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[1]:
```python
# Imports et chargement des données
import pandas as pd
import numpy as np
import random
import tensorflow as tf
from sklearn.model_selection import TimeSeriesSplit
from sklearn.preprocessing import MinMaxScaler
import joblib
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, LSTM, Bidirectional,␣
 ↪Dense, Input, Dropout, GRU
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam

# Définir les graines aléatoires pour la reproductibilité
def set_seed(seed=42):
    random.seed(seed)
    np.random.seed(seed)
    tf.random.set_seed(seed)

data = pd.read_csv('stock/AAPL.csv', index_col='Date',␣
 ↪parse_dates=True)['Close']


data
```

[1]:
```
Date
2013-01-02     16.669012
2013-01-03     16.458618
2013-01-04     16.000164
2013-01-07     15.906051
2013-01-08     15.948846
                  …
2022-12-23    130.344498
2022-12-27    128.535492
2022-12-28    124.591385
```

```
2022-12-29    128.120331
2022-12-30    128.436661
Name: Close, Length: 2518, dtype: float64
```

[2]:
```python
# Prétraitement des données



# Normalisation des données
scaler = MinMaxScaler(feature_range=(0, 1))
prices_scaled = scaler.fit_transform(data.values.reshape(-1, 1))

# Sauvegarder le scaler pour une utilisation future
joblib.dump(scaler, 'scaler_minmax_gru.pkl')
```

[2]:
```
['scaler_minmax_gru.pkl']
```

[3]:
```python
#  Création des séquences
# Fonction pour créer les séquences

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

sequence_length = 3
X, y = create_sequences(prices_scaled, sequence_length)

# Diviser les données en ensembles d'entraînement et de test (70% / 30%)
train_size = int(len(X) * 0.7)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

print(f"Forme de X_train: {X_train.shape}")
print(f"Forme de y_train: {y_train.shape}")
print(f"Forme de X_test: {X_test.shape}")
print(f"Forme de y_test: {y_test.shape}")
```

```
Forme de X_train: (1760, 3, 1)
Forme de y_train: (1760, 1)
Forme de X_test: (755, 3, 1)
Forme de y_test: (755, 1)
```

[4]:
```python
#  Définition du modèle

def create_model(input_shape):
```

```
    model = Sequential([
        Input(shape=input_shape),
        Bidirectional(GRU(units=64, activation='tanh', return_sequences=True)),
        Dropout(0.25),
        Bidirectional(GRU(units=256, activation='tanh',␣
 ↪return_sequences=False)),
        Dropout(0.25),
        Dense(units=1)
    ])

    model.compile(optimizer=Adam(learning_rate=0.0001), loss='huber',␣
 ↪metrics=['mae'])
    return model
```

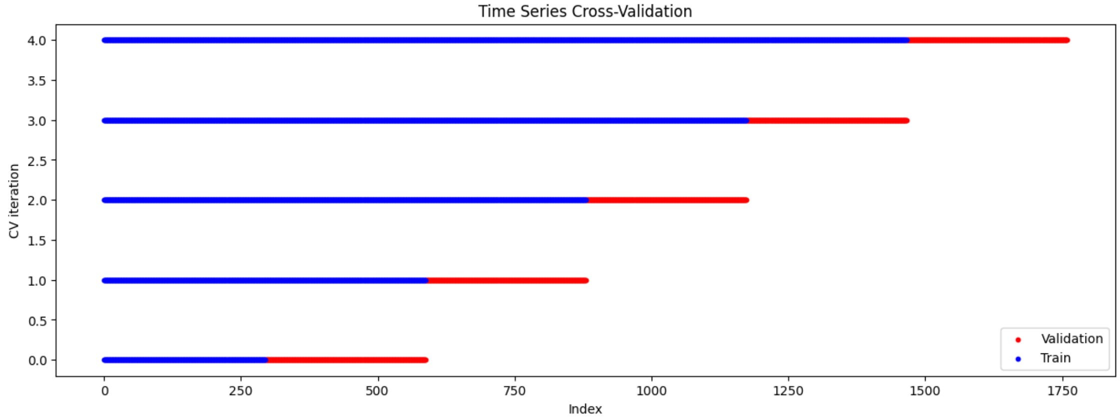
[5]:

```
# Validation croisée temporelle
# Définir la validation croisée temporelle
set_seed(42)
tscv = TimeSeriesSplit(n_splits=5)

# Initialiser les listes pour stocker les métriques
val_losses = []
val_maes = []
val_mses = []
val_r2s = []
val_smapes = []

# Fonction pour calculer le SMAPE (Symmetric Mean Absolute Percentage Error)
def calculate_smape(y_true, y_pred):
    return 100 * np.mean(2 * np.abs(y_pred - y_true) / (np.abs(y_true) + np.
 ↪abs(y_pred)))

# Visualiser les splits de validation croisée
plt.figure(figsize=(15, 5))
for i, (train_idx, val_idx) in enumerate(tscv.split(X_train)):
    plt.scatter(val_idx, [i] * len(val_idx), c='red', s=10, label='Validation'␣
 ↪if i == 0 else "")
    plt.scatter(train_idx, [i] * len(train_idx), c='blue', s=10, label='Train'␣
 ↪if i == 0 else "")

plt.legend()
plt.title('Time Series Cross-Validation')
plt.xlabel('Index')
plt.ylabel('CV iteration')
plt.show()

# Boucle de validation croisée temporelle
for fold, (train_idx, val_idx) in enumerate(tscv.split(X_train)):
```

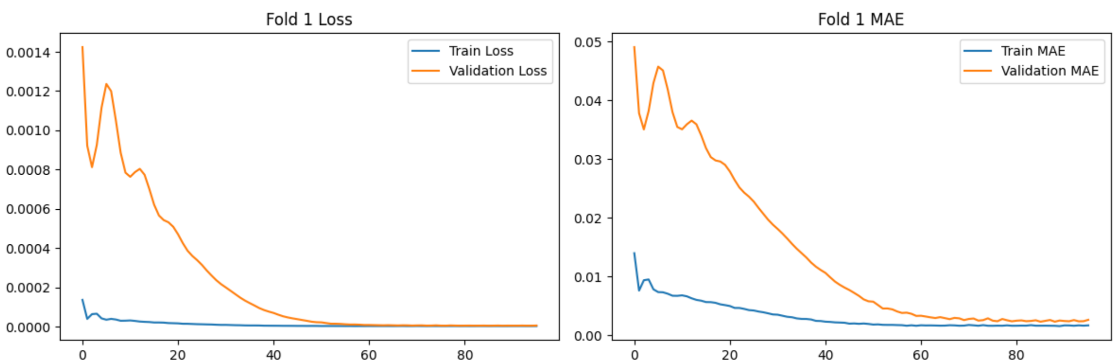
```python
    print(f"Fold {fold+1}/{tscv.n_splits}")

    # Créer les ensembles d'entraînement et de validation pour cette itération
    X_train_fold, X_val_fold = X_train[train_idx], X_train[val_idx]
    y_train_fold, y_val_fold = y_train[train_idx], y_train[val_idx]

    # Créer et compiler le modèle
    model = create_model(input_shape=(X_train.shape[1], X_train.shape[2]))

    # Définir early stopping
    early_stopping = EarlyStopping(monitor='val_loss', patience=10,␣
↪restore_best_weights=True)

    # Entraîner le modèle
    history = model.fit(
        X_train_fold, y_train_fold,
        batch_size=128,
        epochs=100,
        validation_data=(X_val_fold, y_val_fold),
        callbacks=[early_stopping],
        verbose=0
    )

    # Faire des prédictions sur l'ensemble de validation
    y_val_pred = model.predict(X_val_fold)

    # Convertir les prédictions et les valeurs réelles à l'échelle d'origine
    y_val_true_unscaled = scaler.inverse_transform(y_val_fold.reshape(-1, 1))
    y_val_pred_unscaled = scaler.inverse_transform(y_val_pred)

    # Calculer les métriques
    from sklearn.metrics import mean_squared_error, mean_absolute_error,␣
↪r2_score

    mse = mean_squared_error(y_val_true_unscaled, y_val_pred_unscaled)
    mae = mean_absolute_error(y_val_true_unscaled, y_val_pred_unscaled)
    r2 = r2_score(y_val_true_unscaled, y_val_pred_unscaled)
    smape = calculate_smape(y_val_true_unscaled, y_val_pred_unscaled)

    # Stocker les métriques
    val_losses.append(model.evaluate(X_val_fold, y_val_fold, verbose=0)[0])
    val_maes.append(mae)
    val_mses.append(mse)
    val_r2s.append(r2)
    val_smapes.append(smape)

    print(f"Fold {fold+1} validation metrics:")
```

```python
    print(f"  Loss: {val_losses[-1]:.4f}")
    print(f"  MSE: {mse:.4f}")
    print(f"  MAE: {mae:.4f}")
    print(f"  R²: {r2:.4f}")
    print(f"  SMAPE: {smape:.2f}%")

    # Tracer les courbes d'apprentissage
    plt.figure(figsize=(12, 4))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.title(f'Fold {fold+1} Loss')
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(history.history['mae'], label='Train MAE')
    plt.plot(history.history['val_mae'], label='Validation MAE')
    plt.title(f'Fold {fold+1} MAE')
    plt.legend()

    plt.tight_layout()
    plt.show()

# Calculer les moyennes et écarts-types des métriques
mean_loss = np.mean(val_losses)
std_loss = np.std(val_losses)

mean_mae = np.mean(val_maes)
std_mae = np.std(val_maes)

mean_mse = np.mean(val_mses)
std_mse = np.std(val_mses)

mean_r2 = np.mean(val_r2s)
std_r2 = np.std(val_r2s)

mean_smape = np.mean(val_smapes)
std_smape = np.std(val_smapes)

# Afficher les performances moyennes de la validation croisée avec écarts-types
print("\nRésultats de la validation croisée temporelle:")
print(f"Loss: {mean_loss:.4f} ± {std_loss:.4f}")
print(f"MSE: {mean_mse:.4f} ± {std_mse:.4f}")
print(f"MAE: {mean_mae:.4f} ± {std_mae:.4f}")
print(f"R²: {mean_r2:.4f} ± {std_r2:.4f}")
print(f"SMAPE: {mean_smape:.2f}% ± {std_smape:.2f}%")
```

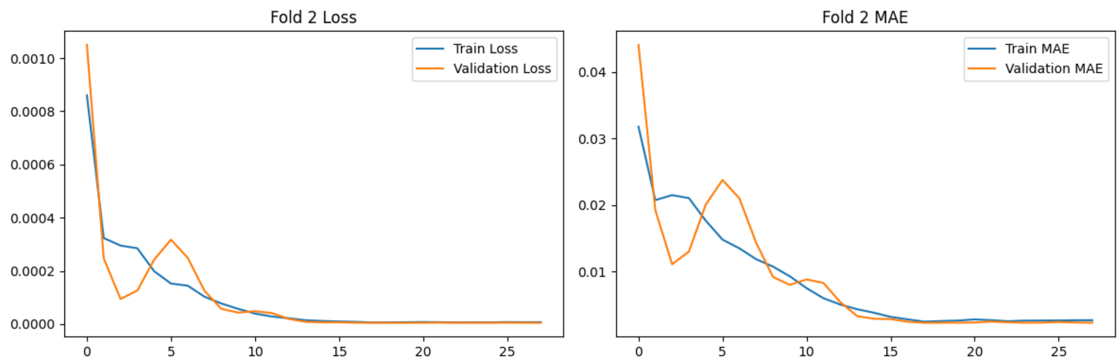
```python
# Visualiser les métriques par fold
plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
plt.bar(range(1, tscv.n_splits + 1), val_mses)
plt.errorbar(range(1, tscv.n_splits + 1), val_mses, yerr=std_mse, fmt='o',␣
↪color='r')
plt.title('MSE par fold')
plt.xlabel('Fold')
plt.ylabel('MSE')

plt.subplot(2, 2, 2)
plt.bar(range(1, tscv.n_splits + 1), val_maes)
plt.errorbar(range(1, tscv.n_splits + 1), val_maes, yerr=std_mae, fmt='o',␣
↪color='r')
plt.title('MAE par fold')
plt.xlabel('Fold')
plt.ylabel('MAE')

plt.subplot(2, 2, 3)
plt.bar(range(1, tscv.n_splits + 1), val_r2s)
plt.errorbar(range(1, tscv.n_splits + 1), val_r2s, yerr=std_r2, fmt='o',␣
↪color='r')
plt.title('R² par fold')
plt.xlabel('Fold')
plt.ylabel('R²')

plt.subplot(2, 2, 4)
plt.bar(range(1, tscv.n_splits + 1), val_smapes)
plt.errorbar(range(1, tscv.n_splits + 1), val_smapes, yerr=std_smape, fmt='o',␣
↪color='r')
plt.title('SMAPE par fold')
plt.xlabel('Fold')
plt.ylabel('SMAPE (%)')

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



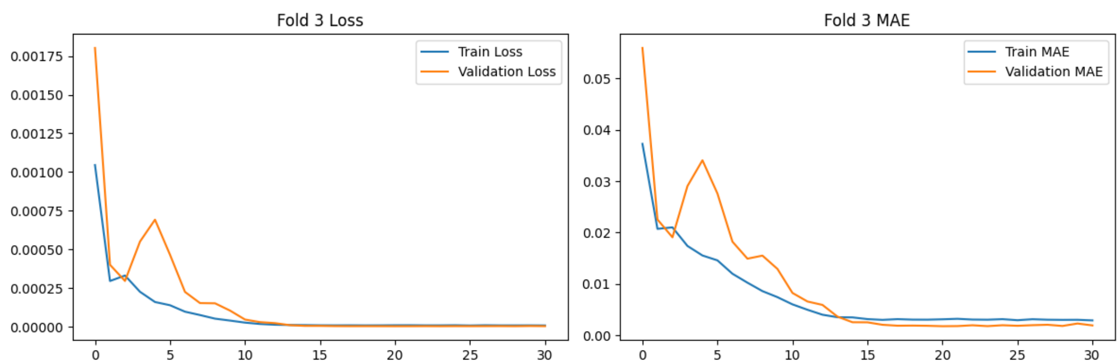

```
Fold 1/5
10/10                 1s 86ms/step
Fold 1 validation metrics:
  Loss: 0.0000
  MSE: 0.2319
  MAE: 0.3806
  R²: 0.9836
  SMAPE: 1.63%
```



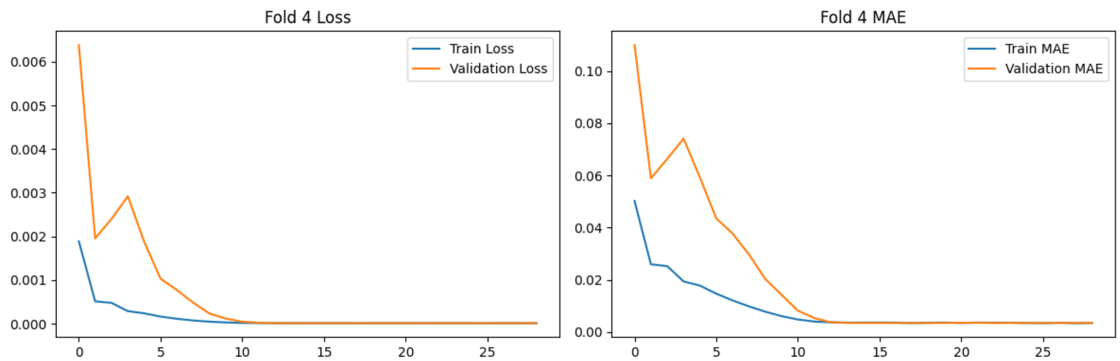

```
Fold 2/5
10/10                 1s 83ms/step
Fold 2 validation metrics:
  Loss: 0.0000
  MSE: 0.2642
  MAE: 0.3821
  R²: 0.9572
  SMAPE: 1.55%
```



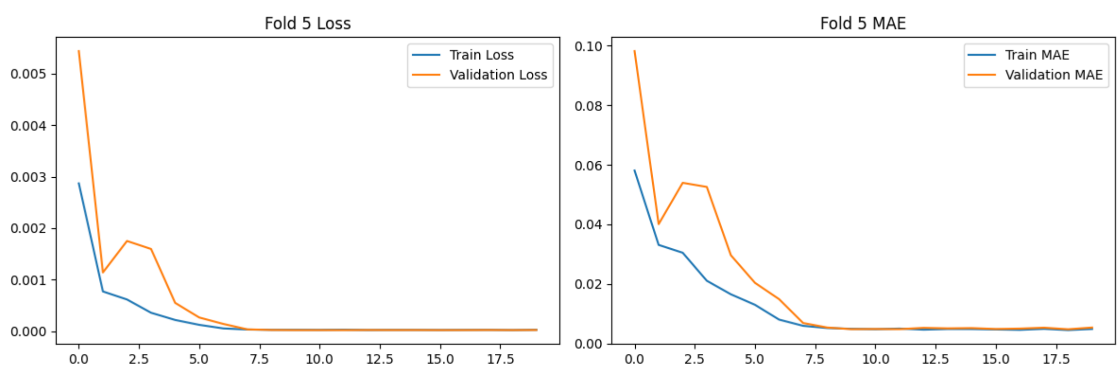
Fold 3/5
10/10 1s 73ms/step
Fold 3 validation metrics:
  Loss: 0.0000
  MSE: 0.1821
  MAE: 0.3015
  R^2: 0.9915
  SMAPE: 1.02%



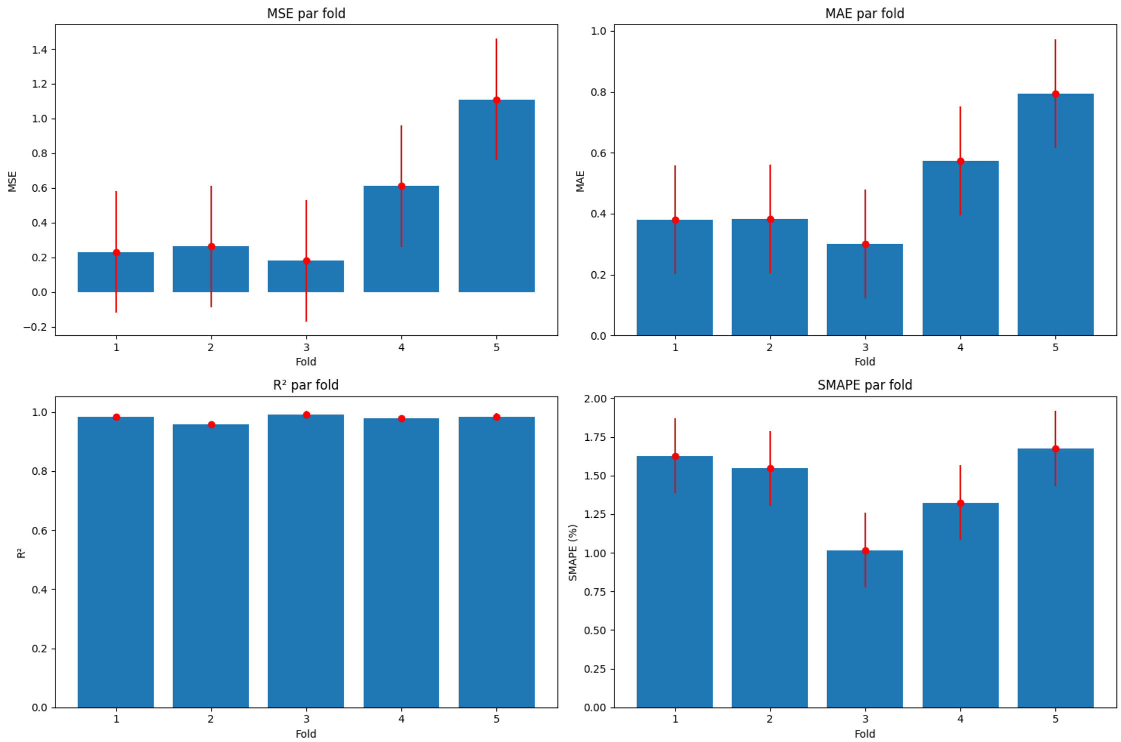
Fold 4/5
10/10 2s 94ms/step
Fold 4 validation metrics:
  Loss: 0.0000
  MSE: 0.6124
  MAE: 0.5733
  R^2: 0.9778
  SMAPE: 1.32%



Fold 5/5
10/10 2s 85ms/step
Fold 5 validation metrics:
  Loss: 0.0000
  MSE: 1.1108
  MAE: 0.7945
  R^2: 0.9849
  SMAPE: 1.67%



Résultats de la validation croisée temporelle:
Loss: 0.0000 ± 0.0000
MSE: 0.4803 ± 0.3499
MAE: 0.4864 ± 0.1782
R^2: 0.9790 ± 0.0117
SMAPE: 1.44% ± 0.24%



[6]:
```python
#  Entraînement du modèle final
# Créer et compiler le modèle final
set_seed(42)
final_model = create_model(input_shape=(X_train.shape[1], X_train.shape[2]))

# Définir early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=10,␣
 ↪restore_best_weights=True)

# Entraîner le modèle sur l'ensemble complet des données d'entraînement
final_history = final_model.fit(
    X_train, y_train,
    batch_size=128,
    epochs=100,
    verbose=1
)
```

```
Epoch 1/100
14/14              7s 27ms/step -
loss: 0.0060 - mae: 0.0865
Epoch 2/100
14/14              1s 46ms/step -
loss: 9.7045e-04 - mae: 0.0369
Epoch 3/100
```

```
14/14              1s 37ms/step -
loss: 7.8444e-04 - mae: 0.0339
Epoch 4/100
14/14              0s 33ms/step -
loss: 4.1222e-04 - mae: 0.0233
Epoch 5/100
14/14              0s 29ms/step -
loss: 2.1201e-04 - mae: 0.0171
Epoch 6/100
14/14              0s 27ms/step -
loss: 1.0101e-04 - mae: 0.0117
Epoch 7/100
14/14              1s 38ms/step -
loss: 5.1336e-05 - mae: 0.0075
Epoch 8/100
14/14              1s 44ms/step -
loss: 3.5294e-05 - mae: 0.0059
Epoch 9/100
14/14              0s 32ms/step -
loss: 3.3387e-05 - mae: 0.0056
Epoch 10/100
14/14              1s 36ms/step -
loss: 3.3705e-05 - mae: 0.0056
Epoch 11/100
14/14              1s 34ms/step -
loss: 3.8567e-05 - mae: 0.0059
Epoch 12/100
14/14              0s 29ms/step -
loss: 3.2999e-05 - mae: 0.0055
Epoch 13/100
14/14              0s 29ms/step -
loss: 3.4407e-05 - mae: 0.0056
Epoch 14/100
14/14              0s 27ms/step -
loss: 3.5767e-05 - mae: 0.0057
Epoch 15/100
14/14              0s 32ms/step -
loss: 3.7950e-05 - mae: 0.0059
Epoch 16/100
14/14              1s 38ms/step -
loss: 3.4705e-05 - mae: 0.0057
Epoch 17/100
14/14              1s 41ms/step -
loss: 3.6671e-05 - mae: 0.0058
Epoch 18/100
14/14              1s 39ms/step -
loss: 3.2124e-05 - mae: 0.0054
Epoch 19/100
```

```
14/14              1s 39ms/step -
loss: 3.3548e-05 - mae: 0.0055
Epoch 20/100
14/14              1s 43ms/step -
loss: 2.9997e-05 - mae: 0.0053
Epoch 21/100
14/14              1s 43ms/step -
loss: 3.0947e-05 - mae: 0.0055
Epoch 22/100
14/14              1s 40ms/step -
loss: 3.2319e-05 - mae: 0.0055
Epoch 23/100
14/14              1s 34ms/step -
loss: 2.9323e-05 - mae: 0.0052
Epoch 24/100
14/14              1s 37ms/step -
loss: 3.1983e-05 - mae: 0.0053
Epoch 25/100
14/14              1s 41ms/step -
loss: 3.1962e-05 - mae: 0.0053
Epoch 26/100
14/14              1s 36ms/step -
loss: 3.2582e-05 - mae: 0.0055
Epoch 27/100
14/14              1s 42ms/step -
loss: 3.5308e-05 - mae: 0.0057
Epoch 28/100
14/14              1s 35ms/step -
loss: 3.5561e-05 - mae: 0.0056
Epoch 29/100
14/14              1s 44ms/step -
loss: 3.1757e-05 - mae: 0.0054
Epoch 30/100
14/14              1s 51ms/step -
loss: 2.8965e-05 - mae: 0.0053
Epoch 31/100
14/14              1s 50ms/step -
loss: 3.0622e-05 - mae: 0.0054
Epoch 32/100
14/14              1s 42ms/step -
loss: 3.2283e-05 - mae: 0.0055
Epoch 33/100
14/14              1s 42ms/step -
loss: 2.9908e-05 - mae: 0.0052
Epoch 34/100
14/14              1s 38ms/step -
loss: 3.4492e-05 - mae: 0.0054
Epoch 35/100
```

```
14/14            1s 46ms/step -
loss: 3.3622e-05 - mae: 0.0056
Epoch 36/100
14/14            1s 48ms/step -
loss: 2.6570e-05 - mae: 0.0051
Epoch 37/100
14/14            1s 42ms/step -
loss: 3.2275e-05 - mae: 0.0053
Epoch 38/100
14/14            1s 34ms/step -
loss: 2.8532e-05 - mae: 0.0051
Epoch 39/100
14/14            1s 42ms/step -
loss: 2.7868e-05 - mae: 0.0051
Epoch 40/100
14/14            1s 42ms/step -
loss: 2.9684e-05 - mae: 0.0053
Epoch 41/100
14/14            1s 38ms/step -
loss: 3.0878e-05 - mae: 0.0052
Epoch 42/100
14/14            1s 38ms/step -
loss: 2.8097e-05 - mae: 0.0051
Epoch 43/100
14/14            1s 40ms/step -
loss: 2.7917e-05 - mae: 0.0051
Epoch 44/100
14/14            1s 38ms/step -
loss: 2.7044e-05 - mae: 0.0050
Epoch 45/100
14/14            1s 36ms/step -
loss: 2.8284e-05 - mae: 0.0051
Epoch 46/100
14/14            1s 37ms/step -
loss: 2.8903e-05 - mae: 0.0053
Epoch 47/100
14/14            1s 64ms/step -
loss: 3.0119e-05 - mae: 0.0051
Epoch 48/100
14/14            1s 41ms/step -
loss: 2.9008e-05 - mae: 0.0051
Epoch 49/100
14/14            1s 54ms/step -
loss: 2.6867e-05 - mae: 0.0049
Epoch 50/100
14/14            1s 39ms/step -
loss: 2.9229e-05 - mae: 0.0052
Epoch 51/100
```

```
14/14              0s 31ms/step -
loss: 2.6034e-05 - mae: 0.0049
Epoch 52/100
14/14              1s 40ms/step -
loss: 2.6933e-05 - mae: 0.0050
Epoch 53/100
14/14              0s 33ms/step -
loss: 2.5994e-05 - mae: 0.0050
Epoch 54/100
14/14              1s 36ms/step -
loss: 2.4363e-05 - mae: 0.0048
Epoch 55/100
14/14              1s 50ms/step -
loss: 2.7309e-05 - mae: 0.0050
Epoch 56/100
14/14              1s 42ms/step -
loss: 2.7506e-05 - mae: 0.0049
Epoch 57/100
14/14              1s 33ms/step -
loss: 2.4497e-05 - mae: 0.0049
Epoch 58/100
14/14              1s 40ms/step -
loss: 2.9297e-05 - mae: 0.0051
Epoch 59/100
14/14              1s 36ms/step -
loss: 2.6301e-05 - mae: 0.0050
Epoch 60/100
14/14              1s 35ms/step -
loss: 2.7001e-05 - mae: 0.0050
Epoch 61/100
14/14              1s 43ms/step -
loss: 2.3902e-05 - mae: 0.0048
Epoch 62/100
14/14              1s 41ms/step -
loss: 2.3467e-05 - mae: 0.0047
Epoch 63/100
14/14              1s 45ms/step -
loss: 2.6540e-05 - mae: 0.0050
Epoch 64/100
14/14              1s 47ms/step -
loss: 2.2499e-05 - mae: 0.0046
Epoch 65/100
14/14              1s 38ms/step -
loss: 3.0051e-05 - mae: 0.0051
Epoch 66/100
14/14              1s 38ms/step -
loss: 2.1330e-05 - mae: 0.0046
Epoch 67/100
```

```
14/14            1s 35ms/step -
loss: 2.5437e-05 - mae: 0.0049
Epoch 68/100
14/14            1s 36ms/step -
loss: 2.5819e-05 - mae: 0.0049
Epoch 69/100
14/14            0s 32ms/step -
loss: 2.3900e-05 - mae: 0.0047
Epoch 70/100
14/14            1s 36ms/step -
loss: 2.4757e-05 - mae: 0.0048
Epoch 71/100
14/14            1s 39ms/step -
loss: 2.5033e-05 - mae: 0.0049
Epoch 72/100
14/14            1s 38ms/step -
loss: 2.3856e-05 - mae: 0.0048
Epoch 73/100
14/14            1s 41ms/step -
loss: 2.1706e-05 - mae: 0.0047
Epoch 74/100
14/14            1s 39ms/step -
loss: 2.4235e-05 - mae: 0.0047
Epoch 75/100
14/14            1s 36ms/step -
loss: 2.1978e-05 - mae: 0.0046
Epoch 76/100
14/14            1s 38ms/step -
loss: 2.2632e-05 - mae: 0.0047
Epoch 77/100
14/14            1s 37ms/step -
loss: 2.1667e-05 - mae: 0.0046
Epoch 78/100
14/14            1s 44ms/step -
loss: 2.1659e-05 - mae: 0.0046
Epoch 79/100
14/14            1s 33ms/step -
loss: 2.0640e-05 - mae: 0.0044
Epoch 80/100
14/14            0s 33ms/step -
loss: 2.5640e-05 - mae: 0.0049
Epoch 81/100
14/14            1s 33ms/step -
loss: 2.3336e-05 - mae: 0.0047
Epoch 82/100
14/14            1s 34ms/step -
loss: 2.3616e-05 - mae: 0.0047
Epoch 83/100
```

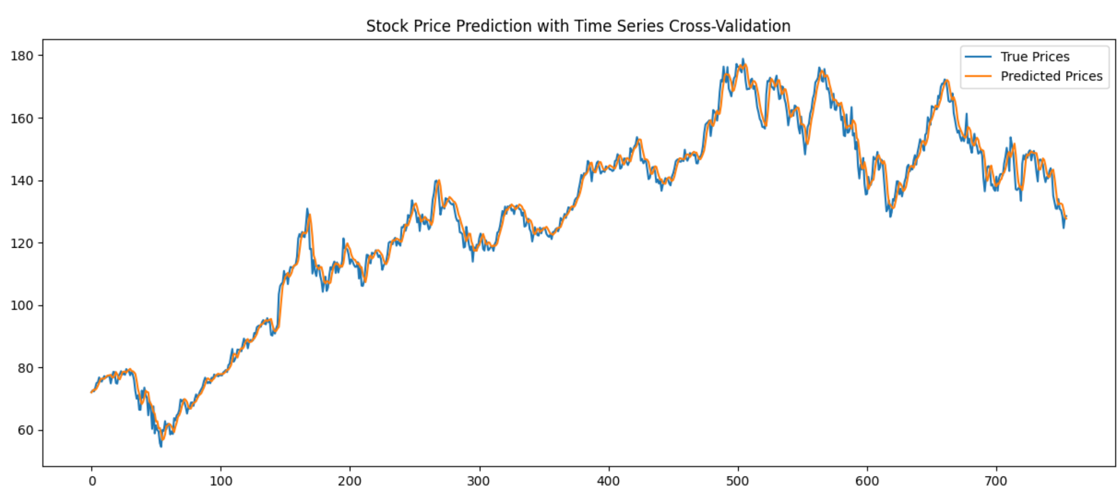
```
14/14             1s 34ms/step -
loss: 2.5276e-05 - mae: 0.0048
Epoch 84/100
14/14             1s 36ms/step -
loss: 2.4588e-05 - mae: 0.0048
Epoch 85/100
14/14             1s 38ms/step -
loss: 2.1805e-05 - mae: 0.0045
Epoch 86/100
14/14             1s 35ms/step -
loss: 2.1932e-05 - mae: 0.0046
Epoch 87/100
14/14             1s 39ms/step -
loss: 2.4519e-05 - mae: 0.0047
Epoch 88/100
14/14             1s 43ms/step -
loss: 2.1957e-05 - mae: 0.0046
Epoch 89/100
14/14             1s 38ms/step -
loss: 2.1911e-05 - mae: 0.0046
Epoch 90/100
14/14             1s 44ms/step -
loss: 2.2123e-05 - mae: 0.0046
Epoch 91/100
14/14             1s 34ms/step -
loss: 2.1689e-05 - mae: 0.0045
Epoch 92/100
14/14             0s 32ms/step -
loss: 2.2172e-05 - mae: 0.0047
Epoch 93/100
14/14             1s 42ms/step -
loss: 2.2367e-05 - mae: 0.0046
Epoch 94/100
14/14             1s 43ms/step -
loss: 2.3459e-05 - mae: 0.0048
Epoch 95/100
14/14             1s 37ms/step -
loss: 2.1600e-05 - mae: 0.0046
Epoch 96/100
14/14             1s 38ms/step -
loss: 2.3988e-05 - mae: 0.0047
Epoch 97/100
14/14             1s 37ms/step -
loss: 2.3409e-05 - mae: 0.0048
Epoch 98/100
14/14             1s 39ms/step -
loss: 2.4175e-05 - mae: 0.0049
Epoch 99/100
```

```
14/14              1s 42ms/step -
loss: 2.0334e-05 - mae: 0.0045
Epoch 100/100
14/14              1s 34ms/step -
loss: 2.0950e-05 - mae: 0.0045
```

[7]:

```
# Évaluation du modèle final
# Évaluer le modèle sur l'ensemble de test
test_loss, test_mae = final_model.evaluate(X_test, y_test)
print(f"Test Loss: {test_loss:.4f}, Test MAE: {test_mae:.4f}")

# Faire des prédictions
y_pred = final_model.predict(X_test)

# Convertir les prix prédits et réels à l'échelle initiale
y_test_unscaled = scaler.inverse_transform(y_test.reshape(-1, 1))
y_pred_unscaled = scaler.inverse_transform(y_pred)

# Tracer les résultats
plt.figure(figsize=(15, 6))
plt.plot(y_test_unscaled, label='True Prices')
plt.plot(y_pred_unscaled, label='Predicted Prices')
plt.title('Stock Price Prediction with Time Series Cross-Validation')
plt.legend()
plt.show()
```

```
24/24              1s 6ms/step - loss:
1.4397e-04 - mae: 0.0124
Test Loss: 0.0002, Test MAE: 0.0148
24/24              2s 38ms/step
```



[8]:

```
# Métriques d'évaluation détaillées
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

def calculate_mape(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

def calculate_directional_accuracy(y_true, y_pred):
    # Calcul des différences entre les points consécutifs
    y_true_direction = np.diff(y_true.flatten())
    y_pred_direction = np.diff(y_pred.flatten())

    # Calcul de la précision directionnelle
    correct_direction = np.sum((y_true_direction * y_pred_direction) > 0)
    return (correct_direction / len(y_true_direction)) * 100

# Calculer les métriques
mse = mean_squared_error(y_test_unscaled, y_pred_unscaled)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test_unscaled, y_pred_unscaled)
r2 = r2_score(y_test_unscaled, y_pred_unscaled)
mape = calculate_mape(y_test_unscaled, y_pred_unscaled)
da = calculate_directional_accuracy(y_test_unscaled, y_pred_unscaled)

# Afficher les métriques
print("Métriques d'évaluation:")
print(f"MSE: {mse:.4f}")
print(f"RMSE: {rmse:.4f}")
print(f"MAE: {mae:.4f}")
print(f"R²: {r2:.4f}")
print(f"MAPE: {mape:.2f}%")
print(f"Directional Accuracy: {da:.2f}%")
```

```
Métriques d'évaluation:
MSE: 10.6627
RMSE: 3.2654
MAE: 2.4731
R²: 0.9885
MAPE: 1.98%
Directional Accuracy: 47.08%
```

[9]:

```
#Sauvegarder le modèle final
final_model.save('model_bigru.keras')
print("Modèle sauvegardé avec succès!")
```

```
Modèle sauvegardé avec succès!
```