```python
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 TensorDataset, DataLoader
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, r2_score
import re
# Set device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f'Using device: {device}')
```

```
Using device: cuda
```

```python
data =
pd.read_csv("/kaggle/input/datasets/alhanoufalqahtani/azt1dataset/
dataset.csv")

print(f"Dataset shape: {data.shape}")
print(f"Columns: {data.columns.tolist()}")
print(data.head())

data['EventDateTime'] = pd.to_datetime(data['EventDateTime'])
print(f"\nMissing values:\n{data.isnull().sum()}")
data.dropna(inplace=True)
```

```
Dataset shape: (306712, 12)
Columns: ['Subject_ID', 'EventDateTime', 'DeviceMode', 'BolusType',
'Basal', 'CorrectionDelivered', 'TotalBolusInsulinDelivered',
'FoodDelivered', 'CarbSize', 'CGM', 'Readings (CGM / BGM)',
'delta_CGM']
   Subject_ID        EventDateTime DeviceMode BolusType  Basal  \
0           1  2024-01-01 00:00:00          0         0    0.0
1           1  2024-01-01 00:05:00          0         0    0.0
2           1  2024-01-01 00:10:00          0         0    0.0
3           1  2024-01-01 00:15:00          0         0    0.0
4           1  2024-01-01 00:20:00          0         0    0.0

   CorrectionDelivered  TotalBolusInsulinDelivered  FoodDelivered
CarbSize  \
0                  0.0                         0.0            0.0
0.0
1                  0.0                         0.0            0.0
0.0
2                  0.0                         0.0            0.0
0.0
3                  0.0                         0.0            0.0
0.0
```

```
4                  0.0                           0.0           0.0
0.0

    CGM  Readings (CGM / BGM)  delta_CGM
0  91.0                   0.0        0.0
1  88.0                   0.0        0.0
2  85.0                   0.0       -3.0
3  80.0                   0.0       -3.0
4  77.0                   0.0       -5.0

Missing values:
Subject_ID                   0
EventDateTime                0
DeviceMode                   0
BolusType                    0
Basal                        0
CorrectionDelivered          0
TotalBolusInsulinDelivered   0
FoodDelivered                0
CarbSize                     0
CGM                          0
Readings (CGM / BGM)         0
delta_CGM                    0
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306712 entries, 0 to 306711
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   Subject_ID                  306712 non-null  int64
 1   EventDateTime               306712 non-null  datetime64[ns]
 2   DeviceMode                  306712 non-null  object
 3   BolusType                   306712 non-null  object
 4   Basal                       306712 non-null  float64
 5   CorrectionDelivered         306712 non-null  float64
 6   TotalBolusInsulinDelivered  306712 non-null  float64
 7   FoodDelivered               306712 non-null  float64
 8   CarbSize                    306712 non-null  float64
 9   CGM                         306712 non-null  float64
 10  Readings (CGM / BGM)        306712 non-null  float64
 11  delta_CGM                   306712 non-null  float64
dtypes: datetime64[ns](1), float64(8), int64(1), object(2)
memory usage: 28.1+ MB
```

```
# Extract time features
data['hour'] = data['EventDateTime'].dt.hour
data['day_of_week'] = data['EventDateTime'].dt.dayofweek
```

```
data['month'] = data['EventDateTime'].dt.month

print(f"\nData after preprocessing: {data.shape}")
```

```
Data after preprocessing: (306712, 15)
```

```
print(data['BolusType'].unique())
```

```
['0' 'Automatic Bolus/Correction' 'BLE Standard Bolus/Correction'
 'Standard/Correction' 'BLE Standard Bolus' 'Standard'
 'Extended 50.00%/15.49' 'Extended/Correction 50.00%/23.75'
 'Extended/Correction 50.00%/22.50' 'Extended 50.00%/23.75'
 'Extended/Correction 70.00%/23.75' 'Extended 50.00%/8.57'
 'Extended 50.00%/8.31' 'Extended/Correction 50.00%/5.00'
 'Extended 50.00%/4.29' 'Extended/Correction 50.00%/6.86'
 'Extended/Correction 50.00%/7.14' 'Extended 50.00%/5.40'
 'Extended/Correction 50.00%/6.92' 'Extended 25.00%/4.16'
 'Extended/Correction 50.00%/2.50' 'Extended 60.00%/3.27'
 'Extended 65.00%/3.18' 'Extended/Correction 65.00%/4.57'
 'Extended/Correction 65.00%/3.18' 'Extended/Correction 70.00%/3.18'
 'Extended 50.00%/0.41' 'Extended/Correction 75.00%/2.73'
 'Extended 50.00%/0.00' 'Extended 5.00%/0.00' 'Quick'
 'Extended 25.00%/1.85' 'Extended 10.00%/0.00' 'Extended 50.00%/3.00'
 'Extended/Correction 30.00%/4.75' 'Extended 25.00%/5.60'
 'Extended 25.00%/3.75' 'Extended 50.00%/12.00' 'Extended 5.00%/4.50'
 'Extended 50.00%/11.86' 'Extended 75.00%/13.33' 'Extended
75.00%/6.67'
 'Extended 50.00%/1.50' 'Extended 20.00%/0.00' 'Extended 50.00%/15.64'
 'Extended 50.00%/20.00' 'Extended 50.00%/14.21' 'Extended
60.00%/25.00'
 'Extended 50.00%/25.00' 'Extended 50.00%/15.00' 'Extended
60.00%/0.00'
 'Extended 60.00%/12.50' 'Extended 70.00%/19.90' 'Extended
50.00%/10.00'
 'Extended 75.00%/11.67' 'Extended 50.00%/8.50' 'Extended 50.00%/2.50'
 'Extended 50.00%/4.07' 'Extended 50.00%/3.80' 'Extended 50.00%/2.00'
 'Extended 50.00%/5.00' 'Extended 75.00%/0.00' 'Extended 50.00%/3.60']
```

```
def parse_extended_bolus(bolus_type):
    """Extract percentage and duration from extended bolus"""
    if pd.isna(bolus_type) or 'Extended' not in str(bolus_type):
        return pd.Series({'percentage': 0, 'duration_hours': 0})

    match = re.search(r'(\d+\.?\d*)%/(\d+\.?\d*)', str(bolus_type))

    if match:
        return pd.Series({
            'percentage': float(match.group(1)),
            'duration_hours': float(match.group(2))
        })
```

```
    else:
        return pd.Series({'percentage': 0, 'duration_hours': 0})

def encode_bolus_type(df):
    """Encode BolusType into binary flags and numeric features"""

    # Binary flags
    df['is_extended'] = df['BolusType'].str.contains('Extended',
na=False).astype(int)
    df['is_standard'] = df['BolusType'].str.contains('Standard',
na=False).astype(int)
    df['is_automatic'] = df['BolusType'].str.contains('Automatic',
na=False).astype(int)
    df['is_quick'] = df['BolusType'].str.contains('Quick',
na=False).astype(int)
    df['has_correction'] = df['BolusType'].str.contains('Correction',
na=False).astype(int)
    df['is_ble'] = df['BolusType'].str.contains('BLE',
na=False).astype(int)
    df['is_no_bolus'] = (df['BolusType'].isna() | (df['BolusType'] ==
'0')).astype(int)

    # Numeric features for extended boluses
    df[['extended_pct', 'extended_hrs']] =
df['BolusType'].apply(parse_extended_bolus)

    return df

# Apply encoding
data = encode_bolus_type(data)

data = data.sort_values(["Subject_ID",
"EventDateTime"]).reset_index(drop=True)

data=data.drop(['Readings (CGM / BGM)', 'delta_CGM','BolusType'],
axis=1)

data_naive = data[['EventDateTime', 'CGM']].copy(deep=True)
data_naive['prev_CGM'] = data_naive['CGM'].shift(1)
data_naive.dropna(inplace=True)
data_naive['difference'] = data_naive['CGM'] - data_naive['prev_CGM']
data_naive['square_error'] = data_naive['difference'] ** 2

naive_mse = data_naive['square_error'].mean()
print(f'Naive Approach Mean Square Error: {naive_mse:.4f}')
```

```
Naive Approach Mean Square Error: 41.8435
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306712 entries, 0 to 306711
Data columns (total 21 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   Subject_ID                    306712 non-null  int64
 1   EventDateTime                 306712 non-null  datetime64[ns]
 2   DeviceMode                    306712 non-null  object
 3   Basal                         306712 non-null  float64
 4   CorrectionDelivered           306712 non-null  float64
 5   TotalBolusInsulinDelivered    306712 non-null  float64
 6   FoodDelivered                 306712 non-null  float64
 7   CarbSize                      306712 non-null  float64
 8   CGM                           306712 non-null  float64
 9   hour                          306712 non-null  int32
 10  day_of_week                   306712 non-null  int32
 11  month                         306712 non-null  int32
 12  is_extended                   306712 non-null  int64
 13  is_standard                   306712 non-null  int64
 14  is_automatic                  306712 non-null  int64
 15  is_quick                      306712 non-null  int64
 16  has_correction                306712 non-null  int64
 17  is_ble                        306712 non-null  int64
 18  is_no_bolus                   306712 non-null  int64
 19  extended_pct                  306712 non-null  float64
 20  extended_hrs                  306712 non-null  float64
dtypes: datetime64[ns](1), float64(8), int32(3), int64(8), object(1)
memory usage: 45.6+ MB
```

```
data_enc = pd.get_dummies(data, columns=["DeviceMode"],
dummy_na=False)

feature_columns = [c for c in data_enc.columns if c not in
['Subject_ID','EventDateTime']]
input_data = data_enc[feature_columns].copy()

# Hyperparameters
T = 96 #Sequence length
D = input_data.shape[1] #Input dimensions
N = len(input_data) - T #Total sequences
H = 1

print(f"Sequence length (T): {T}")
print(f"Input dimensions (D): {D}")
print(f"Total sequences (N): {N}")
```

```
Sequence length (T): 96
Input dimensions (D): 22
Total sequences (N): 306616
```

```python
# Train/Val/Test split
train_size = int(len(input_data) * 0.70)
val_size = int(len(input_data) * 0.15)
test_size = N - train_size - val_size

print(f"\nTrain size: {train_size}")
print(f"Validation size: {val_size}")
print(f"Test size: {test_size}")
```

```
Train size: 214698
Validation size: 46006
Test size: 45912
```

```python
# Fit scaler on training data only
scaler = StandardScaler()
scaler.fit(input_data[:train_size + T - 1])

# Transform all data using training statistics
input_data_scaled = scaler.transform(input_data)

print(f" Scaler fit on training data only (indices 0 to {train_size +
T - 1})")
```

```
 Scaler fit on training data only (indices 0 to 214793)
```

```python
# Extract the index column to scale targets consistently
ot_column_idx = feature_columns.index('CGM')
# Get scaled OT values for targets
targets_scaled = input_data_scaled[:, ot_column_idx]

def create_sequences(data, targets, start_idx, end_idx, T):
    """Create input sequences and targets"""
    n_sequences = end_idx - start_idx
    X = np.zeros((n_sequences, T, data.shape[1]))
    y = np.zeros((n_sequences, 1))

    for i in range(n_sequences):
        t = i + start_idx
        X[i, :, :] = data[t:t+T]
        y[i] = targets[t+T]

    return X, y

# Create sequences
X_train, y_train = create_sequences(input_data_scaled, targets_scaled,
0, train_size, T)
X_val, y_val = create_sequences(input_data_scaled, targets_scaled,
train_size, train_size + val_size, T)
X_test, y_test = create_sequences(input_data_scaled, targets_scaled,
train_size + val_size, N, T)
```

```python
# Convert to PyTorch tensors
X_train = torch.from_numpy(X_train.astype(np.float32))
y_train = torch.from_numpy(y_train.astype(np.float32))
X_val = torch.from_numpy(X_val.astype(np.float32))
y_val = torch.from_numpy(y_val.astype(np.float32))
X_test = torch.from_numpy(X_test.astype(np.float32))
y_test = torch.from_numpy(y_test.astype(np.float32))

print(f"Tensor shapes:")
print(f"X_train: {X_train.shape}, y_train: {y_train.shape}")
print(f"X_val: {X_val.shape}, y_val: {y_val.shape}")
print(f"X_test: {X_test.shape}, y_test: {y_test.shape}")
```

```
Tensor shapes:
X_train: torch.Size([214698, 96, 22]), y_train: torch.Size([214698,
1])
X_val: torch.Size([46006, 96, 22]), y_val: torch.Size([46006, 1])
X_test: torch.Size([45912, 96, 22]), y_test: torch.Size([45912, 1])
```

```python
BATCH_SIZE = 64

train_dataset = TensorDataset(X_train, y_train)
val_dataset = TensorDataset(X_val, y_val)
test_dataset = TensorDataset(X_test, y_test)

train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE,
shuffle=True, drop_last=True)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE,
shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=BATCH_SIZE,
shuffle=False)

print(f"\nBatch size: {BATCH_SIZE}")
print(f"Training batches per epoch: {len(train_loader)}")
```

```

Batch size: 64
Training batches per epoch: 3354
```

```python
class PositionalEncoding(nn.Module):
    """Adds positional information to the input embeddings"""
    def __init__(self, d_model, max_len=5000, dropout=0.1):
        super(PositionalEncoding, self).__init__()
        self.dropout = nn.Dropout(p=dropout)

        # Create positional encoding matrix
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len,
dtype=torch.float).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2).float() * (-
np.log(10000.0) / d_model))
```

```
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0)  # Add batch dimension

        self.register_buffer('pe', pe)

    def forward(self, x):
        # x shape: (batch_size, seq_len, d_model)
        x = x + self.pe[:, :x.size(1), :]
        return self.dropout(x)


class TransformerModel(nn.Module):
    """Transformer model for time series prediction"""
    def __init__(self, input_dim, d_model=128, nhead=8, num_layers=2,
                 dim_feedforward=512, dropout=0.2, output_dim=1):
        super(TransformerModel, self).__init__()

        # Input projection layer
        self.input_projection = nn.Linear(input_dim, d_model)

        # Positional encoding
        self.pos_encoder = PositionalEncoding(d_model,
dropout=dropout)

        # Transformer encoder layers
        encoder_layer = nn.TransformerEncoderLayer(
            d_model=d_model,
            nhead=nhead,
            dim_feedforward=dim_feedforward,
            dropout=dropout,
            batch_first=True  # Input shape: (batch, seq, feature)
        )
        self.transformer_encoder =
nn.TransformerEncoder(encoder_layer, num_layers=num_layers)

        # Output layer
        self.fc_out = nn.Linear(d_model, output_dim)

        self.d_model = d_model

    def forward(self, x):
        # x shape: (batch_size, seq_len, input_dim)

        # Project input to d_model dimensions
        x = self.input_projection(x)  # (batch, seq, d_model)

        # Add positional encoding
        x = self.pos_encoder(x)
```

```
        # Pass through transformer encoder
        x = self.transformer_encoder(x)  # (batch, seq, d_model)

        # Take the output from the last time step
        x = x[:, -1, :]  # (batch, d_model)

        # Final prediction
        output = self.fc_out(x)  # (batch, output_dim)

        return output

# Model hyperparameters
d_model = 64          # Dimension of the model
nhead = 8              # Number of attention heads
num_layers = 2         # Number of transformer layers
dim_feedforward = 128  # Dimension of feedforward network
dropout = 0.5          # Dropout rate
output_dim = 1         # Single output (CGM prediction)

# Create model
model = TransformerModel(
    input_dim=D,
    d_model=d_model,
    nhead=nhead,
    num_layers=num_layers,
    dim_feedforward=dim_feedforward,
    dropout=dropout,
    output_dim=output_dim
)
model.to(device)

print(f"\nModel: {sum(p.numel() for p in model.parameters())}
parameters")
```

```
Model: 68481 parameters
```

```
def train(model, train_loader, val_loader, learning_rate=0.001,
epochs=100, patience=15):

    criterion = nn.MSELoss()
    optimizer = torch.optim.AdamW(model.parameters(),
lr=learning_rate, weight_decay=1e-5)
    scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
        optimizer, mode='min', factor=0.5, patience=5
    )

    train_losses = []
    val_losses = []
    best_val_loss = float('inf')
    patience_counter = 0
```

```
    for epoch in range(epochs):
        # Training
        model.train()
        train_loss_batches = []

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

            optimizer.zero_grad()
            outputs = model(batch_X)
            loss = criterion(outputs, batch_y)

            loss.backward()
            torch.nn.utils.clip_grad_norm_(model.parameters(),
max_norm=1.0)
            optimizer.step()

            train_loss_batches.append(loss.item())

        avg_train_loss = np.mean(train_loss_batches)
        train_losses.append(avg_train_loss)

        # Validation
        model.eval()
        val_loss_batches = []

        with torch.no_grad():
            for batch_X, batch_y in val_loader:
                batch_X, batch_y = batch_X.to(device),
batch_y.to(device)
                outputs = model(batch_X)
                loss = criterion(outputs, batch_y)
                val_loss_batches.append(loss.item())

        avg_val_loss = np.mean(val_loss_batches)
        val_losses.append(avg_val_loss)

        scheduler.step(avg_val_loss)

        # Early stopping
        if avg_val_loss < best_val_loss:
            best_val_loss = avg_val_loss
            patience_counter = 0
            torch.save(model.state_dict(),
'best_transformer_model.pth')
        else:
            patience_counter += 1

        if (epoch + 1) % 5 == 0:
```

```python
            print(f'Epoch {epoch+1}/{epochs} - Train Loss: 
{avg_train_loss:.4f}, Val Loss: {avg_val_loss:.4f}')

        if patience_counter >= patience:
            print(f'\nEarly stopping at epoch {epoch+1}')
            break

    # Load best model
    model.load_state_dict(torch.load('best_transformer_model.pth'))
    return train_losses, val_losses

train_losses, val_losses = train(
    model, train_loader, val_loader,
    learning_rate=0.001, epochs=100, patience=15
)
```

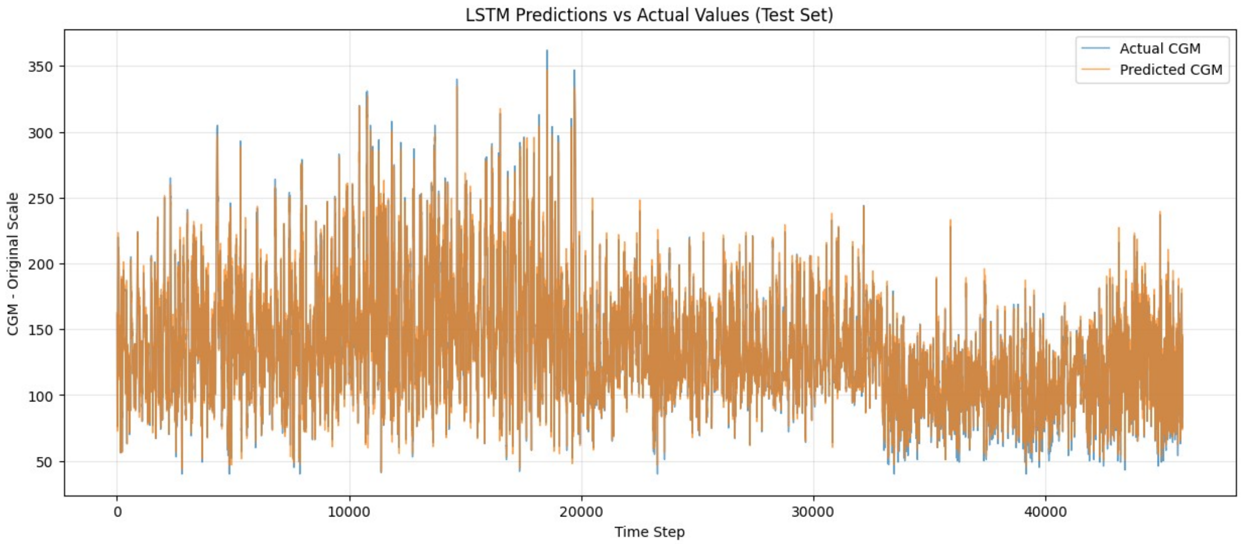
```
Epoch 5/100 - Train Loss: 0.0385, Val Loss: 0.0173
Epoch 10/100 - Train Loss: 0.0361, Val Loss: 0.0222
Epoch 15/100 - Train Loss: 0.0306, Val Loss: 0.0240
Epoch 20/100 - Train Loss: 0.0277, Val Loss: 0.0225

Early stopping at epoch 20
```

```python
# Plot
plt.figure(figsize=(10, 6))
plt.plot(train_losses, label='Train Loss', alpha=0.7)
plt.plot(val_losses, label='Validation Loss', alpha=0.7)
plt.xlabel('Epoch')
plt.ylabel('MSE Loss (Scaled)')
plt.title('Training History')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()

model.eval()
test_predictions_scaled = []
test_targets_scaled = []

with torch.no_grad():
    for batch_X, batch_y in test_loader:
        batch_X = batch_X.to(device)
        outputs = model(batch_X)

test_predictions_scaled.extend(outputs.cpu().numpy().flatten())
        test_targets_scaled.extend(batch_y.numpy().flatten())

test_predictions_scaled = np.array(test_predictions_scaled)
test_targets_scaled = np.array(test_targets_scaled)

# Get scaler parameters for OT column
ot_mean = scaler.mean_[ot_column_idx]
```

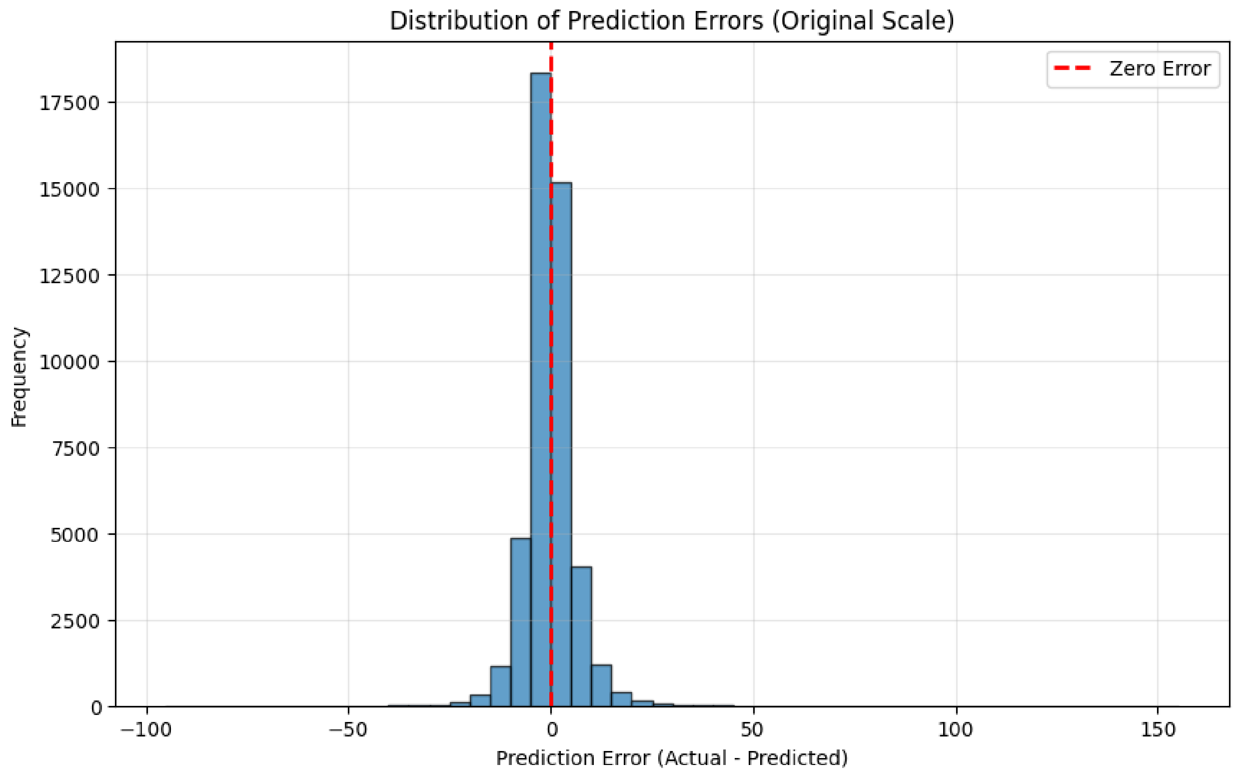
```
ot_std = scaler.scale_[ot_column_idx]

# Inverse transform: original = scaled * std + mean
test_predictions = test_predictions_scaled * ot_std + ot_mean
test_targets = test_targets_scaled * ot_std + ot_mean

print(f"Predictions and targets converted to original scale")

# Calculate metrics on ORIGINAL scale
mse = np.mean((test_targets - test_predictions) ** 2)
rmse = np.sqrt(mse)
mae = np.mean(np.abs(test_targets - test_predictions))
r2   = r2_score(test_targets, test_predictions)

print(f"  MSE:  {mse:.4f}")
print(f"  RMSE: {rmse:.4f}")
print(f"  MAE:  {mae:.4f}")
print(f"  R2:  {r2:.4f}")
```

```
Predictions and targets converted to original scale
  MSE:  36.3333
  RMSE: 6.0277
  MAE:  4.0278
  R2:  0.9804
```

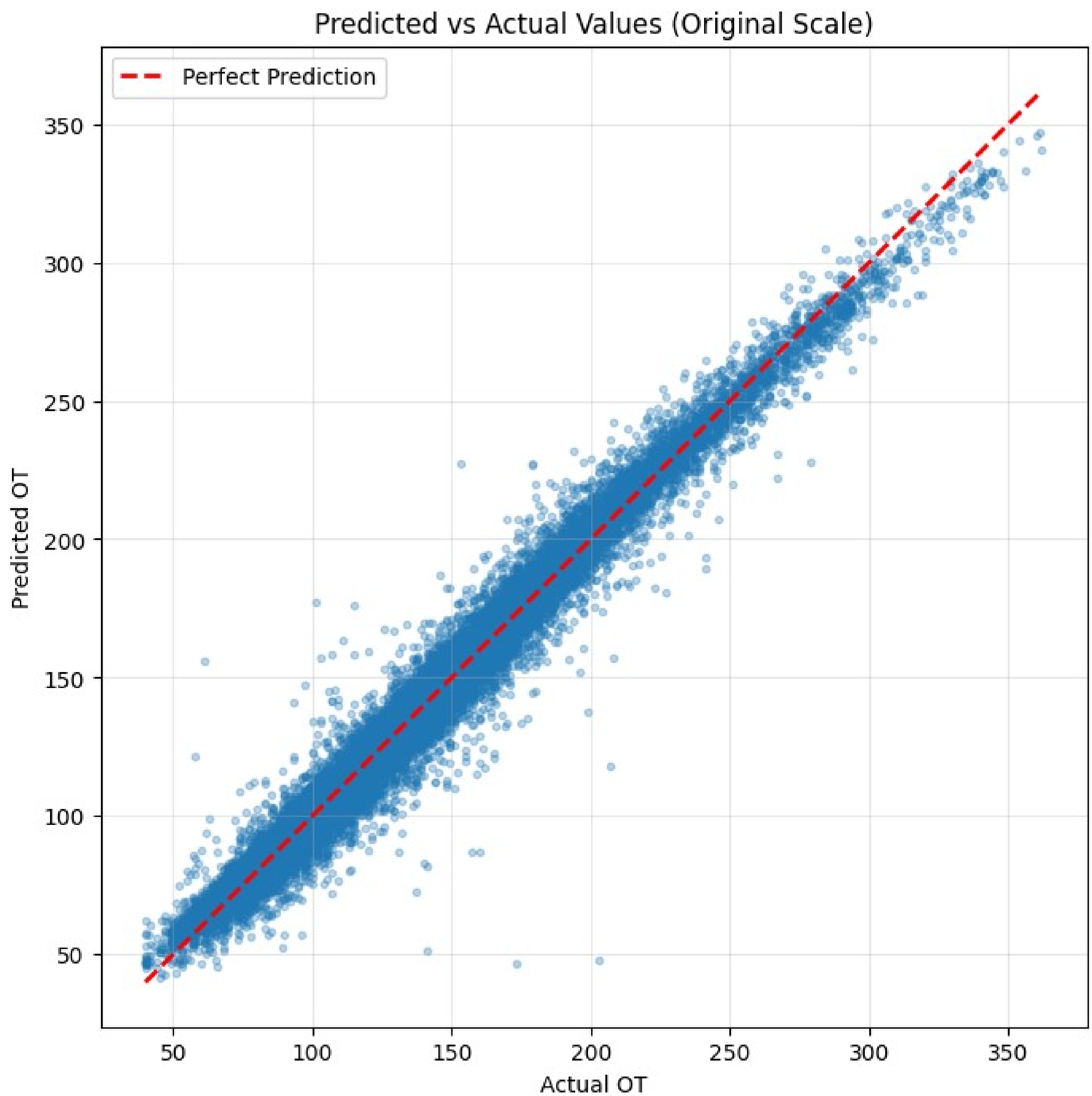
```
plt.figure(figsize=(15, 6))
plot_samples = min(len(test_predictions), len(test_predictions))
plt.plot(test_targets[:plot_samples], label='Actual CGM', linewidth=1,
alpha=0.7)
plt.plot(test_predictions[:plot_samples], label='Predicted CGM',
linewidth=1, alpha=0.7)
plt.xlabel('Time Step')
plt.ylabel('CGM - Original Scale')
plt.title('LSTM Predictions vs Actual Values (Test Set)')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```




```
errors = test_targets - test_predictions
plt.figure(figsize=(10, 6))
plt.hist(errors, bins=50, edgecolor='black', alpha=0.7)
plt.xlabel('Prediction Error (Actual - Predicted)')
plt.ylabel('Frequency')
plt.title('Distribution of Prediction Errors (Original Scale)')
plt.axvline(x=0, color='r', linestyle='--', linewidth=2, label='Zero
Error')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```




```
plt.figure(figsize=(8, 8))
plt.scatter(test_targets, test_predictions, alpha=0.3, s=10)
plt.plot([test_targets.min(), test_targets.max()],
         [test_targets.min(), test_targets.max()],
         'r--', linewidth=2, label='Perfect Prediction')
plt.xlabel('Actual OT')
plt.ylabel('Predicted OT')
plt.title('Predicted vs Actual Values (Original Scale)')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```


Predicted vs Actual Values (Original Scale)
Perfect Prediction
Predicted OT
Actual OT
50
100
150
200
250
300
350