shitij-HQLSTM-Perplexity-Priority-1-Better-5

October 26, 2025

[ ]:

[42]:

```python
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import pennylane as qml


# ============================================================
# REPRODUCIBILITY / SEED
# ============================================================
SEED = 42
import random
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False


# ============================================================
# DATA PREPARATION
# ============================================================
# Paths
train_path = r"C:\Users\acer\OneDrive\QPoland\X_train.csv"
test_path  = r"C:\Users\acer\OneDrive\QPoland\X_test.csv"

X_train = pd.read_csv(train_path).sort_values("Date")
X_test = pd.read_csv(test_path).sort_values("Date")

def add_simple_features(df):
```

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    df = df.copy()
    df['Price_Range'] = df['High'] - df['Low']
    df['HL_Ratio'] = df['High'] / (df['Low'] + 1e-10)
    df['Volume_MA_3'] = df['Volume'].rolling(window=3, min_periods=1).mean()
    return df.bfill().ffill()

X_train = add_simple_features(X_train)
X_test = add_simple_features(X_test)

features = ["Open", "High", "Low", "Volume", "Price_Range", "HL_Ratio",␣
 ↪"Volume_MA_3"]
target = "Close"

scaler_X = MinMaxScaler()
scaler_y = MinMaxScaler()
X_train_scaled = scaler_X.fit_transform(X_train[features])
y_train_scaled = scaler_y.fit_transform(X_train[[target]])

SEQ_LEN = 8

def create_sequences(X, y, seq_len):
    X_seq, y_seq = [], []
    for i in range(len(X) - seq_len):
        X_seq.append(X[i:i+seq_len])
        y_seq.append(y[i+seq_len])
    return np.array(X_seq), np.array(y_seq)

X_seq, y_seq = create_sequences(X_train_scaled, y_train_scaled, SEQ_LEN)

split = int(len(X_seq) * 0.65)
X_train_t = torch.tensor(X_seq[:split], dtype=torch.float32)
y_train_t = torch.tensor(y_seq[:split], dtype=torch.float32)
X_val_t = torch.tensor(X_seq[split:], dtype=torch.float32)
y_val_t = torch.tensor(y_seq[split:], dtype=torch.float32)

print(f"Training: {len(X_train_t)}, Validation: {len(X_val_t)}, Seq Length:␣
 ↪{SEQ_LEN}\n")


# ============================================================
# HYBRID LSTM + QNN PARAMETERS
# ============================================================
input_size = len(features)
n_qubits = 4  # max qubits
hidden_size = n_qubits
dropout_rate = 0.1  # CHANGED: Increased from 0.05 to 0.2 to combat overfitting
n_layers = 2
```

```python
def xavier_init(in_size, out_size):
    limit = np.sqrt(6.0 / (in_size + out_size))
    return torch.randn(in_size, out_size) * limit

# Classical LSTM gates
W_ii = nn.Parameter(xavier_init(input_size, hidden_size))
W_hi = nn.Parameter(xavier_init(hidden_size, hidden_size))
b_i = nn.Parameter(torch.zeros(hidden_size))

W_if = nn.Parameter(xavier_init(input_size, hidden_size))
W_hf = nn.Parameter(xavier_init(hidden_size, hidden_size))
b_f = nn.Parameter(torch.ones(hidden_size))

W_io = nn.Parameter(xavier_init(input_size, hidden_size))
W_ho = nn.Parameter(xavier_init(hidden_size, hidden_size))
b_o = nn.Parameter(torch.zeros(hidden_size))

W_out = nn.Parameter(xavier_init(hidden_size, 1))
b_out = nn.Parameter(torch.zeros(1))

dropout = nn.Dropout(dropout_rate)


# ============================================================
# QUANTUM LAYER SETUP
# ============================================================
dev = qml.device("default.qubit", wires=n_qubits)

shape = qml.BasicEntanglerLayers.shape(n_layers=n_layers, n_wires=n_qubits)
weights = nn.Parameter(0.01 * torch.randn(*shape))

# @qml.qnode(dev, interface="torch")
# def quantum_node(inputs, weights):
#     qml.templates.AngleEmbedding(inputs, wires=range(n_qubits))
#     qml.BasicEntanglerLayers(weights=weights, wires=range(n_qubits))
#     return [qml.expval(qml.PauliZ(i)) for i in range(n_qubits)]

@qml.qnode(dev, interface="torch", diff_method="backprop",
 ↪max_diff_method="finite-diff")
def quantum_node_batch(inputs, weights):
    # inputs shape: (batch_size, n_qubits)
    qml.templates.AngleEmbedding(inputs, wires=range(n_qubits))
    qml.BasicEntanglerLayers(weights=weights, wires=range(n_qubits))
    return [qml.expval(qml.PauliZ(i)) for i in range(n_qubits)]
```

```python
# PCA transformer to reduce input to 4 qubits
pca = PCA(n_components=n_qubits)

# Collect parameters
lstm_params = [W_ii, W_hi, b_i, W_if, W_hf, b_f, W_io, W_ho, b_o, W_out, b_out,␣
↪weights]


# ============================================================
# HYBRID LSTM FORWARD FUNCTION
# ============================================================
def lstm_forward(x_batch, training=True):
    batch_size = x_batch.shape[0]
    seq_length = x_batch.shape[1]
    h_t = torch.zeros(batch_size, hidden_size)
    c_t = torch.zeros(batch_size, hidden_size)

    for t in range(seq_length):
        x_t = x_batch[:, t, :]
        i_t = torch.sigmoid(x_t @ W_ii + h_t @ W_hi + b_i)
        f_t = torch.sigmoid(x_t @ W_if + h_t @ W_hf + b_f)
        o_t = torch.sigmoid(x_t @ W_io + h_t @ W_ho + b_o)

        # Quantum cell candidate
        concat_input = torch.cat([x_t, h_t], dim=1)
        q_input = torch.tensor(pca.fit_transform(concat_input.detach().
↪numpy()), dtype=torch.float32)

        q_outputs = []
        for i in range(q_input.shape[0]):
            q_out = quantum_node(q_input[i], weights)
            q_outputs.append(torch.tensor(q_out, dtype=torch.float32))
        c_tilde = torch.stack(q_outputs, dim=0)
        c_tilde = torch.tanh(c_tilde)

        if training:
            c_tilde = dropout(c_tilde)

        c_t = f_t * c_t + i_t * c_tilde
        h_t = o_t * torch.tanh(c_t)

    if training:
        h_t = dropout(h_t)

    output = h_t @ W_out + b_out
    return output
```

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# ============================================================
# TRAINING LOOP WITH PRIORITY 1 IMPROVEMENTS
# ============================================================
# CHANGED: Using Adam optimizer with weight decay (L2 regularization)
lr = 0.001
wd = 1e-6
optimizer = optim.Adam(lstm_params, lr=lr, weight_decay=wd)

# CHANGED: Using Huber loss instead of MSE for robustness
beta = 1.0
criterion = nn.SmoothL1Loss(beta=beta)

EPOCHS = 1000  # CHANGED: Increased max epochs (early stopping will prevent␣
 ↪overtraining)
train_losses, val_losses = [], []

# NEW: Early stopping parameters
best_val_loss = float('inf')
patience = 50  # Stop if no improvement for 10 epochs
patience_counter = 0
best_state_dict = None

print("Training Hybrid LSTM + QNN with Priority 1 improvements...")
print(f"- Dropout: {dropout_rate}")
print(f"- Learning Rate: {lr}")
print(f"- Weight Decay: {wd}")
#print(f"- Optimizer: Adam with weight_decay=1e-4")
print(f"- Loss: Huber (SmoothL1) with Beta : {beta}")
print(f"- Early stopping patience: {patience}\n")

for epoch in range(1, EPOCHS + 1):
    # Training phase
    dropout.train()
    optimizer.zero_grad()
    train_pred = lstm_forward(X_train_t, training=True)
    train_loss = criterion(train_pred, y_train_t)
    train_loss.backward()
    torch.nn.utils.clip_grad_norm_(lstm_params, max_norm=1.0)
    optimizer.step()
    train_losses.append(train_loss.item())

    # Validation phase
    dropout.eval()
    with torch.no_grad():
        val_pred = lstm_forward(X_val_t, training=False)
        val_loss = criterion(val_pred, y_val_t)
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        val_losses.append(val_loss.item())

    # NEW: Early stopping logic
    if val_loss.item() < best_val_loss:
        best_val_loss = val_loss.item()
        patience_counter = 0
        # Save best model state
        best_state_dict = {
            'W_ii': W_ii.data.clone(),
            'W_hi': W_hi.data.clone(),
            'b_i': b_i.data.clone(),
            'W_if': W_if.data.clone(),
            'W_hf': W_hf.data.clone(),
            'b_f': b_f.data.clone(),
            'W_io': W_io.data.clone(),
            'W_ho': W_ho.data.clone(),
            'b_o': b_o.data.clone(),
            'W_out': W_out.data.clone(),
            'b_out': b_out.data.clone(),
            'weights': weights.data.clone()
        }
        print(f"Epoch {epoch:2d} | Train Loss: {train_loss.item():.6f} | Val Loss: {val_loss.item():.6f}  (best)")
    else:
        patience_counter += 1
        print(f"Epoch {epoch:2d} | Train Loss: {train_loss.item():.6f} | Val Loss: {val_loss.item():.6f} | Patience: {patience_counter}/{patience}")

    # NEW: Stop training if no improvement
    if patience_counter >= patience:
        print(f"\n Early stopping triggered at epoch {epoch}. Best val loss: {best_val_loss:.6f}")
        break

# NEW: Restore best model weights
if best_state_dict is not None:
    print("\n Restoring best model weights from validation...")
    W_ii.data = best_state_dict['W_ii']
    W_hi.data = best_state_dict['W_hi']
    b_i.data = best_state_dict['b_i']
    W_if.data = best_state_dict['W_if']
    W_hf.data = best_state_dict['W_hf']
    b_f.data = best_state_dict['b_f']
    W_io.data = best_state_dict['W_io']
    W_ho.data = best_state_dict['W_ho']
    b_o.data = best_state_dict['b_o']
    W_out.data = best_state_dict['W_out']
```

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    b_out.data = best_state_dict['b_out']
    weights.data = best_state_dict['weights']


# ============================================================
# PLOTTING TRAINING CURVES
# ============================================================
plt.figure(figsize=(10, 5))
plt.plot(train_losses, label='Train Loss', linewidth=2)
plt.plot(val_losses, label='Validation Loss', linewidth=2)
plt.axvline(x=len(val_losses) - patience_counter, color='red', linestyle='--',
            label=f'Best Model (epoch {len(val_losses) - patience_counter})',␣
 ↪alpha=0.7)
plt.title('Hybrid LSTM + QNN Training Progress (with Early Stopping)')
plt.xlabel('Epoch')
plt.ylabel('Huber Loss')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()


# ============================================================
# EVALUATION ON TRAIN/VALIDATION
# ============================================================
dropout.eval()
with torch.no_grad():
    train_pred_final = lstm_forward(X_train_t, training=False).numpy()
    val_pred_final = lstm_forward(X_val_t, training=False).numpy()

train_pred_rescaled = scaler_y.inverse_transform(train_pred_final)
val_pred_rescaled = scaler_y.inverse_transform(val_pred_final)
y_train_orig = scaler_y.inverse_transform(y_train_t.numpy())
y_val_orig = scaler_y.inverse_transform(y_val_t.numpy())

train_mse = mean_squared_error(y_train_orig, train_pred_rescaled)
train_r2 = r2_score(y_train_orig, train_pred_rescaled)
val_mse = mean_squared_error(y_val_orig, val_pred_rescaled)
val_r2 = r2_score(y_val_orig, val_pred_rescaled)

print("\n" + "="*60)
print("FINAL METRICS (Best Model from Early Stopping)")
print("="*60)
print(f"TRAIN - MSE: {train_mse:.4f}, R²: {train_r2:.4f}, RMSE: {np.
 ↪sqrt(train_mse):.2f}")
print(f"VAL   - MSE: {val_mse:.4f}, R²: {val_r2:.4f}, RMSE: {np.sqrt(val_mse):.
 ↪2f}")
```

```python
print("="*60)

# NEW: Show overfitting gap
r2_gap = train_r2 - val_r2
if r2_gap > 0.2:
    print(f"  WARNING: Large overfitting gap detected (Train R² - Val R² = {r2_gap:.4f})")
    print("   Consider: increasing dropout, reducing model complexity, or adding more data")
elif r2_gap > 0.1:
    print(f"  Moderate overfitting detected (Train R² - Val R² = {r2_gap:.4f})")
else:
    print(f"  Good generalization (Train R² - Val R² = {r2_gap:.4f})")
print("="*60)


# ============================================================
# PLOT VALIDATION ACTUAL vs PREDICTED
# ============================================================
plt.figure(figsize=(12, 6))
plt.plot(y_val_orig, label='Actual', linewidth=2, marker='o', markersize=4)
plt.plot(val_pred_rescaled, label='Predicted', linewidth=2, marker='s', markersize=4)
plt.title(f'Validation: Actual vs Predicted (R² = {val_r2:.4f})')
plt.xlabel('Sample')
plt.ylabel('Close Price')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()


# ============================================================
# PREDICTIONS ON TEST DATA
# ============================================================
X_test_scaled = scaler_X.transform(X_test[features])
combined = np.concatenate([X_train_scaled[-SEQ_LEN:], X_test_scaled])
X_test_seq = [combined[i:i+SEQ_LEN] for i in range(len(combined) - SEQ_LEN)]
X_test_t = torch.tensor(np.array(X_test_seq), dtype=torch.float32)

with torch.no_grad():
    test_pred = lstm_forward(X_test_t, training=False).numpy()
test_pred_rescaled = scaler_y.inverse_transform(test_pred)

predicted_closes = pd.DataFrame({
    "Date": X_test["Date"].values[:len(test_pred_rescaled)],
    "Predicted_Close": test_pred_rescaled.flatten()
```

```
})

print("\n" + "="*60)
print("TEST SET PREDICTIONS")
print("="*60)
print(predicted_closes.to_string(index=False))
print("="*60)


# ============================================================
# PLOT TEST PREDICTIONS
# ============================================================
plt.figure(figsize=(12, 6))
plt.plot(X_test["Date"].values[:len(test_pred_rescaled)], test_pred_rescaled.
 ↪flatten(),
         label='Predicted', linewidth=2, marker='s', markersize=4)
plt.title('Test Set Predictions (Best Model)')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.xticks(rotation=45)
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```

```
Training: 102, Validation: 55, Seq Length: 8

Training Hybrid LSTM + QNN with Priority 1 improvements…
- Dropout: 0.1
- Learning Rate: 0.001
- Weight Decay: 1e-06
- Loss: Huber (SmoothL1) with Beta : 1.0
- Early stopping patience: 50
```

```
C:\Users\acer\anaconda3\Lib\site-packages\pennylane\workflow\qnode.py:135:
UserWarning: Received gradient_kwarg max_diff_method, which is not included in
the list of standard qnode gradient kwargs.
  warnings.warn(
```

```
Epoch   1 | Train Loss: 0.233422 | Val Loss: 0.055734   (best)
Epoch   2 | Train Loss: 0.230053 | Val Loss: 0.053522   (best)
Epoch   3 | Train Loss: 0.245483 | Val Loss: 0.051355   (best)
Epoch   4 | Train Loss: 0.212411 | Val Loss: 0.049249   (best)
Epoch   5 | Train Loss: 0.208945 | Val Loss: 0.047194   (best)
Epoch   6 | Train Loss: 0.212351 | Val Loss: 0.045192   (best)
Epoch   7 | Train Loss: 0.212122 | Val Loss: 0.043229   (best)
Epoch   8 | Train Loss: 0.210388 | Val Loss: 0.041314   (best)
Epoch   9 | Train Loss: 0.197015 | Val Loss: 0.039460   (best)
```

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Epoch 10 | Train Loss: 0.209175 | Val Loss: 0.037645  (best)
Epoch 11 | Train Loss: 0.200148 | Val Loss: 0.035876  (best)
Epoch 12 | Train Loss: 0.177837 | Val Loss: 0.034163  (best)
Epoch 13 | Train Loss: 0.176740 | Val Loss: 0.032503  (best)
Epoch 14 | Train Loss: 0.186339 | Val Loss: 0.030900  (best)
Epoch 15 | Train Loss: 0.181005 | Val Loss: 0.029352  (best)
Epoch 16 | Train Loss: 0.184694 | Val Loss: 0.027845  (best)
Epoch 17 | Train Loss: 0.178018 | Val Loss: 0.026384  (best)
Epoch 18 | Train Loss: 0.164018 | Val Loss: 0.024976  (best)
Epoch 19 | Train Loss: 0.162167 | Val Loss: 0.023631  (best)
Epoch 20 | Train Loss: 0.160975 | Val Loss: 0.022328  (best)
Epoch 21 | Train Loss: 0.166571 | Val Loss: 0.021076  (best)
Epoch 22 | Train Loss: 0.148871 | Val Loss: 0.019870  (best)
Epoch 23 | Train Loss: 0.156160 | Val Loss: 0.018712  (best)
Epoch 24 | Train Loss: 0.149582 | Val Loss: 0.017604  (best)
Epoch 25 | Train Loss: 0.151916 | Val Loss: 0.016549  (best)
Epoch 26 | Train Loss: 0.143517 | Val Loss: 0.015535  (best)
Epoch 27 | Train Loss: 0.138224 | Val Loss: 0.014570  (best)
Epoch 28 | Train Loss: 0.123705 | Val Loss: 0.013651  (best)
Epoch 29 | Train Loss: 0.133458 | Val Loss: 0.012779  (best)
Epoch 30 | Train Loss: 0.155420 | Val Loss: 0.011951  (best)
Epoch 31 | Train Loss: 0.140851 | Val Loss: 0.011166  (best)
Epoch 32 | Train Loss: 0.129420 | Val Loss: 0.010426  (best)
Epoch 33 | Train Loss: 0.117455 | Val Loss: 0.009731  (best)
Epoch 34 | Train Loss: 0.116433 | Val Loss: 0.009080  (best)
Epoch 35 | Train Loss: 0.124770 | Val Loss: 0.008467  (best)
Epoch 36 | Train Loss: 0.127047 | Val Loss: 0.007890  (best)
Epoch 37 | Train Loss: 0.114883 | Val Loss: 0.007354  (best)
Epoch 38 | Train Loss: 0.098370 | Val Loss: 0.006853  (best)
Epoch 39 | Train Loss: 0.099923 | Val Loss: 0.006391  (best)
Epoch 40 | Train Loss: 0.112040 | Val Loss: 0.005959  (best)
Epoch 41 | Train Loss: 0.098198 | Val Loss: 0.005559  (best)
Epoch 42 | Train Loss: 0.096957 | Val Loss: 0.005193  (best)
Epoch 43 | Train Loss: 0.089948 | Val Loss: 0.004859  (best)
Epoch 44 | Train Loss: 0.105086 | Val Loss: 0.004558  (best)
Epoch 45 | Train Loss: 0.089044 | Val Loss: 0.004287  (best)
Epoch 46 | Train Loss: 0.106175 | Val Loss: 0.004043  (best)
Epoch 47 | Train Loss: 0.092981 | Val Loss: 0.003829  (best)
Epoch 48 | Train Loss: 0.091996 | Val Loss: 0.003640  (best)
Epoch 49 | Train Loss: 0.102632 | Val Loss: 0.003476  (best)
Epoch 50 | Train Loss: 0.080826 | Val Loss: 0.003338  (best)
Epoch 51 | Train Loss: 0.089385 | Val Loss: 0.003226  (best)
Epoch 52 | Train Loss: 0.076926 | Val Loss: 0.003139  (best)
Epoch 53 | Train Loss: 0.094700 | Val Loss: 0.003077  (best)
Epoch 54 | Train Loss: 0.081696 | Val Loss: 0.003036  (best)
Epoch 55 | Train Loss: 0.079432 | Val Loss: 0.003018  (best)
Epoch 56 | Train Loss: 0.080826 | Val Loss: 0.003021 | Patience: 1/50
Epoch 57 | Train Loss: 0.084116 | Val Loss: 0.003044 | Patience: 2/50
```

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Epoch 58 | Train Loss: 0.063110 | Val Loss: 0.003088 | Patience: 3/50
Epoch 59 | Train Loss: 0.081234 | Val Loss: 0.003148 | Patience: 4/50
Epoch 60 | Train Loss: 0.089714 | Val Loss: 0.003223 | Patience: 5/50
Epoch 61 | Train Loss: 0.064980 | Val Loss: 0.003312 | Patience: 6/50
Epoch 62 | Train Loss: 0.071085 | Val Loss: 0.003418 | Patience: 7/50
Epoch 63 | Train Loss: 0.070749 | Val Loss: 0.003536 | Patience: 8/50
Epoch 64 | Train Loss: 0.075675 | Val Loss: 0.003668 | Patience: 9/50
Epoch 65 | Train Loss: 0.068577 | Val Loss: 0.003813 | Patience: 10/50
Epoch 66 | Train Loss: 0.057230 | Val Loss: 0.003972 | Patience: 11/50
Epoch 67 | Train Loss: 0.058779 | Val Loss: 0.004146 | Patience: 12/50
Epoch 68 | Train Loss: 0.059905 | Val Loss: 0.004330 | Patience: 13/50
Epoch 69 | Train Loss: 0.067675 | Val Loss: 0.004525 | Patience: 14/50
Epoch 70 | Train Loss: 0.040930 | Val Loss: 0.004730 | Patience: 15/50
Epoch 71 | Train Loss: 0.068092 | Val Loss: 0.004940 | Patience: 16/50
Epoch 72 | Train Loss: 0.060276 | Val Loss: 0.005164 | Patience: 17/50
Epoch 73 | Train Loss: 0.075793 | Val Loss: 0.005392 | Patience: 18/50
Epoch 74 | Train Loss: 0.052472 | Val Loss: 0.005631 | Patience: 19/50
Epoch 75 | Train Loss: 0.064348 | Val Loss: 0.005877 | Patience: 20/50
Epoch 76 | Train Loss: 0.061953 | Val Loss: 0.006135 | Patience: 21/50
Epoch 77 | Train Loss: 0.078071 | Val Loss: 0.006394 | Patience: 22/50
Epoch 78 | Train Loss: 0.055053 | Val Loss: 0.006667 | Patience: 23/50
Epoch 79 | Train Loss: 0.054929 | Val Loss: 0.006950 | Patience: 24/50
Epoch 80 | Train Loss: 0.045714 | Val Loss: 0.007240 | Patience: 25/50
Epoch 81 | Train Loss: 0.055936 | Val Loss: 0.007538 | Patience: 26/50
Epoch 82 | Train Loss: 0.075177 | Val Loss: 0.007838 | Patience: 27/50
Epoch 83 | Train Loss: 0.039239 | Val Loss: 0.008148 | Patience: 28/50
Epoch 84 | Train Loss: 0.046254 | Val Loss: 0.008467 | Patience: 29/50
Epoch 85 | Train Loss: 0.074730 | Val Loss: 0.008784 | Patience: 30/50
Epoch 86 | Train Loss: 0.042992 | Val Loss: 0.009102 | Patience: 31/50
Epoch 87 | Train Loss: 0.048612 | Val Loss: 0.009426 | Patience: 32/50
Epoch 88 | Train Loss: 0.061960 | Val Loss: 0.009743 | Patience: 33/50
Epoch 89 | Train Loss: 0.058667 | Val Loss: 0.010063 | Patience: 34/50
Epoch 90 | Train Loss: 0.052734 | Val Loss: 0.010383 | Patience: 35/50
Epoch 91 | Train Loss: 0.045166 | Val Loss: 0.010700 | Patience: 36/50
Epoch 92 | Train Loss: 0.058232 | Val Loss: 0.011013 | Patience: 37/50
Epoch 93 | Train Loss: 0.065347 | Val Loss: 0.011322 | Patience: 38/50
Epoch 94 | Train Loss: 0.072238 | Val Loss: 0.011617 | Patience: 39/50
Epoch 95 | Train Loss: 0.048796 | Val Loss: 0.011904 | Patience: 40/50
Epoch 96 | Train Loss: 0.050282 | Val Loss: 0.012198 | Patience: 41/50
Epoch 97 | Train Loss: 0.060904 | Val Loss: 0.012477 | Patience: 42/50
Epoch 98 | Train Loss: 0.036803 | Val Loss: 0.012770 | Patience: 43/50
Epoch 99 | Train Loss: 0.049025 | Val Loss: 0.013061 | Patience: 44/50
Epoch 100 | Train Loss: 0.074740 | Val Loss: 0.013337 | Patience: 45/50
Epoch 101 | Train Loss: 0.040063 | Val Loss: 0.013611 | Patience: 46/50
Epoch 102 | Train Loss: 0.055178 | Val Loss: 0.013879 | Patience: 47/50
Epoch 103 | Train Loss: 0.056842 | Val Loss: 0.014149 | Patience: 48/50
Epoch 104 | Train Loss: 0.042425 | Val Loss: 0.014426 | Patience: 49/50
Epoch 105 | Train Loss: 0.051506 | Val Loss: 0.014695 | Patience: 50/50
```
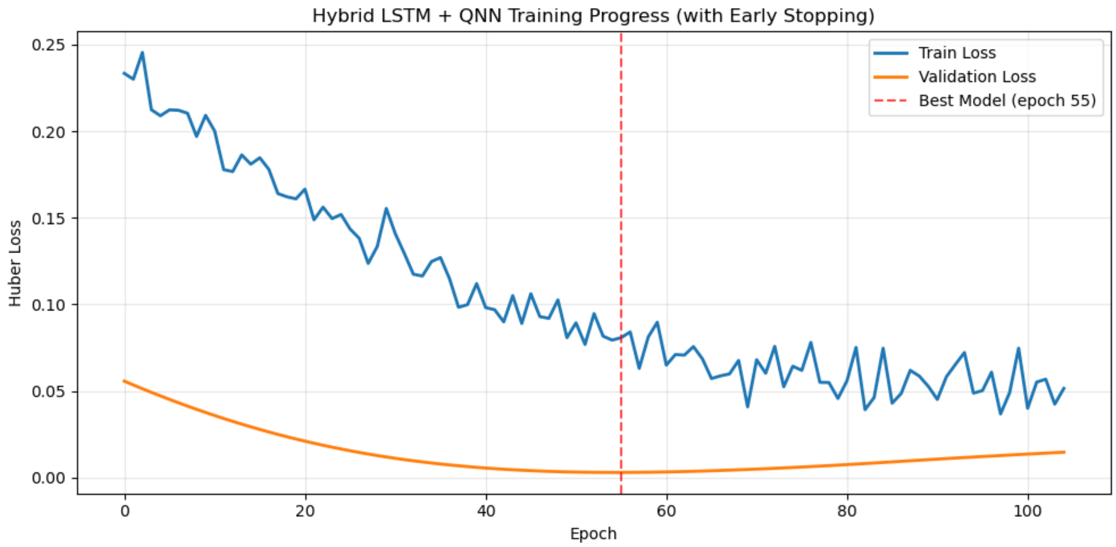
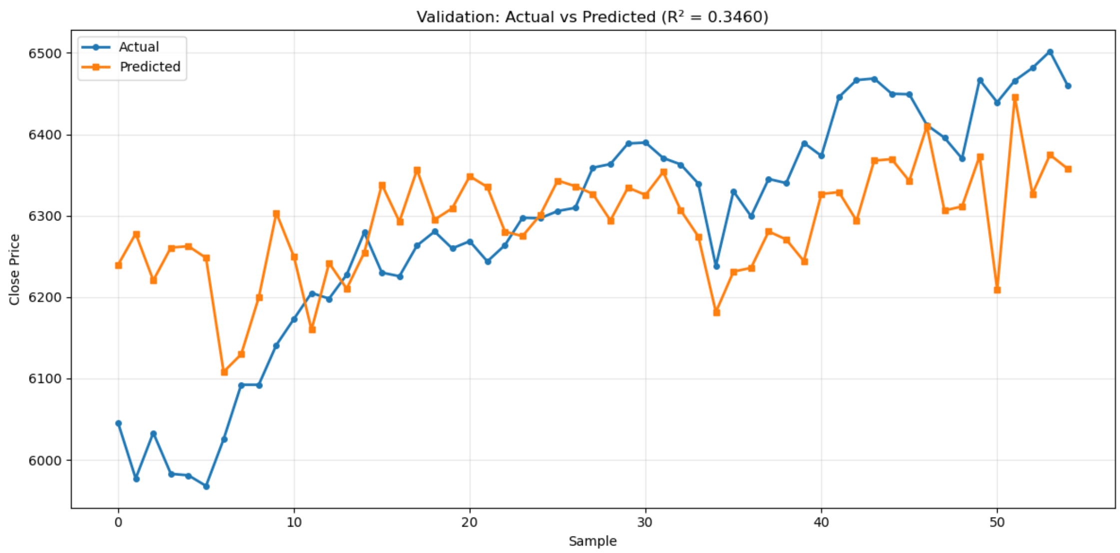
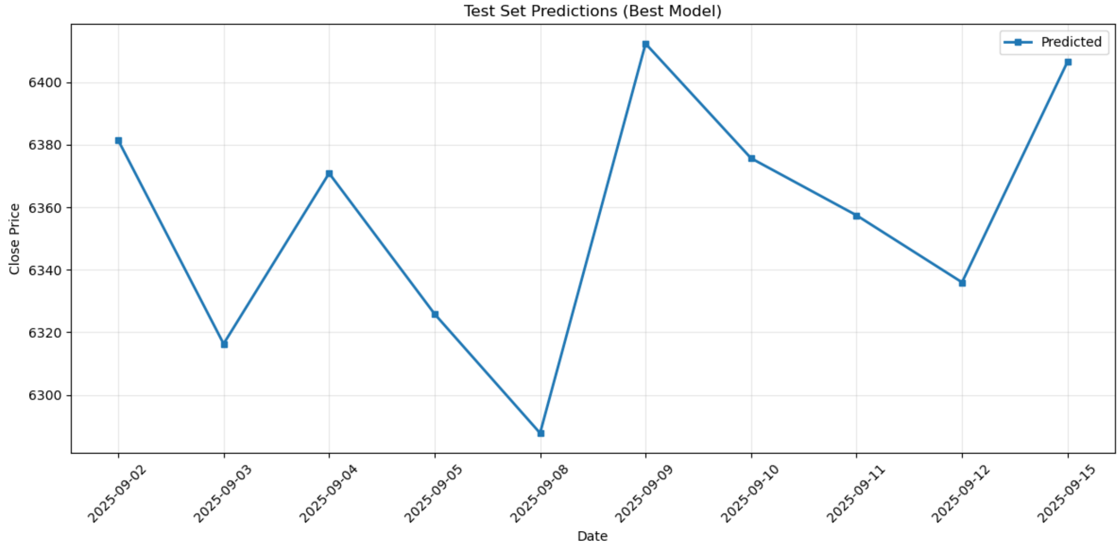

```
Early stopping triggered at epoch 105. Best val loss: 0.003018

Restoring best model weights from validation…
```




```
============================================================
FINAL METRICS (Best Model from Early Stopping)
============================================================
TRAIN - MSE: 163798.4531, R²: -1.2207, RMSE: 404.72
VAL   - MSE: 13927.7197, R²: 0.3460, RMSE: 118.02
============================================================
 Good generalization (Train R² - Val R² = -1.5667)
============================================================
```




```
============================================================
TEST SET PREDICTIONS
============================================================
      Date  Predicted_Close
2025-09-02      6381.488770
2025-09-03      6316.316895
2025-09-04      6370.878906
2025-09-05      6325.871094
2025-09-08      6287.756836
2025-09-09      6412.341309
2025-09-10      6375.680176
2025-09-11      6357.419922
2025-09-12      6335.991211
2025-09-15      6406.552246
============================================================
```



[ ]:

[ ]:

[ ]:

[44]:

```
import torch

# Save all parameters to a dictionary
model_params = {
    'W_ii': W_ii.data,
    'W_hi': W_hi.data,
    'b_i': b_i.data,
    'W_if': W_if.data,
    'W_hf': W_hf.data,
    'b_f': b_f.data,
    'W_io': W_io.data,
    'W_ho': W_ho.data,
    'b_o': b_o.data,
    'W_out': W_out.data,
    'b_out': b_out.data,
    'weights': weights.data,
    "scaler_X": scaler_X,        # Save feature scaler
    "scaler_y": scaler_y,        # Save target scaler
    "pca": pca                   # Save PCA transformer
}

# Choose your output file name
```

```python
torch.save(model_params, 'hybrid_qlstm_model_5.pth')
print("Saved model parameters to hybrid_qlstm_model_5.pth")

'''
# Load model parameters
checkpoint = torch.load('hybrid_qlstm_model.pth')

# Restore each parameter
W_ii.data = checkpoint['W_ii']
W_hi.data = checkpoint['W_hi']
b_i.data = checkpoint['b_i']
W_if.data = checkpoint['W_if']
W_hf.data = checkpoint['W_hf']
b_f.data = checkpoint['b_f']
W_io.data = checkpoint['W_io']
W_ho.data = checkpoint['W_ho']
b_o.data = checkpoint['b_o']
W_out.data = checkpoint['W_out']
b_out.data = checkpoint['b_out']
weights.data = checkpoint['weights']

# Restore scalers and PCA
scaler_X = checkpoint['scaler_X']
scaler_y = checkpoint['scaler_y']
pca = checkpoint['pca']

print("Loaded model parameters from hybrid_qlstm_model.pth")
'''

import json
def to_serializable(val):
    if isinstance(val, (np.generic, np.ndarray)):
        return val.item()  # Converts NumPy scalars to native Python types
    elif isinstance(val, torch.Tensor):
        return val.item()  # Converts 0-dim tensor to Python scalar
    else:
        return val

run_info = {k: to_serializable(v) for k, v in {
    "train_mse": train_mse,
    "train_r2": train_r2,
    "val_mse": val_mse,
    "val_r2": val_r2,
    "dropout_rate": dropout_rate,
    "early_stopping_patience": patience,
    "epochs_run": epoch
}.items()}
```

```python
with open("hybrid_qlstm_metadata_5.json", "w") as f:
    json.dump(run_info, f, indent=2)
```

```
Saved model parameters to hybrid_qlstm_model_5.pth
```

[92]:
```python
import pandas as pd

# Data as a dictionary
data = {
    "Date": [
        "2025-09-02", "2025-09-03", "2025-09-04", "2025-09-05", "2025-09-08",
        "2025-09-09", "2025-09-10", "2025-09-11", "2025-09-12", "2025-09-15"
    ],
    "Predicted_Close": [
        6381.488770, 6316.316895, 6370.878906, 6325.871094, 6287.756836,
        6412.341309, 6375.680176, 6357.419922, 6335.991211, 6406.552246
    ]
}

# Create DataFrame
df = pd.DataFrame(data)

# Save to CSV file
df.to_csv("test_set_predictions.csv", index=False)

print("Data saved to 'test_set_predictions.csv'.")
```

```
Data saved to 'test_set_predictions.csv'.
```

[ ]:
```python

```