```python
In [ ]:   import os
          import sys

          import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          from sklearn.linear_model import LinearRegression
          from sklearn.pipeline import Pipeline
          from sklearn.preprocessing import StandardScaler, PolynomialFeatures
          from sklearn.metrics import mean_squared_error, r2_score
          import torch
          import torch.nn as nn
          import torch.optim as optim
          from torch.utils.data import DataLoader, TensorDataset

          # vars
          w0 = 5
          pfe = 1
          split = 0.8
          use_previous_speed = False # True if use previous speed as feature
          min_speed = 5
          learning_rate = 0.0005
          decay = 1e-7
          num_epochs = 1000
          np.random.seed(420)
          paths = [
              'data/shell_1_strokes_2025-04-07.csv',
              'data/shell_2_strokes_2025-04-07.csv'
          ]
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```python
In [ ]:   def process_df(path):
              # 3) Concatenate
              df = pd.read_csv(path)
              df = df.dropna()
              # 4.5 m/s = 1:51.1 per 500 --paddling
              # 4.75 = 1:45 -- easy steady rowing
              # 5 is 1:40  -- medium rowing
              # 5.25 is 1:35 -- hard rowing
              # 5.5 is 1:31 -- Around base pace
              df = df[df['speed_mps'] > min_speed]
              new_features = []

              for stroke_num, same_stroke in df.groupby('crew_stroke_number'):
                  # make sure we are getting data from more than half the boat
                  if len(same_stroke) < 5: # this condition and in speed req filter out spinning
                      continue
                  features = {
                      'crew_stroke_number':stroke_num,
                      'ave_power':same_stroke['power_w'].mean(),
                      'power_var':same_stroke['power_w'].var(),
                      'rate_spm':same_stroke['rating_spm'].mean(),
                      'ave_work':same_stroke['work_j'].mean(),
                      'work_var':same_stroke['work_j'].var(),
                      'catch_angle':same_stroke['catch_angle_deg'].mean(),
                      'catch_angle_var':same_stroke['catch_angle_deg'].var(),
                      'slip_angle':same_stroke['slip_deg'].mean(),
                      'slip_var':same_stroke['slip_deg'].var(),
                      'wash_angle':same_stroke['wash_deg'].mean(),
                      'wash_var':same_stroke['wash_deg'].var(),
                      'connected_angle':same_stroke['connected_length_deg'].mean(),
                      'connected_var':same_stroke['connected_length_deg'].var(),
                      'finish_angle':same_stroke['release_angle_deg'].mean(),
                      'finish_angle_var':same_stroke['release_angle_deg'].var(),
                      'peak_force_angle':same_stroke['peak_force_angle_deg'].mean(),
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```python
                    'peak_force_angle_var':same_stroke['peak_force_angle_deg'].var(),
                    'catch_time':same_stroke['catch_timestamp_ms'].mean(),
                    'catch_time_var':same_stroke['catch_timestamp_ms'].var(),
                    'stroke_duration':same_stroke['stroke_duration_ms'].mean(),
                    'stroke_duration_var':same_stroke['stroke_duration_ms'].var(),
                    'speed_mps':same_stroke['speed_mps'].mean(),
                }
                new_features.append(features)

        cleaned_df = pd.DataFrame.from_records(new_features)
        cleaned_df = cleaned_df.drop_duplicates(subset=['crew_stroke_number'])
        cleaned_df = cleaned_df.sort_values('crew_stroke_number').reset_index(drop=True)

        # use the speed from stroke n-1 to predict speed of stroke n
        if use_previous_speed:
            cleaned_df['speed_prev'] = cleaned_df['speed_mps'].shift(1)
            cleaned_df = cleaned_df.dropna(subset=['speed_prev'])

        # cube root power metrics
        cleaned_df['ave_power'] = np.cbrt(cleaned_df['ave_power'])
        cleaned_df['power_var'] = np.cbrt(cleaned_df['power_var'])
        cleaned_df['ave_work'] = np.cbrt(cleaned_df['ave_work'])
        cleaned_df['work_var'] = np.cbrt(cleaned_df['work_var'])

        df = cleaned_df
        # number data points
        print (f'Number of data points: {len(df)}')
        return df

df1 = process_df(paths[0])
df2 = process_df(paths[1])
df = pd.concat([df1, df2])

# sanity check on distance per stroke not being a feature b/c speed = distance/stroke
feature_cols = [
    col for col in df.columns if col not in ['crew_stroke_number', 'speed_mps', 'dist
target_col = 'speed_mps'
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Number of data points: 570
Number of data points: 487
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In [ ]: df_train = df.sample(frac=split)
        df_test = df.drop(df_train.index)
        X_train = df_train[feature_cols].values
        y_train = (df_train[target_col] - w0).values.reshape(-1, 1)
        X_test = df_test[feature_cols].values
        y_test = df_test[target_col].values.reshape(-1, 1)

        #standardize the data
        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_test_scaled = scaler.transform(X_test)

        X_train_tensor = torch.FloatTensor(X_train_scaled)
        y_train_tensor = torch.FloatTensor(y_train)
        X_test_tensor = torch.FloatTensor(X_test_scaled)
        y_test_tensor = torch.FloatTensor(y_test)

        train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
        train_loader = DataLoader(dataset=train_dataset, batch_size=16, shuffle=True)

        class RegressionNN(nn.Module):
            def __init__(self, input_dim):
                super(RegressionNN, self).__init__()
                self.layer1 = nn.Linear(input_dim, 64)
                self.layer2 = nn.Linear(64, 32)
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```python
        self.layer3 = nn.Linear(32, 16)
        self.layer4 = nn.Linear(16, 1)
        self.relu = nn.ReLU()
        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        x = self.dropout(self.relu(self.layer1(x)))
        x = self.dropout(self.relu(self.layer2(x)))
        x = self.dropout(self.relu(self.layer3(x)))
        x = self.layer4(x)
        return x

input_dim = X_train_scaled.shape[1]
model = RegressionNN(input_dim)

loss_func = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate, weight_decay=decay)

loss_history = []

model.train()
for epoch in range(num_epochs):
    epoch_loss = 0.0
    for X_batch, y_batch in train_loader:
        # Forward pass
        outputs = model(X_batch)
        loss = loss_func(outputs, y_batch)
        # Backward and optimize
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        epoch_loss += loss.item()
    avg_loss = epoch_loss / len(train_loader)
    loss_history.append(avg_loss)
    # Print progress every 10 epochs
    if (epoch+1) % 25 == 0:
        print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {avg_loss:.4f}')

model.eval()
with torch.no_grad():
    y_pred_tensor = model(X_test_tensor)
    y_pred = y_pred_tensor.numpy() + w0
    y_true = y_test

plt.figure(figsize=(10, 4))
plt.plot(loss_history)
plt.title('Training Loss')
plt.xlabel('Epoch')
plt.ylabel('MSE Loss')
plt.grid(True)
plt.show()

y_true_vals = y_true.flatten()
y_pred_vals = y_pred.flatten()


mse = mean_squared_error(y_true_vals, y_pred_vals)
r2 = r2_score(y_true_vals, y_pred_vals)

plt.figure(figsize=(6, 6))
plt.scatter(y_true_vals, y_pred_vals)
min_val = min(y_true_vals.min(), y_pred_vals.min())
max_val = max(y_true_vals.max(), y_pred_vals.max())
plt.plot([min_val, max_val], [min_val, max_val])
plt.xlabel('True speed (m/s)')
plt.ylabel('Predicted speed (m/s)')
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```python
plt.title('Predicted vs True Speed')
plt.tight_layout()
plt.show()

print(f'Number of data points: {len(df)}')
print(f'MSE: {mse:.4f}')
print(f'R2 score: {r2:.4f}')

# Calculate mean average percent error
pct_errors = (y_pred_vals - y_true_vals) / y_true_vals * 100
mape = np.mean(np.abs(pct_errors))
print(f"MAPE: {mape:.2f}%")

# Calculate 500m split time error
time_true = 500.0 / y_true_vals
time_pred = 500.0 / y_pred_vals
time_err = time_pred - time_true
mean_abs_time = np.mean(np.abs(time_err))
print(f"Split error over 500 m: {mean_abs_time:.2f} s")
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```
Epoch [25/1000], Loss: 0.0036
Epoch [50/1000], Loss: 0.0030
Epoch [75/1000], Loss: 0.0029
Epoch [100/1000], Loss: 0.0025
Epoch [125/1000], Loss: 0.0024
Epoch [150/1000], Loss: 0.0021
Epoch [175/1000], Loss: 0.0019
Epoch [200/1000], Loss: 0.0020
Epoch [225/1000], Loss: 0.0019
Epoch [250/1000], Loss: 0.0017
Epoch [275/1000], Loss: 0.0016
Epoch [300/1000], Loss: 0.0016
Epoch [325/1000], Loss: 0.0016
Epoch [350/1000], Loss: 0.0016
Epoch [375/1000], Loss: 0.0016
Epoch [400/1000], Loss: 0.0016
Epoch [425/1000], Loss: 0.0014
Epoch [450/1000], Loss: 0.0014
Epoch [475/1000], Loss: 0.0014
Epoch [500/1000], Loss: 0.0013
Epoch [525/1000], Loss: 0.0013
Epoch [550/1000], Loss: 0.0014
Epoch [575/1000], Loss: 0.0013
Epoch [600/1000], Loss: 0.0014
Epoch [625/1000], Loss: 0.0012
Epoch [650/1000], Loss: 0.0013
Epoch [675/1000], Loss: 0.0012
Epoch [700/1000], Loss: 0.0014
Epoch [725/1000], Loss: 0.0012
Epoch [750/1000], Loss: 0.0011
Epoch [775/1000], Loss: 0.0012
Epoch [800/1000], Loss: 0.0012
Epoch [825/1000], Loss: 0.0012
Epoch [850/1000], Loss: 0.0011
Epoch [875/1000], Loss: 0.0012
Epoch [900/1000], Loss: 0.0012
Epoch [925/1000], Loss: 0.0012
Epoch [950/1000], Loss: 0.0012
Epoch [975/1000], Loss: 0.0011
Epoch [1000/1000], Loss: 0.0012
```
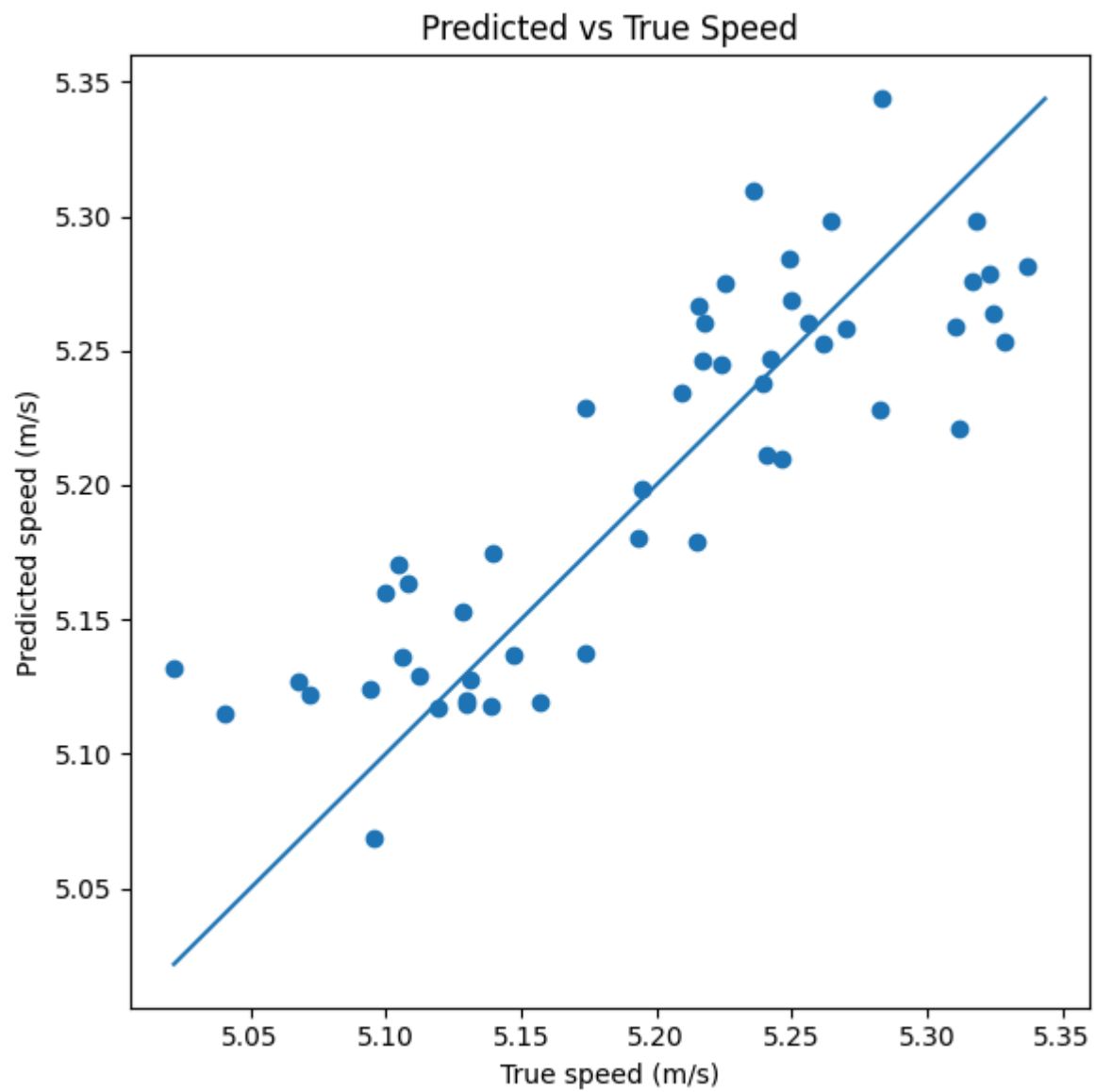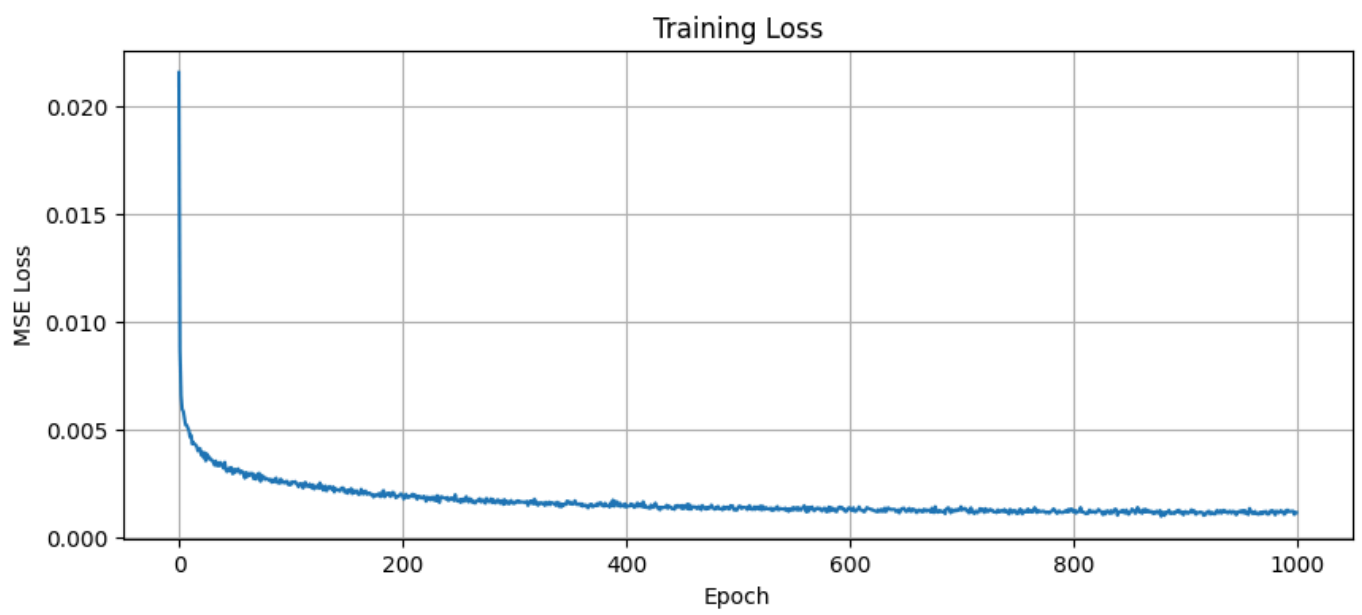
Number of data points: 1057
MSE: 0.0019
R2 score: 0.7205
MAPE: 0.71%
Split error over 500 m: 0.68 s