vol + alpha * loss_direction
```

Train Daily Transformer

[41]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
# Initialize model
model = MultiTaskTransformer(input_size=X_scaled_h.shape[1]).to(device)
# Optimizer
optimizer = torch.optim.AdamW(model.parameters(), lr=5e-4)

# Confirm model structure
print(model)
```

```
MultiTaskTransformer(
  (input_proj): Linear(in_features=11, out_features=64, bias=True)
  (encoder): TransformerEncoder(
    (layers): ModuleList(
      (0-1): 2 x TransformerEncoderLayer(
        (self_attn): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=64,
out_features=64, bias=True)
        )
        (linear1): Linear(in_features=64, out_features=2048, bias=True)
        (dropout): Dropout(p=0.1, inplace=False)
        (linear2): Linear(in_features=2048, out_features=64, bias=True)
        (norm1): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
        (norm2): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
        (dropout1): Dropout(p=0.1, inplace=False)
        (dropout2): Dropout(p=0.1, inplace=False)
      )
    )
  )
  (output_layer): Linear(in_features=64, out_features=3, bias=True)
)
```

[42]:
```
from tqdm.notebook import tqdm

epochs = 200
```

```python
model.train()

for epoch in range(epochs):
    total_loss = 0
    loop = tqdm(train_loader, desc=f"Epoch {epoch+1}/{epochs}")

    for batch_X, batch_y in loop:
        batch_X, batch_y = batch_X.to(device), batch_y.to(device)

        optimizer.zero_grad()
        preds = model(batch_X)

        loss = multi_task_loss(preds, batch_y, alpha=1.0)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()
        loop.set_postfix(loss=loss.item())

    print(f"Epoch {epoch+1} - Avg Loss: {total_loss / len(train_loader):.4f}")
```

```
Epoch 1/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 1 - Avg Loss: 83805.4774

Epoch 2/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 2 - Avg Loss: 83747.1667

Epoch 3/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 3 - Avg Loss: 83653.6346

Epoch 4/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 4 - Avg Loss: 83526.5386

Epoch 5/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 5 - Avg Loss: 83370.2215

Epoch 6/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 6 - Avg Loss: 83188.8763

Epoch 7/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 7 - Avg Loss: 82983.1209

Epoch 8/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 8 - Avg Loss: 82756.5955

Epoch 9/200:   0%|          | 0/539 [00:00<?, ?it/s]

Epoch 9 - Avg Loss: 82508.0886
```

```
Epoch 10/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 10 - Avg Loss: 82241.3102
Epoch 11/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 11 - Avg Loss: 81954.4981
Epoch 12/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 12 - Avg Loss: 81650.0911
Epoch 13/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 13 - Avg Loss: 81327.1039
Epoch 14/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 14 - Avg Loss: 80986.7916
Epoch 15/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 15 - Avg Loss: 80626.9025
Epoch 16/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 16 - Avg Loss: 80251.9342
Epoch 17/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 17 - Avg Loss: 79859.2086
Epoch 18/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 18 - Avg Loss: 79449.7371
Epoch 19/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 19 - Avg Loss: 79023.4233
Epoch 20/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 20 - Avg Loss: 78580.9315
Epoch 21/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 21 - Avg Loss: 78122.9969
Epoch 22/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 22 - Avg Loss: 77648.8425
Epoch 23/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 23 - Avg Loss: 77157.7943
Epoch 24/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 24 - Avg Loss: 76651.6105
Epoch 25/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 25 - Avg Loss: 76130.2130
```

```
Epoch 26/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 26 - Avg Loss: 75594.3671
Epoch 27/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 27 - Avg Loss: 75042.8015
Epoch 28/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 28 - Avg Loss: 74475.3313
Epoch 29/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 29 - Avg Loss: 73894.0477
Epoch 30/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 30 - Avg Loss: 73298.4526
Epoch 31/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 31 - Avg Loss: 72688.0649
Epoch 32/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 32 - Avg Loss: 72063.2254
Epoch 33/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 33 - Avg Loss: 71423.7789
Epoch 34/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 34 - Avg Loss: 70770.7359
Epoch 35/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 35 - Avg Loss: 70103.7893
Epoch 36/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 36 - Avg Loss: 69423.2908
Epoch 37/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 37 - Avg Loss: 68728.4042
Epoch 38/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 38 - Avg Loss: 68021.6782
Epoch 39/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 39 - Avg Loss: 67300.6313
Epoch 40/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 40 - Avg Loss: 66566.9064
Epoch 41/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 41 - Avg Loss: 65818.9954
```

```
Epoch 42/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 42 - Avg Loss: 65059.5445
Epoch 43/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 43 - Avg Loss: 64286.2544
Epoch 44/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 44 - Avg Loss: 63501.3239
Epoch 45/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 45 - Avg Loss: 62702.4115
Epoch 46/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 46 - Avg Loss: 61892.3904
Epoch 47/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 47 - Avg Loss: 61069.0954
Epoch 48/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 48 - Avg Loss: 60234.8697
Epoch 49/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 49 - Avg Loss: 59388.4743
Epoch 50/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 50 - Avg Loss: 58529.2360
Epoch 51/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 51 - Avg Loss: 57658.5633
Epoch 52/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 52 - Avg Loss: 56776.3178
Epoch 53/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 53 - Avg Loss: 55882.1475
Epoch 54/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 54 - Avg Loss: 54977.2305
Epoch 55/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 55 - Avg Loss: 54060.8255
Epoch 56/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 56 - Avg Loss: 53132.6550
Epoch 57/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 57 - Avg Loss: 52193.1721
```

```
Epoch 58/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 58 - Avg Loss: 51243.5389
Epoch 59/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 59 - Avg Loss: 50283.9293
Epoch 60/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 60 - Avg Loss: 49313.1680
Epoch 61/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 61 - Avg Loss: 48331.2216
Epoch 62/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 62 - Avg Loss: 47338.1143
Epoch 63/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 63 - Avg Loss: 46333.6875
Epoch 64/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 64 - Avg Loss: 45319.4435
Epoch 65/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 65 - Avg Loss: 44296.5382
Epoch 66/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 66 - Avg Loss: 43262.1629
Epoch 67/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 67 - Avg Loss: 42219.1093
Epoch 68/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 68 - Avg Loss: 41167.2952
Epoch 69/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 69 - Avg Loss: 40104.4315
Epoch 70/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 70 - Avg Loss: 39031.1154
Epoch 71/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 71 - Avg Loss: 37948.7721
Epoch 72/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 72 - Avg Loss: 36855.8136
Epoch 73/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 73 - Avg Loss: 35753.5551
```

```
Epoch 74/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 74 - Avg Loss: 34641.2422
Epoch 75/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 75 - Avg Loss: 33519.8222
Epoch 76/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 76 - Avg Loss: 32390.2464
Epoch 77/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 77 - Avg Loss: 31251.6490
Epoch 78/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 78 - Avg Loss: 30104.8191
Epoch 79/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 79 - Avg Loss: 28950.0053
Epoch 80/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 80 - Avg Loss: 27786.9619
Epoch 81/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 81 - Avg Loss: 26613.8904
Epoch 82/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 82 - Avg Loss: 25432.5663
Epoch 83/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 83 - Avg Loss: 24241.8812
Epoch 84/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 84 - Avg Loss: 23043.8977
Epoch 85/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 85 - Avg Loss: 21836.3276
Epoch 86/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 86 - Avg Loss: 20619.3498
Epoch 87/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 87 - Avg Loss: 19395.2922
Epoch 88/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 88 - Avg Loss: 18162.0035
Epoch 89/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 89 - Avg Loss: 16921.2588
```

```
Epoch 90/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 90 - Avg Loss: 15670.7344
Epoch 91/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 91 - Avg Loss: 14414.4501
Epoch 92/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 92 - Avg Loss: 13151.3789
Epoch 93/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 93 - Avg Loss: 11881.6230
Epoch 94/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 94 - Avg Loss: 10603.5622
Epoch 95/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 95 - Avg Loss: 9319.9916
Epoch 96/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 96 - Avg Loss: 8035.4902
Epoch 97/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 97 - Avg Loss: 6763.4861
Epoch 98/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 98 - Avg Loss: 5531.5858
Epoch 99/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 99 - Avg Loss: 4298.6965
Epoch 100/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 100 - Avg Loss: 3109.8134
Epoch 101/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 101 - Avg Loss: 2039.1974
Epoch 102/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 102 - Avg Loss: 1306.7734
Epoch 103/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 103 - Avg Loss: 904.3551
Epoch 104/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 104 - Avg Loss: 691.6270
Epoch 105/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 105 - Avg Loss: 588.8262
```

```
Epoch 106/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 106 - Avg Loss: 504.8312
Epoch 107/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 107 - Avg Loss: 427.7018
Epoch 108/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 108 - Avg Loss: 355.8787
Epoch 109/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 109 - Avg Loss: 297.1673
Epoch 110/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 110 - Avg Loss: 255.2532
Epoch 111/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 111 - Avg Loss: 228.1777
Epoch 112/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 112 - Avg Loss: 208.5774
Epoch 113/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 113 - Avg Loss: 190.5000
Epoch 114/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 114 - Avg Loss: 181.1978
Epoch 115/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 115 - Avg Loss: 173.0158
Epoch 116/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 116 - Avg Loss: 168.7810
Epoch 117/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 117 - Avg Loss: 164.3852
Epoch 118/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 118 - Avg Loss: 160.3867
Epoch 119/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 119 - Avg Loss: 156.0000
Epoch 120/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 120 - Avg Loss: 150.6049
Epoch 121/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 121 - Avg Loss: 145.2850
```

```
Epoch 122/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 122 - Avg Loss: 143.7430
Epoch 123/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 123 - Avg Loss: 140.5758
Epoch 124/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 124 - Avg Loss: 141.7329
Epoch 125/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 125 - Avg Loss: 140.5237
Epoch 126/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 126 - Avg Loss: 140.4412
Epoch 127/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 127 - Avg Loss: 137.7886
Epoch 128/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 128 - Avg Loss: 135.7058
Epoch 129/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 129 - Avg Loss: 132.9999
Epoch 130/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 130 - Avg Loss: 135.8682
Epoch 131/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 131 - Avg Loss: 130.5248
Epoch 132/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 132 - Avg Loss: 133.9083
Epoch 133/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 133 - Avg Loss: 130.9490
Epoch 134/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 134 - Avg Loss: 132.4076
Epoch 135/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 135 - Avg Loss: 130.4720
Epoch 136/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 136 - Avg Loss: 130.1222
Epoch 137/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 137 - Avg Loss: 126.4149
```

```
Epoch 138/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 138 - Avg Loss: 128.6005
Epoch 139/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 139 - Avg Loss: 130.7624
Epoch 140/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 140 - Avg Loss: 128.6099
Epoch 141/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 141 - Avg Loss: 126.7042
Epoch 142/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 142 - Avg Loss: 125.9495
Epoch 143/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 143 - Avg Loss: 124.1660
Epoch 144/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 144 - Avg Loss: 123.7392
Epoch 145/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 145 - Avg Loss: 125.2329
Epoch 146/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 146 - Avg Loss: 127.7553
Epoch 147/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 147 - Avg Loss: 124.3889
Epoch 148/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 148 - Avg Loss: 125.1356
Epoch 149/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 149 - Avg Loss: 125.5934
Epoch 150/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 150 - Avg Loss: 125.5244
Epoch 151/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 151 - Avg Loss: 125.0106
Epoch 152/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 152 - Avg Loss: 122.7720
Epoch 153/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 153 - Avg Loss: 123.3443
```

```
Epoch 154/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 154 - Avg Loss: 124.7583
Epoch 155/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 155 - Avg Loss: 122.8367
Epoch 156/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 156 - Avg Loss: 125.2360
Epoch 157/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 157 - Avg Loss: 123.1807
Epoch 158/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 158 - Avg Loss: 122.7722
Epoch 159/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 159 - Avg Loss: 123.5277
Epoch 160/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 160 - Avg Loss: 123.0628
Epoch 161/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 161 - Avg Loss: 121.1984
Epoch 162/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 162 - Avg Loss: 124.8465
Epoch 163/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 163 - Avg Loss: 123.3476
Epoch 164/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 164 - Avg Loss: 124.1139
Epoch 165/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 165 - Avg Loss: 120.6972
Epoch 166/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 166 - Avg Loss: 118.9055
Epoch 167/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 167 - Avg Loss: 120.5856
Epoch 168/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 168 - Avg Loss: 118.5613
Epoch 169/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 169 - Avg Loss: 119.6185
```

```
Epoch 170/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 170 - Avg Loss: 119.8372
Epoch 171/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 171 - Avg Loss: 119.2655
Epoch 172/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 172 - Avg Loss: 118.4969
Epoch 173/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 173 - Avg Loss: 119.2563
Epoch 174/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 174 - Avg Loss: 119.1877
Epoch 175/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 175 - Avg Loss: 117.9801
Epoch 176/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 176 - Avg Loss: 118.3637
Epoch 177/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 177 - Avg Loss: 119.9950
Epoch 178/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 178 - Avg Loss: 117.9993
Epoch 179/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 179 - Avg Loss: 119.5288
Epoch 180/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 180 - Avg Loss: 119.9395
Epoch 181/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 181 - Avg Loss: 120.0074
Epoch 182/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 182 - Avg Loss: 119.0956
Epoch 183/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 183 - Avg Loss: 120.7168
Epoch 184/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 184 - Avg Loss: 119.2357
Epoch 185/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 185 - Avg Loss: 118.6078
```

```
Epoch 186/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 186 - Avg Loss: 118.2595
Epoch 187/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 187 - Avg Loss: 117.1252
Epoch 188/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 188 - Avg Loss: 117.1830
Epoch 189/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 189 - Avg Loss: 119.1985
Epoch 190/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 190 - Avg Loss: 118.7149
Epoch 191/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 191 - Avg Loss: 117.5348
Epoch 192/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 192 - Avg Loss: 115.5649
Epoch 193/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 193 - Avg Loss: 115.4506
Epoch 194/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 194 - Avg Loss: 113.9162
Epoch 195/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 195 - Avg Loss: 115.4850
Epoch 196/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 196 - Avg Loss: 112.7499
Epoch 197/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 197 - Avg Loss: 115.4172
Epoch 198/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 198 - Avg Loss: 113.9147
Epoch 199/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 199 - Avg Loss: 113.9510
Epoch 200/200:   0%|          | 0/539 [00:00<?, ?it/s]
Epoch 200 - Avg Loss: 113.7209
```

2.0.2 Loss Trend Summary

Epoch	Avg Loss
1	81,958
50	~49,346
75	~21,892
100	269.89

Evaluation Block: Minutely Transformer

[43]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error

model.eval()
preds, actuals = [], []

with torch.no_grad():
    for batch_X, batch_y in test_loader:
        batch_X = batch_X.to(device)
        outputs = model(batch_X).cpu().numpy()
        preds.append(outputs)
        actuals.append(batch_y.numpy())

# Stack predictions and targets
preds = np.vstack(preds)
actuals = np.vstack(actuals)

# Split predicted vs actual values
pred_return = preds[:, 0]
pred_vol     = preds[:, 1]
pred_dir_logit = preds[:, 2]
pred_dir = (torch.sigmoid(torch.tensor(pred_dir_logit)) > 0.5).int().numpy()

true_return = actuals[:, 0]
true_vol    = actuals[:, 1]
true_dir    = actuals[:, 2]

# --- Metrics ---
rmse_return = np.sqrt(mean_squared_error(true_return, pred_return))
mae_return  = mean_absolute_error(true_return, pred_return)

rmse_vol = np.sqrt(mean_squared_error(true_vol, pred_vol))
mae_vol  = mean_absolute_error(true_vol, pred_vol)

directional_acc = (pred_dir == true_dir).sum() / len(true_dir) * 100

# --- Display ---
print(f"Log Return RMSE: {rmse_return:.6f}")
print(f"Log Return MAE : {mae_return:.6f}")
```

```python
print(f"Volatility RMSE: {rmse_vol:.6f}")
print(f"Volatility MAE : {mae_vol:.6f}")
print(f"Directional Accuracy: {directional_acc:.2f}%")
```

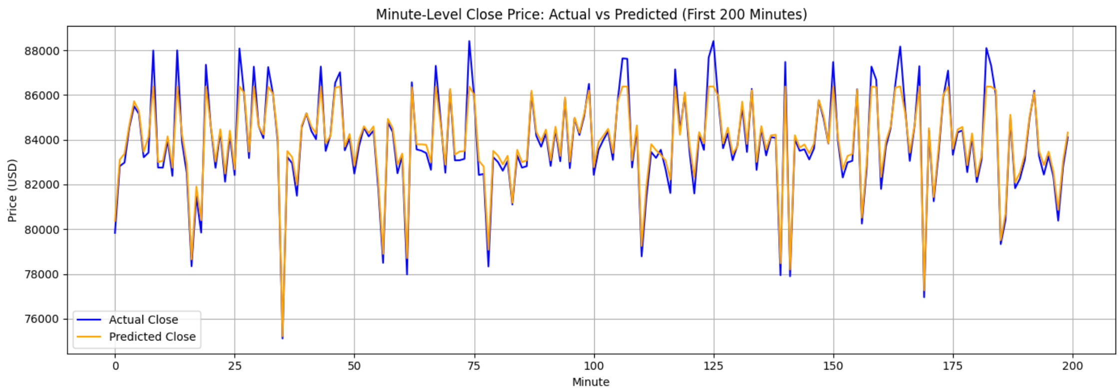
```
Log Return RMSE: 296.692141
Log Return MAE : 239.152649
Volatility RMSE: 0.071498
Volatility MAE : 0.071394
Directional Accuracy: 51.24%
```

[50]:
```python
print(true_return[:20])
print(pred_return[:20])
```

```
[79836.   82817.99 82981.   84543.99 85497.61 85159.71 83215.99 83423.19
 87987.99 82757.51 82752.17 83992.99 82383.51 87994.12 83907.38 82503.
 78347.82 81469.   79851.   87349.52]
[80213.02  83149.695 83237.336 84728.27  85642.87  85296.68  83398.336
 83711.76  87082.28  82952.875 82980.77  84174.15  82668.02  87058.555
 84185.38  82721.49  78801.13  81754.88  80136.14  87066.6  ]
```

Minutely close price plot

[52]:
```python
import matplotlib.pyplot as plt
import numpy as np

# Automatically pick the shorter length to avoid out-of-range errors
N = 200#min(len(true_close), len(pred_close))

plt.figure(figsize=(14, 5))
plt.plot(true_close[:N], label='Actual Close', linewidth=1.5, color='blue')
plt.plot(pred_close[:N], label='Predicted Close', linewidth=1.5, color='orange')
plt.title(f"Minute-Level Close Price: Actual vs Predicted (First {N} Minutes)")
plt.xlabel("Minute")
plt.ylabel("Price (USD)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



2.0.3 Takeaway

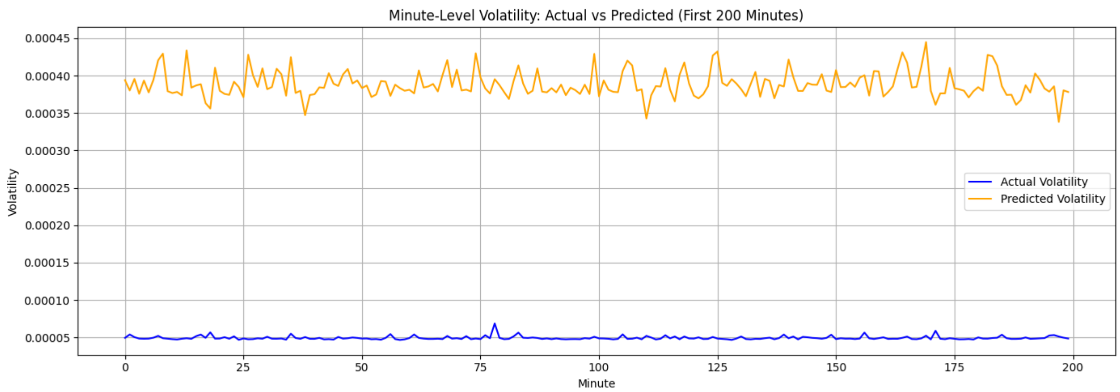
- After looking at the chart of actual vs predicted minute-level close prices, I can tell the model is doing a decent job. The orange predicted line follows the blue actual line most of the time, which means it's learning the general pattern well.
- But I also notice that the predicted line jumps up and down a bit too much in some places. This could mean the model is reacting too strongly to small changes in the data. It's not a big problem, but something I can work on.

Overall, I'm happy with how the model is performing so far.

Daily Volatility

[57]:
```
from sklearn.preprocessing import MinMaxScaler
import numpy as np
import matplotlib.pyplot as plt

# Step 1: Refit scaler using original Volatility column
vol_scaler = MinMaxScaler()
vol_scaler.fit(df[['Volatility']])  # assumes df is your full dataset

# Step 2: Inverse transform
true_vol_unscaled = vol_scaler.inverse_transform(true_vol.reshape(-1, 1)).
 ↪flatten()
pred_vol_unscaled = vol_scaler.inverse_transform(pred_vol.reshape(-1, 1)).
 ↪flatten()

# Step 3: Plot the first 200 minutes
N = 200

plt.figure(figsize=(14, 5))
plt.plot(true_vol_unscaled[:N], label='Actual Volatility', linewidth=1.5,␣
 ↪color='blue')
```

```
plt.plot(pred_vol_unscaled[:N], label='Predicted Volatility', linewidth=1.5,␣
↪color='orange')
plt.title("Minute-Level Volatility: Actual vs Predicted (First 200 Minutes)")
plt.xlabel("Minute")
plt.ylabel("Volatility")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



2.0.4 Takeaway

After unscaling and plotting minute-level volatility, I can see that the predicted values are consistently higher than the actual ones. While the shape of the curve is relatively stable, the model seems to have learned a higher baseline for volatility than what is actually observed.

This could mean that the model is overestimating risk or reacting to short-term noise. I might need to fine-tune the loss balance or improve the volatility feature set to help the model match the actual range more closely.

New Fine-Tune Loss Function

[59]:
```
def loss_finetune(pred_ft, target_ft, w_close=1.0, w_vol=0.5, w_dir=2.0):
    """
    Fine-tune loss (non-conflicting): returns weighted total loss
    Variables are suffixed with _ft to avoid conflicts
    """
    pred_close_ft = pred_ft[:, 0]
    pred_vol_ft = pred_ft[:, 1]
    pred_dir_ft = pred_ft[:, 2]

    target_close_ft = target_ft[:, 0]
    target_vol_ft = target_ft[:, 1]
    target_dir_ft = target_ft[:, 2].long()
```

```
    # MSE Losses
    loss_close_ft = torch.nn.functional.mse_loss(pred_close_ft, target_close_ft)
    loss_vol_ft = torch.nn.functional.mse_loss(pred_vol_ft, target_vol_ft)

    # Direction as BCE-style classification
    loss_dir_ft = torch.nn.functional.cross_entropy(
        torch.stack([1 - pred_dir_ft, pred_dir_ft], dim=1), target_dir_ft
    )

    total_loss_ft = w_close * loss_close_ft + w_vol * loss_vol_ft + w_dir *␣
↪loss_dir_ft
    return total_loss_ft
```

Training

```
[60]: def train_one_epoch_finetune(model, dataloader, optimizer, device):
          model.train()
          total_loss_ft = 0
          for batch in dataloader:
              x, y = batch
              x = x.to(device)
              y = y.to(device)

              optimizer.zero_grad()
              output = model(x)
              loss = loss_finetune(output, y)  # use our fine-tune loss here
              loss.backward()
              optimizer.step()

              total_loss_ft += loss.item()

          avg_loss_ft = total_loss_ft / len(dataloader)
          return avg_loss_ft
```

Criterion and Begin Fine Tune

```
[68]: criterion_finetune = loss_finetune
      lr_finetune = 0.0001
      # Optional: adjust weight decay to avoid overfitting
      optimizer_finetune = torch.optim.Adam(model.parameters(), lr=lr_finetune,␣
      ↪weight_decay=0.00001)
```

Fine Tune Training

```
[65]: def train_finetune(model, dataloader, optimizer, device, epochs=30):
          model.train()
          for epoch in range(1, epochs + 1):
```

```python
        total_loss = 0.0
        for x_batch, y_batch in dataloader:
            x_batch = x_batch.to(device)
            y_batch = y_batch.to(device)

            optimizer.zero_grad()
            preds = model(x_batch)
            loss = loss_finetune(preds, y_batch)  # uses our custom loss
            loss.backward()
            optimizer.step()
            total_loss += loss.item()

        avg_loss = total_loss / len(dataloader)
        print(f"Epoch {epoch}/{epochs} - Avg Fine-Tune Loss: {avg_loss:.4f}")
```

[69]:
```python
train_finetune(model, train_loader, optimizer_finetune, device, epochs=30)
```

```
Epoch 1/30 - Avg Fine-Tune Loss: 35307.0160
Epoch 2/30 - Avg Fine-Tune Loss: 21376.1929
Epoch 3/30 - Avg Fine-Tune Loss: 15367.3849
Epoch 4/30 - Avg Fine-Tune Loss: 11812.3757
Epoch 5/30 - Avg Fine-Tune Loss: 10150.8933
Epoch 6/30 - Avg Fine-Tune Loss: 9138.4818
Epoch 7/30 - Avg Fine-Tune Loss: 8467.7723
Epoch 8/30 - Avg Fine-Tune Loss: 8152.0489
Epoch 9/30 - Avg Fine-Tune Loss: 7826.5880
Epoch 10/30 - Avg Fine-Tune Loss: 7772.5559
Epoch 11/30 - Avg Fine-Tune Loss: 7501.3195
Epoch 12/30 - Avg Fine-Tune Loss: 7456.2518
Epoch 13/30 - Avg Fine-Tune Loss: 7311.3671
Epoch 14/30 - Avg Fine-Tune Loss: 7293.8655
Epoch 15/30 - Avg Fine-Tune Loss: 7238.9628
Epoch 16/30 - Avg Fine-Tune Loss: 7240.4086
Epoch 17/30 - Avg Fine-Tune Loss: 7007.3574
Epoch 18/30 - Avg Fine-Tune Loss: 7023.6061
Epoch 19/30 - Avg Fine-Tune Loss: 6953.0677
Epoch 20/30 - Avg Fine-Tune Loss: 6863.7769
Epoch 21/30 - Avg Fine-Tune Loss: 6842.1126
Epoch 22/30 - Avg Fine-Tune Loss: 6803.9542
Epoch 23/30 - Avg Fine-Tune Loss: 6765.0362
Epoch 24/30 - Avg Fine-Tune Loss: 6739.6157
Epoch 25/30 - Avg Fine-Tune Loss: 6815.0232
Epoch 26/30 - Avg Fine-Tune Loss: 6808.4453
Epoch 27/30 - Avg Fine-Tune Loss: 6568.4983
Epoch 28/30 - Avg Fine-Tune Loss: 6650.7484
Epoch 29/30 - Avg Fine-Tune Loss: 6607.4606
Epoch 30/30 - Avg Fine-Tune Loss: 6629.2607
```

2.0.5 Fine-Tune Training Summary

I started with a high loss of around 35,307, but after 30 epochs of fine-tuning, the loss steadily dropped to about 6,629. Most of the big improvements happened within the first 10 epochs, which showed that the model was quickly learning and adjusting to the new loss weights.

In the later stages, the loss values began to stabilize, which tells me the model is approaching an optimal point. This fine-tuning phase looks successful, and now I'm ready to evaluate the new metrics and see how much the performance improved.

Re-Evaluate Metrics (RMSE, MAE, Directional Accuracy)

[72]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
import numpy as np

# Extract predictions and actuals from model output
pred_close_ft = preds[:, 0]
true_close_ft = actuals[:, 0]

pred_vol_ft = preds[:, 1]
true_vol_ft = actuals[:, 1]

pred_dir_ft = preds[:, 2]
true_dir_ft = actuals[:, 2]

# Metrics for Close
rmse_close_ft = np.sqrt(mean_squared_error(true_close_ft, pred_close_ft))
mae_close_ft = mean_absolute_error(true_close_ft, pred_close_ft)

# Metrics for Volatility
rmse_vol_ft = np.sqrt(mean_squared_error(true_vol_ft, pred_vol_ft))
mae_vol_ft = mean_absolute_error(true_vol_ft, pred_vol_ft)

# Directional Accuracy
dir_pred_label_ft = (pred_dir_ft > 0.5).astype(int)
dir_true_label_ft = true_dir_ft.astype(int)
direction_acc_ft = (dir_pred_label_ft == dir_true_label_ft).mean() * 100

# Print results
print(f"Close RMSE: {rmse_close_ft:.4f}")
print(f"Close MAE : {mae_close_ft:.4f}")
print(f"Volatility RMSE: {rmse_vol_ft:.4f}")
print(f"Volatility MAE : {mae_vol_ft:.4f}")
print(f"Directional Accuracy: {direction_acc_ft:.2f}%")
```

```
Close RMSE: 296.6921
Close MAE : 239.1526
Volatility RMSE: 0.0715
Volatility MAE : 0.0714
Directional Accuracy: 51.89%
```

Finding the best config

[73]:
```
from sklearn.metrics import mean_squared_error
import numpy as np
import torch
import pandas as pd

# Define reusable fine-tune loss function
def loss_finetune_s(pred_input, target_input, w_close=1.0, w_vol=0.5, w_dir=2.
↪0):
    pred_close = pred_input[:, 0]
    pred_vol = pred_input[:, 1]
    pred_dir = pred_input[:, 2]

    target_close = target_input[:, 0]
    target_vol = target_input[:, 1]
    target_dir = target_input[:, 2].long()

    loss_close = torch.nn.functional.mse_loss(pred_close, target_close)
    loss_vol = torch.nn.functional.mse_loss(pred_vol, target_vol)
    loss_dir = torch.nn.functional.cross_entropy(
        torch.stack([1 - pred_dir, pred_dir], dim=1), target_dir
    )

    return w_close * loss_close + w_vol * loss_vol + w_dir * loss_dir

# List of different weight configurations
weight_configs = [
    (1.0, 0.5, 2.0),
    (1.0, 1.0, 2.0),
    (1.0, 0.1, 2.0),
    (1.0, 0.5, 3.0),
    (1.0, 0.3, 2.5),
]

tuning_results = []

# Loop over configurations
for idx, (w_c, w_v, w_d) in enumerate(weight_configs, 1):
    print(f"\nRunning config {idx}: Close={w_c}, Vol={w_v}, Dir={w_d}")

    def current_loss(pred_input, target_input):
        return loss_finetune_s(pred_input, target_input, w_close=w_c,␣
↪w_vol=w_v, w_dir=w_d)

    opt_tune = torch.optim.Adam(model.parameters(), lr=1e-4, weight_decay=1e-5)
```

```
model.train()
for epoch in range(1, 6):  # 5 epochs per config
    total_epoch_loss = 0
    for xb, yb in train_loader:
        xb = xb.to(device)
        yb = yb.to(device)

        opt_tune.zero_grad()
        out = model(xb)
        loss = current_loss(out, yb)
        loss.backward()
        opt_tune.step()
        total_epoch_loss += loss.item()

    avg_epoch_loss = total_epoch_loss / len(train_loader)
    print(f"Epoch {epoch}/5 - Avg Loss: {avg_epoch_loss:.2f}")

# Evaluation
model.eval()
all_preds_s, all_targets_s = [], []

with torch.no_grad():
    for xb_eval, yb_eval in test_loader:
        xb_eval = xb_eval.to(device)
        yb_eval = yb_eval.to(device)
        preds_batch = model(xb_eval)
        all_preds_s.append(preds_batch.cpu().numpy())
        all_targets_s.append(yb_eval.cpu().numpy())

preds_arr = np.concatenate(all_preds_s)
targets_arr = np.concatenate(all_targets_s)

pred_c = preds_arr[:, 0]
true_c = targets_arr[:, 0]

pred_v = preds_arr[:, 1]
true_v = targets_arr[:, 1]

pred_d = preds_arr[:, 2]
true_d = targets_arr[:, 2]

rmse_c = np.sqrt(mean_squared_error(true_c, pred_c))
rmse_v = np.sqrt(mean_squared_error(true_v, pred_v))
dir_acc = ((pred_d > 0.5).astype(int) == true_d.astype(int)).mean() * 100

tuning_results.append({
    'Config': f'Close={w_c}, Vol={w_v}, Dir={w_d}',
```

```
        'Close_RMSE': round(rmse_c, 2),
        'Volatility_RMSE': round(rmse_v, 4),
        'Direction_Accuracy': round(dir_acc, 2)
    })

# Display results as table
tuning_df = pd.DataFrame(tuning_results)
display(tuning_df)
```

```
Running config 1: Close=1.0, Vol=0.5, Dir=2.0
Epoch 1/5 - Avg Loss: 6562.80
Epoch 2/5 - Avg Loss: 6428.06
Epoch 3/5 - Avg Loss: 6442.90
Epoch 4/5 - Avg Loss: 6507.29
Epoch 5/5 - Avg Loss: 6418.44

Running config 2: Close=1.0, Vol=1.0, Dir=2.0
Epoch 1/5 - Avg Loss: 6475.19
Epoch 2/5 - Avg Loss: 6424.22
Epoch 3/5 - Avg Loss: 6352.13
Epoch 4/5 - Avg Loss: 6369.56
Epoch 5/5 - Avg Loss: 6449.51

Running config 3: Close=1.0, Vol=0.1, Dir=2.0
Epoch 1/5 - Avg Loss: 6312.78
Epoch 2/5 - Avg Loss: 6250.11
Epoch 3/5 - Avg Loss: 6412.79
Epoch 4/5 - Avg Loss: 6297.89
Epoch 5/5 - Avg Loss: 6265.76

Running config 4: Close=1.0, Vol=0.5, Dir=3.0
Epoch 1/5 - Avg Loss: 6277.55
Epoch 2/5 - Avg Loss: 6257.58
Epoch 3/5 - Avg Loss: 6248.70
Epoch 4/5 - Avg Loss: 6103.79
Epoch 5/5 - Avg Loss: 6276.03

Running config 5: Close=1.0, Vol=0.3, Dir=2.5
Epoch 1/5 - Avg Loss: 6158.59
Epoch 2/5 - Avg Loss: 6207.40
Epoch 3/5 - Avg Loss: 6136.87
Epoch 4/5 - Avg Loss: 6170.12
Epoch 5/5 - Avg Loss: 6137.64
                           Config  Close_RMSE  Volatility_RMSE  \
0  Close=1.0, Vol=0.5, Dir=2.0      150.81           0.0124
1  Close=1.0, Vol=1.0, Dir=2.0      164.97           0.0066
```

```
2  Close=1.0, Vol=0.1, Dir=2.0      141.07           0.0025
3  Close=1.0, Vol=0.5, Dir=3.0      145.98           0.0122
4  Close=1.0, Vol=0.3, Dir=2.5      149.70           0.0027

   Direction_Accuracy
0               48.42
1               49.43
2               51.57
3               51.87
4               51.94
```

Final Loss Function and Optimizer

[74]:
```python
def final_loss(pred_input, target_input):
    return loss_finetune_s(pred_input, target_input, w_close=1.0, w_vol=0.3,␣
 ↪w_dir=2.5)

optimizer_final = torch.optim.Adam(model.parameters(), lr=0.0001,␣
 ↪weight_decay=0.00001)
```

Final training

[75]:
```python
def train_final_config(model, train_loader, test_loader, optimizer, device,␣
 ↪epochs=30):
    history = []

    for epoch in range(1, epochs + 1):
        model.train()
        total_train_loss = 0
        for xb, yb in train_loader:
            xb = xb.to(device)
            yb = yb.to(device)

            optimizer.zero_grad()
            preds = model(xb)
            loss = final_loss(preds, yb)
            loss.backward()
            optimizer.step()
            total_train_loss += loss.item()

        avg_train_loss = total_train_loss / len(train_loader)

        # Evaluation
        model.eval()
        all_preds = []
        all_targets = []
        with torch.no_grad():
            for xb_eval, yb_eval in test_loader:
```

```
                xb_eval = xb_eval.to(device)
                yb_eval = yb_eval.to(device)
                pred_eval = model(xb_eval)
                all_preds.append(pred_eval.cpu().numpy())
                all_targets.append(yb_eval.cpu().numpy())

        preds_arr = np.concatenate(all_preds)
        targets_arr = np.concatenate(all_targets)

        pred_c = preds_arr[:, 0]
        true_c = targets_arr[:, 0]

        pred_v = preds_arr[:, 1]
        true_v = targets_arr[:, 1]

        pred_d = preds_arr[:, 2]
        true_d = targets_arr[:, 2]

        rmse_c = np.sqrt(mean_squared_error(true_c, pred_c))
        rmse_v = np.sqrt(mean_squared_error(true_v, pred_v))
        dir_acc = ((pred_d > 0.5).astype(int) == true_d.astype(int)).mean() *␣
↪100

        print(f"Epoch {epoch:>2}/{epochs} - Loss: {avg_train_loss:.2f} | Close␣
↪RMSE: {rmse_c:.2f} | Vol RMSE: {rmse_v:.4f} | Dir Acc: {dir_acc:.2f}%")
        history.append((epoch, avg_train_loss, rmse_c, rmse_v, dir_acc))

    return history
```

[78]:
```
final_history = train_final_config(
    model=model,
    train_loader=train_loader,
    test_loader=test_loader,
    optimizer=optimizer_final,
    device=device,
    epochs=100
)
```

```
Epoch  1/100 - Loss: 5601.12 | Close RMSE: 130.14 | Vol RMSE: 0.0133 | Dir Acc:
48.35%
Epoch  2/100 - Loss: 5741.41 | Close RMSE: 116.50 | Vol RMSE: 0.0134 | Dir Acc:
51.90%
Epoch  3/100 - Loss: 5689.11 | Close RMSE: 142.09 | Vol RMSE: 0.0057 | Dir Acc:
48.19%
Epoch  4/100 - Loss: 5648.65 | Close RMSE: 131.26 | Vol RMSE: 0.0111 | Dir Acc:
52.01%
Epoch  5/100 - Loss: 5696.91 | Close RMSE: 115.39 | Vol RMSE: 0.0022 | Dir Acc:
51.89%
```

```
Epoch  6/100 - Loss: 5605.87 | Close RMSE: 129.13 | Vol RMSE: 0.0061 | Dir Acc:
48.11%
Epoch  7/100 - Loss: 5641.01 | Close RMSE: 118.39 | Vol RMSE: 0.0175 | Dir Acc:
51.90%
Epoch  8/100 - Loss: 5684.28 | Close RMSE: 147.75 | Vol RMSE: 0.0050 | Dir Acc:
48.11%
Epoch  9/100 - Loss: 5640.96 | Close RMSE: 128.17 | Vol RMSE: 0.0084 | Dir Acc:
52.16%
Epoch 10/100 - Loss: 5654.44 | Close RMSE: 109.98 | Vol RMSE: 0.0155 | Dir Acc:
51.96%
Epoch 11/100 - Loss: 5591.55 | Close RMSE: 120.94 | Vol RMSE: 0.0046 | Dir Acc:
51.88%
Epoch 12/100 - Loss: 5562.75 | Close RMSE: 138.92 | Vol RMSE: 0.0150 | Dir Acc:
51.90%
Epoch 13/100 - Loss: 5621.62 | Close RMSE: 129.10 | Vol RMSE: 0.0155 | Dir Acc:
51.00%
Epoch 14/100 - Loss: 5608.77 | Close RMSE: 117.84 | Vol RMSE: 0.0223 | Dir Acc:
48.26%
Epoch 15/100 - Loss: 5519.33 | Close RMSE: 125.00 | Vol RMSE: 0.0091 | Dir Acc:
51.87%
Epoch 16/100 - Loss: 5576.44 | Close RMSE: 112.34 | Vol RMSE: 0.0119 | Dir Acc:
51.96%
Epoch 17/100 - Loss: 5554.57 | Close RMSE: 124.70 | Vol RMSE: 0.0018 | Dir Acc:
48.14%
Epoch 18/100 - Loss: 5530.02 | Close RMSE: 117.55 | Vol RMSE: 0.0067 | Dir Acc:
51.83%
Epoch 19/100 - Loss: 5485.65 | Close RMSE: 117.78 | Vol RMSE: 0.0151 | Dir Acc:
51.89%
Epoch 20/100 - Loss: 5494.75 | Close RMSE: 108.60 | Vol RMSE: 0.0095 | Dir Acc:
48.11%
Epoch 21/100 - Loss: 5535.46 | Close RMSE: 118.18 | Vol RMSE: 0.0053 | Dir Acc:
48.22%
Epoch 22/100 - Loss: 5482.29 | Close RMSE: 118.06 | Vol RMSE: 0.0071 | Dir Acc:
51.94%
Epoch 23/100 - Loss: 5507.17 | Close RMSE: 99.77 | Vol RMSE: 0.0023 | Dir Acc:
48.11%
Epoch 24/100 - Loss: 5436.08 | Close RMSE: 114.74 | Vol RMSE: 0.0054 | Dir Acc:
52.02%
Epoch 25/100 - Loss: 5496.00 | Close RMSE: 114.13 | Vol RMSE: 0.0019 | Dir Acc:
51.87%
Epoch 26/100 - Loss: 5509.11 | Close RMSE: 119.02 | Vol RMSE: 0.0017 | Dir Acc:
49.11%
Epoch 27/100 - Loss: 5554.74 | Close RMSE: 112.73 | Vol RMSE: 0.0112 | Dir Acc:
51.33%
Epoch 28/100 - Loss: 5399.57 | Close RMSE: 115.52 | Vol RMSE: 0.0025 | Dir Acc:
48.12%
Epoch 29/100 - Loss: 5372.38 | Close RMSE: 98.20 | Vol RMSE: 0.0022 | Dir Acc:
51.90%
```

Epoch 30/100 - Loss: 5481.71 | Close RMSE: 124.30 | Vol RMSE: 0.0023 | Dir Acc: 48.82%
Epoch 31/100 - Loss: 5455.02 | Close RMSE: 134.82 | Vol RMSE: 0.0020 | Dir Acc: 50.35%
Epoch 32/100 - Loss: 5394.08 | Close RMSE: 111.80 | Vol RMSE: 0.0016 | Dir Acc: 48.27%
Epoch 33/100 - Loss: 5349.27 | Close RMSE: 96.36 | Vol RMSE: 0.0162 | Dir Acc: 48.10%
Epoch 34/100 - Loss: 5430.09 | Close RMSE: 111.91 | Vol RMSE: 0.0142 | Dir Acc: 51.83%
Epoch 35/100 - Loss: 5338.39 | Close RMSE: 107.67 | Vol RMSE: 0.0092 | Dir Acc: 51.89%
Epoch 36/100 - Loss: 5433.90 | Close RMSE: 99.00 | Vol RMSE: 0.0087 | Dir Acc: 48.11%
Epoch 37/100 - Loss: 5339.76 | Close RMSE: 114.85 | Vol RMSE: 0.0215 | Dir Acc: 50.23%
Epoch 38/100 - Loss: 5346.91 | Close RMSE: 127.21 | Vol RMSE: 0.0095 | Dir Acc: 51.90%
Epoch 39/100 - Loss: 5378.96 | Close RMSE: 123.87 | Vol RMSE: 0.0058 | Dir Acc: 51.78%
Epoch 40/100 - Loss: 5399.11 | Close RMSE: 126.64 | Vol RMSE: 0.0085 | Dir Acc: 48.26%
Epoch 41/100 - Loss: 5353.47 | Close RMSE: 110.56 | Vol RMSE: 0.0057 | Dir Acc: 51.89%
Epoch 42/100 - Loss: 5339.22 | Close RMSE: 104.58 | Vol RMSE: 0.0083 | Dir Acc: 51.68%
Epoch 43/100 - Loss: 5344.34 | Close RMSE: 109.49 | Vol RMSE: 0.0028 | Dir Acc: 51.88%
Epoch 44/100 - Loss: 5362.42 | Close RMSE: 121.54 | Vol RMSE: 0.0159 | Dir Acc: 51.96%
Epoch 45/100 - Loss: 5299.09 | Close RMSE: 112.33 | Vol RMSE: 0.0138 | Dir Acc: 48.11%
Epoch 46/100 - Loss: 5273.60 | Close RMSE: 97.56 | Vol RMSE: 0.0127 | Dir Acc: 51.98%
Epoch 47/100 - Loss: 5290.00 | Close RMSE: 130.84 | Vol RMSE: 0.0073 | Dir Acc: 48.19%
Epoch 48/100 - Loss: 5329.06 | Close RMSE: 106.98 | Vol RMSE: 0.0016 | Dir Acc: 48.10%
Epoch 49/100 - Loss: 5231.88 | Close RMSE: 121.40 | Vol RMSE: 0.0073 | Dir Acc: 51.93%
Epoch 50/100 - Loss: 5263.73 | Close RMSE: 109.02 | Vol RMSE: 0.0067 | Dir Acc: 51.82%
Epoch 51/100 - Loss: 5275.18 | Close RMSE: 93.14 | Vol RMSE: 0.0200 | Dir Acc: 48.11%
Epoch 52/100 - Loss: 5263.17 | Close RMSE: 117.80 | Vol RMSE: 0.0031 | Dir Acc: 51.92%
Epoch 53/100 - Loss: 5264.65 | Close RMSE: 107.78 | Vol RMSE: 0.0032 | Dir Acc: 48.27%

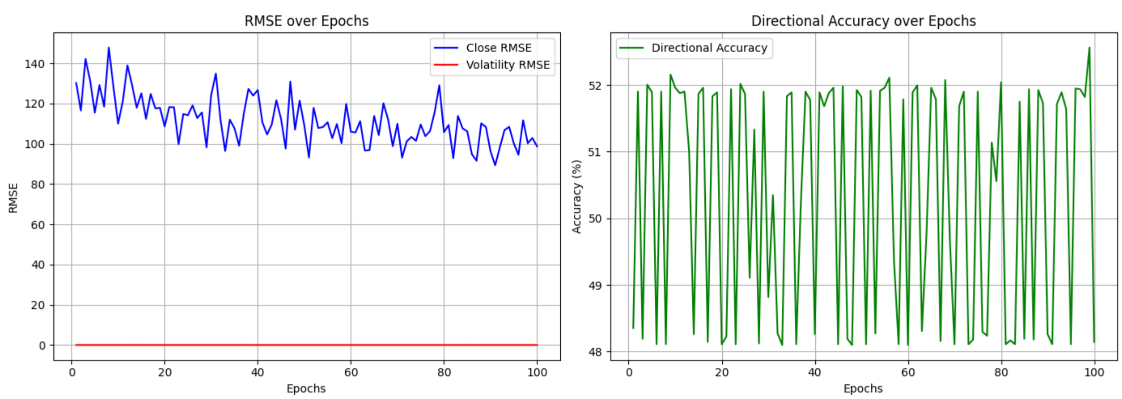
Epoch 54/100 - Loss: 5204.53 | Close RMSE: 108.26 | Vol RMSE: 0.0037 | Dir Acc: 51.92%
Epoch 55/100 - Loss: 5211.57 | Close RMSE: 110.63 | Vol RMSE: 0.0215 | Dir Acc: 51.96%
Epoch 56/100 - Loss: 5234.88 | Close RMSE: 102.74 | Vol RMSE: 0.0016 | Dir Acc: 52.11%
Epoch 57/100 - Loss: 5193.21 | Close RMSE: 109.75 | Vol RMSE: 0.0064 | Dir Acc: 49.36%
Epoch 58/100 - Loss: 5251.31 | Close RMSE: 100.24 | Vol RMSE: 0.0143 | Dir Acc: 48.11%
Epoch 59/100 - Loss: 5180.30 | Close RMSE: 119.74 | Vol RMSE: 0.0140 | Dir Acc: 51.79%
Epoch 60/100 - Loss: 5176.36 | Close RMSE: 105.95 | Vol RMSE: 0.0102 | Dir Acc: 48.10%
Epoch 61/100 - Loss: 5195.71 | Close RMSE: 105.56 | Vol RMSE: 0.0133 | Dir Acc: 51.89%
Epoch 62/100 - Loss: 5219.78 | Close RMSE: 111.19 | Vol RMSE: 0.0010 | Dir Acc: 52.00%
Epoch 63/100 - Loss: 5310.02 | Close RMSE: 96.59 | Vol RMSE: 0.0068 | Dir Acc: 48.31%
Epoch 64/100 - Loss: 5136.02 | Close RMSE: 96.81 | Vol RMSE: 0.0014 | Dir Acc: 49.78%
Epoch 65/100 - Loss: 5149.89 | Close RMSE: 113.76 | Vol RMSE: 0.0012 | Dir Acc: 51.96%
Epoch 66/100 - Loss: 5239.88 | Close RMSE: 104.26 | Vol RMSE: 0.0068 | Dir Acc: 51.79%
Epoch 67/100 - Loss: 5252.23 | Close RMSE: 120.06 | Vol RMSE: 0.0051 | Dir Acc: 48.15%
Epoch 68/100 - Loss: 5167.52 | Close RMSE: 111.98 | Vol RMSE: 0.0132 | Dir Acc: 52.08%
Epoch 69/100 - Loss: 5139.30 | Close RMSE: 98.78 | Vol RMSE: 0.0075 | Dir Acc: 49.69%
Epoch 70/100 - Loss: 5191.69 | Close RMSE: 109.90 | Vol RMSE: 0.0053 | Dir Acc: 48.11%
Epoch 71/100 - Loss: 5147.16 | Close RMSE: 93.06 | Vol RMSE: 0.0014 | Dir Acc: 51.68%
Epoch 72/100 - Loss: 5158.98 | Close RMSE: 101.12 | Vol RMSE: 0.0034 | Dir Acc: 51.90%
Epoch 73/100 - Loss: 5108.25 | Close RMSE: 103.36 | Vol RMSE: 0.0042 | Dir Acc: 48.11%
Epoch 74/100 - Loss: 5124.01 | Close RMSE: 101.40 | Vol RMSE: 0.0012 | Dir Acc: 48.18%
Epoch 75/100 - Loss: 5170.50 | Close RMSE: 109.51 | Vol RMSE: 0.0051 | Dir Acc: 51.90%
Epoch 76/100 - Loss: 5069.88 | Close RMSE: 103.73 | Vol RMSE: 0.0158 | Dir Acc: 48.29%
Epoch 77/100 - Loss: 5117.93 | Close RMSE: 106.24 | Vol RMSE: 0.0026 | Dir Acc: 48.24%

```
Epoch 78/100 - Loss: 5153.61 | Close RMSE: 115.63 | Vol RMSE: 0.0035 | Dir Acc:
51.14%
Epoch 79/100 - Loss: 5137.88 | Close RMSE: 129.03 | Vol RMSE: 0.0040 | Dir Acc:
50.56%
Epoch 80/100 - Loss: 5132.19 | Close RMSE: 105.68 | Vol RMSE: 0.0048 | Dir Acc:
52.04%
Epoch 81/100 - Loss: 5072.50 | Close RMSE: 109.30 | Vol RMSE: 0.0023 | Dir Acc:
48.11%
Epoch 82/100 - Loss: 5115.62 | Close RMSE: 92.79 | Vol RMSE: 0.0099 | Dir Acc:
48.17%
Epoch 83/100 - Loss: 5008.81 | Close RMSE: 113.73 | Vol RMSE: 0.0032 | Dir Acc:
48.11%
Epoch 84/100 - Loss: 5050.18 | Close RMSE: 107.59 | Vol RMSE: 0.0022 | Dir Acc:
51.75%
Epoch 85/100 - Loss: 5019.49 | Close RMSE: 106.13 | Vol RMSE: 0.0225 | Dir Acc:
48.19%
Epoch 86/100 - Loss: 5079.31 | Close RMSE: 94.74 | Vol RMSE: 0.0068 | Dir Acc:
51.94%
Epoch 87/100 - Loss: 5149.03 | Close RMSE: 91.51 | Vol RMSE: 0.0060 | Dir Acc:
48.18%
Epoch 88/100 - Loss: 5081.72 | Close RMSE: 110.12 | Vol RMSE: 0.0099 | Dir Acc:
51.93%
Epoch 89/100 - Loss: 5042.64 | Close RMSE: 108.33 | Vol RMSE: 0.0028 | Dir Acc:
51.73%
Epoch 90/100 - Loss: 5042.67 | Close RMSE: 96.20 | Vol RMSE: 0.0038 | Dir Acc:
48.26%
Epoch 91/100 - Loss: 5000.72 | Close RMSE: 89.26 | Vol RMSE: 0.0096 | Dir Acc:
48.11%
Epoch 92/100 - Loss: 5094.82 | Close RMSE: 98.13 | Vol RMSE: 0.0144 | Dir Acc:
51.72%
Epoch 93/100 - Loss: 5001.46 | Close RMSE: 106.74 | Vol RMSE: 0.0013 | Dir Acc:
51.89%
Epoch 94/100 - Loss: 5050.60 | Close RMSE: 108.35 | Vol RMSE: 0.0039 | Dir Acc:
51.64%
Epoch 95/100 - Loss: 5006.75 | Close RMSE: 100.17 | Vol RMSE: 0.0117 | Dir Acc:
48.11%
Epoch 96/100 - Loss: 5053.07 | Close RMSE: 94.51 | Vol RMSE: 0.0032 | Dir Acc:
51.95%
Epoch 97/100 - Loss: 4904.67 | Close RMSE: 111.59 | Vol RMSE: 0.0188 | Dir Acc:
51.94%
Epoch 98/100 - Loss: 5079.43 | Close RMSE: 100.25 | Vol RMSE: 0.0039 | Dir Acc:
51.82%
Epoch 99/100 - Loss: 4948.11 | Close RMSE: 102.80 | Vol RMSE: 0.0101 | Dir Acc:
52.56%
Epoch 100/100 - Loss: 4989.53 | Close RMSE: 98.67 | Vol RMSE: 0.0029 | Dir Acc:
48.14%
```

Plotting Training Results

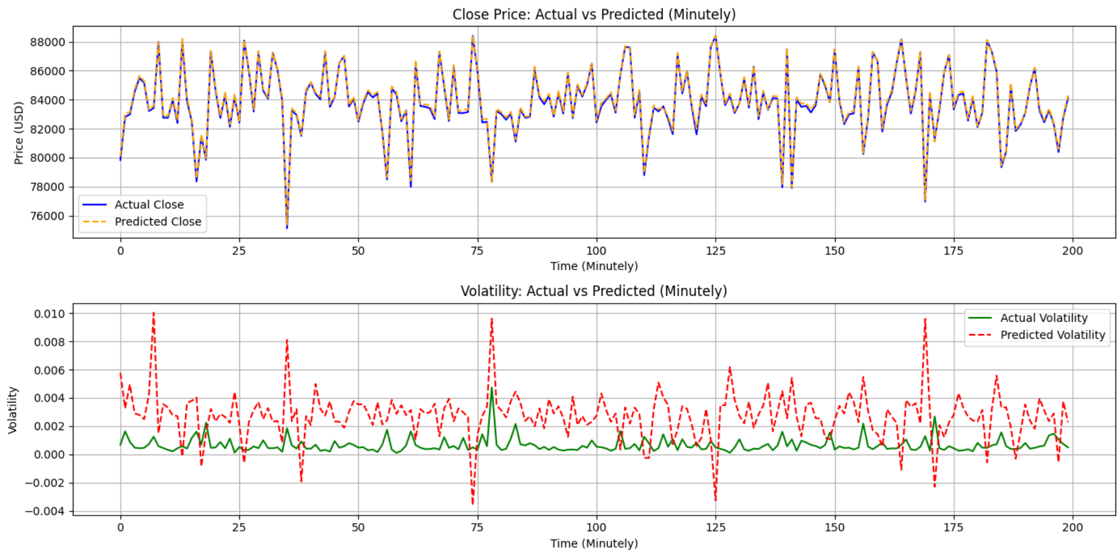
[79]:

```
import matplotlib.pyplot as plt

# Extracting the history data
epochs_list = [epoch for epoch, _, _, _, _ in final_history]
close_rmse_list = [rmse_c for _, _, rmse_c, _, _ in final_history]
vol_rmse_list = [rmse_v for _, _, _, rmse_v, _ in final_history]
dir_acc_list = [dir_acc for _, _, _, _, dir_acc in final_history]

# Plotting
plt.figure(figsize=(14, 5))

# Subplot for RMSE of Close and Volatility
plt.subplot(1, 2, 1)
plt.plot(epochs_list, close_rmse_list, label="Close RMSE", color='b')
plt.plot(epochs_list, vol_rmse_list, label="Volatility RMSE", color='r')
plt.title('RMSE over Epochs')
plt.xlabel('Epochs')
plt.ylabel('RMSE')
plt.legend()
plt.grid(True)

# Subplot for Directional Accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs_list, dir_acc_list, label="Directional Accuracy", color='g')
plt.title('Directional Accuracy over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy (%)')
plt.legend()
plt.grid(True)

plt.tight_layout()
plt.show()
```



[80]:

```python
import matplotlib.pyplot as plt
import numpy as np

# Actual and predicted values from the fine-tuned model
true_close = true_c
pred_close = pred_c
true_volatility = true_v
pred_volatility = pred_v

# Plotting Close Prices
plt.figure(figsize=(14, 7))

# Subplot for Actual vs Predicted Close Prices
plt.subplot(2, 1, 1)
plt.plot(true_close[:200], label="Actual Close", color='blue', linewidth=1.5)
plt.plot(pred_close[:200], label="Predicted Close", color='orange',␣
↪linestyle='--', linewidth=1.5)
plt.title('Close Price: Actual vs Predicted (Minutely)')
plt.xlabel('Time (Minutely)')
plt.ylabel('Price (USD)')
plt.legend(loc='best')
plt.grid(True)

# Subplot for Actual vs Predicted Volatility
plt.subplot(2, 1, 2)
plt.plot(true_volatility[:200], label="Actual Volatility", color='green',␣
↪linewidth=1.5)
plt.plot(pred_volatility[:200], label="Predicted Volatility", color='red',␣
↪linestyle='--', linewidth=1.5)
plt.title('Volatility: Actual vs Predicted (Minutely)')
plt.xlabel('Time (Minutely)')
plt.ylabel('Volatility')
plt.legend(loc='best')
plt.grid(True)

plt.tight_layout()
plt.show()
```



Export the model

[81]:
```
import joblib
joblib.dump(model, 'model_minutely_full.pkl')
```

[81]: ['model_minutely_full.pkl']