Лабораторна робота 6

Використання рекурентних нейронних мереж для прогнозування часових рядів і тексту

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Мета:

Вивчити основи роботи з рекурентними нейронними мережами (RNN) на прикладі прогнозування часових рядів та генерування тексту.

Частина 1: Прогнозування часових рядів

Крок 1: Імпорт бібліотек

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, SimpleRNN, LSTM, GRU
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, KFold
from sklearn.metrics import (
    mean_squared_error,
    mean_absolute_error,
    mean_absolute_percentage_error,
    r2_score
)
```

Крок 2: Завантаження та підготовка даних

In [2]:
```
data = pd.read_csv('Netflix_Stock_Price.csv')
data.head()
```

Out[2]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2018-02-05	262.000000	267.899994	250.029999	254.259995	254.259995	11896100
1	2018-02-06	247.699997	266.700012	245.000000	265.720001	265.720001	12595800
2	2018-02-07	266.579987	272.450012	264.329987	264.559998	264.559998	8981500
3	2018-02-08	267.079987	267.619995	250.000000	250.100006	250.100006	9306700
4	2018-02-09	253.850006	255.800003	236.110001	249.470001	249.470001	16906900

Назва колонки	Опис
Date	Дата, до якої відносяться записані дані про ціну акцій

Назва колонки	Опис
Open	Ціна, за якою акція відкрилася на початку торгового дня
High	Найвища ціна акції протягом торгового дня
Low	Найнижча ціна акції протягом торгового дня
Close	Ціна закриття акції, скоригована з урахуванням поділу акцій
Adj Close	Скоригована ціна закриття, враховуючи поділ акцій, дивіденди та/або розподіл капітального доходу
Volume	Обсяг торгів — кількість акцій, якими торгували протягом дня

Мета даного проєкту — передбачити ціну закриття акцій Netflix на основі даних про торгові дні. Датасет містить історичні дані про ціну акцій Netflix, що включають відкриття, найвищу та найнижчу ціну за день, ціну закриття, скориговану ціну закриття та обсяг торгів.

Цільова ознака: Close — ціна закриття акцій у кінці торгового дня. Вона є основною метою моделювання, оскільки відображає підсумкову ціну акції після завершення всіх торгових операцій.

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1009 entries, 0 to 1008
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Date       1009 non-null   object 
 1   Open       1009 non-null   float64
 2   High       1009 non-null   float64
 3   Low        1009 non-null   float64
 4   Close      1009 non-null   float64
 5   Adj Close  1009 non-null   float64
 6   Volume     1009 non-null   int64  
dtypes: float64(5), int64(1), object(1)
memory usage: 55.3+ KB
```

In [4]:
```
data.describe()
```

Out[4]:

	Open	High	Low	Close	Adj Close	Volume
count	1009.000000	1009.000000	1009.000000	1009.000000	1009.000000	1.009000e+03
mean	419.059673	425.320703	412.374044	419.000733	419.000733	7.570685e+06
std	108.537532	109.262960	107.555867	108.289999	108.289999	5.465535e+06
min	233.919998	250.649994	231.229996	233.880005	233.880005	1.144000e+06
25%	331.489990	336.299988	326.000000	331.619995	331.619995	4.091900e+06
50%	377.769989	383.010010	370.880005	378.670013	378.670013	5.934500e+06
75%	509.130005	515.630005	502.529999	509.079987	509.079987	9.322400e+06
max	692.349976	700.989990	686.090027	691.690002	691.690002	5.890430e+07

In [5]:
```
data.isnull().sum()
```

```
Out[5]: Date         0
        Open         0
        High         0
        Low          0
        Close        0
        Adj Close    0
        Volume       0
        dtype: int64
```

```
In [6]: # Масштабування даних до діапазону [0, 1]
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data[['Open', 'High', 'Low', 'Volume', 'Close']].values)

# Параметр глибини історії
look_back = 10  # кількість попередніх днів для передбачення
```

```
In [7]: # Створення послідовностей для тренування
X, y = [], []
for i in range(len(scaled_data) - look_back):
    X.append(scaled_data[i:i + look_back, :-1])  # Використовуємо всі ознаки, окрім 'Close'
    y.append(scaled_data[i + look_back, -1])    # Цільова змінна — 'Close'
X, y = np.array(X), np.array(y)
```

```
In [8]: # Розділення на тренувальні та тестові набори
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
In [9]: # Виведення форми даних
print(f"X_train shape: {X_train.shape}")  # (кількість зразків, look_back, кількість ознак)
print(f"y_train shape: {y_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_test shape: {y_test.shape}")
```

```
X_train shape: (799, 10, 4)
y_train shape: (799,)
X_test shape: (200, 10, 4)
y_test shape: (200,)
```

Крок 3: Створення та навчання моделі

```
In [10]: # Загальна функція для створення моделей на основі RNN
def create_rnn_model(model_type, input_shape, num_layers=1, units=50, activation='tanh', outp
    model = Sequential()

    # Додавання RNN-шарів
    RNN_LAYER = {'SimpleRNN': SimpleRNN, 'LSTM': LSTM, 'GRU': GRU}[model_type]
    for i in range(num_layers):
        is_last_layer = (i == num_layers - 1)
        # Вказувати input_shape лише для першого шару
        if i == 0:
            model.add(RNN_LAYER(units, activation=activation, return_sequences=not is_last_la
        else:
            model.add(RNN_LAYER(units, activation=activation, return_sequences=not is_last_la

    # Додавання вихідного шару
    model.add(Dense(output_units))

    # Компіляція моделі
    model.compile(optimizer=Adam(), loss='mse')
    return model
```

```
In [11]: # Експериментальні конфігурації моделі
model_configs = [
    {'type': 'SimpleRNN', 'layers': 1, 'units': 50},
    {'type': 'SimpleRNN', 'layers': 2, 'units': 50},
```

```python
    {'type': 'SimpleRNN', 'layers': 2, 'units': 100},
    {'type': 'LSTM', 'layers': 1, 'units': 50},
    {'type': 'LSTM', 'layers': 2, 'units': 50},
    {'type': 'LSTM', 'layers': 2, 'units': 100},
    {'type': 'GRU', 'layers': 1, 'units': 50},
    {'type': 'GRU', 'layers': 2, 'units': 50},
    {'type': 'GRU', 'layers': 2, 'units': 100},
]
```

In [12]:
```python
def calculate_metrics(y_true, y_pred):
    mse = mean_squared_error(y_true, y_pred)
    rmse = mse ** 0.5
    mae = mean_absolute_error(y_true, y_pred)
    mape = mean_absolute_percentage_error(y_true, y_pred)
    r2 = r2_score(y_true, y_pred)

    return {
        "MSE": mse,
        "RMSE": rmse,
        "MAE": mae,
        "MAPE": mape,
        "R2 Score": r2
    }
```

In [13]:
```python
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
```

In [14]:
```python
# Навчання моделей
results = {}
trained_models = {}

for config in model_configs:
    model_type = config['type']
    num_layers = config['layers']
    units = config['units']

    print(f"\nTraining {model_type} with {num_layers} layer(s) and {units} units per layer...

    # Створення моделі
    model = create_rnn_model(
        model_type=model_type,
        input_shape=(look_back, X_train.shape[2]),
        num_layers=num_layers,
        units=units
    )

    # Компіляція моделі
    model.compile(optimizer='adam', loss='mse', metrics=['mae'])

    # Навчання моделі
    history = model.fit(
        X_train, y_train,
        epochs=100,
        batch_size=32,
        validation_data=(X_test, y_test),
        verbose=2,
        callbacks=[early_stopping]
    )

    # Збереження моделі
    key = f"{model_type}_layers{num_layers}_units{units}"
    trained_models[key] = model
    results[key] = history.history
```

```
Training SimpleRNN with 1 layer(s) and 50 units per layer...
Epoch 1/100
25/25 - 2s - loss: 0.0161 - mae: 0.0896 - val_loss: 0.0032 - val_mae: 0.0441 - 2s/epoch - 78m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0037 - mae: 0.0458 - val_loss: 0.0025 - val_mae: 0.0388 - 105ms/epoch - 4
ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0027 - mae: 0.0376 - val_loss: 0.0022 - val_mae: 0.0361 - 103ms/epoch - 4
ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0023 - mae: 0.0353 - val_loss: 0.0023 - val_mae: 0.0358 - 102ms/epoch - 4
ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0020 - mae: 0.0324 - val_loss: 0.0023 - val_mae: 0.0389 - 95ms/epoch - 4m
s/step
Epoch 6/100
25/25 - 0s - loss: 0.0018 - mae: 0.0302 - val_loss: 0.0016 - val_mae: 0.0304 - 106ms/epoch - 4
ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0015 - mae: 0.0275 - val_loss: 0.0015 - val_mae: 0.0290 - 101ms/epoch - 4
ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0015 - mae: 0.0278 - val_loss: 0.0014 - val_mae: 0.0282 - 98ms/epoch - 4m
s/step
Epoch 9/100
25/25 - 0s - loss: 0.0013 - mae: 0.0258 - val_loss: 0.0018 - val_mae: 0.0319 - 118ms/epoch - 5
ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0013 - mae: 0.0258 - val_loss: 0.0012 - val_mae: 0.0266 - 87ms/epoch - 3m
s/step
Epoch 11/100
25/25 - 0s - loss: 0.0012 - mae: 0.0243 - val_loss: 0.0012 - val_mae: 0.0270 - 83ms/epoch - 3m
s/step
Epoch 12/100
25/25 - 0s - loss: 0.0011 - mae: 0.0232 - val_loss: 0.0011 - val_mae: 0.0252 - 87ms/epoch - 3m
s/step
Epoch 13/100
25/25 - 0s - loss: 0.0012 - mae: 0.0249 - val_loss: 0.0011 - val_mae: 0.0253 - 93ms/epoch - 4m
s/step
Epoch 14/100
25/25 - 0s - loss: 0.0011 - mae: 0.0243 - val_loss: 0.0011 - val_mae: 0.0245 - 174ms/epoch - 7
ms/step
Epoch 15/100
25/25 - 0s - loss: 9.8487e-04 - mae: 0.0222 - val_loss: 0.0011 - val_mae: 0.0248 - 108ms/epoch
- 4ms/step
Epoch 16/100
25/25 - 0s - loss: 0.0011 - mae: 0.0245 - val_loss: 0.0010 - val_mae: 0.0237 - 101ms/epoch - 4
ms/step
Epoch 17/100
25/25 - 0s - loss: 9.7406e-04 - mae: 0.0222 - val_loss: 0.0011 - val_mae: 0.0244 - 87ms/epoch
- 3ms/step
Epoch 18/100
25/25 - 0s - loss: 0.0010 - mae: 0.0231 - val_loss: 0.0012 - val_mae: 0.0258 - 98ms/epoch - 4m
s/step
Epoch 19/100
25/25 - 0s - loss: 0.0011 - mae: 0.0252 - val_loss: 9.7948e-04 - val_mae: 0.0231 - 117ms/epoch
- 5ms/step
Epoch 20/100
25/25 - 0s - loss: 9.7784e-04 - mae: 0.0227 - val_loss: 0.0011 - val_mae: 0.0241 - 128ms/epoch
- 5ms/step
Epoch 21/100
25/25 - 0s - loss: 8.9273e-04 - mae: 0.0215 - val_loss: 0.0010 - val_mae: 0.0236 - 134ms/epoch
- 5ms/step
Epoch 22/100
25/25 - 0s - loss: 8.8161e-04 - mae: 0.0209 - val_loss: 9.3318e-04 - val_mae: 0.0221 - 130ms/e
```

```
poch - 5ms/step
Epoch 23/100
25/25 - 0s - loss: 9.8726e-04 - mae: 0.0227 - val_loss: 0.0010 - val_mae: 0.0238 - 105ms/epoch
- 4ms/step
Epoch 24/100
25/25 - 0s - loss: 0.0011 - mae: 0.0243 - val_loss: 0.0010 - val_mae: 0.0239 - 96ms/epoch - 4m
s/step
Epoch 25/100
25/25 - 0s - loss: 8.6278e-04 - mae: 0.0211 - val_loss: 9.1899e-04 - val_mae: 0.0220 - 131ms/e
poch - 5ms/step
Epoch 26/100
25/25 - 0s - loss: 8.9394e-04 - mae: 0.0215 - val_loss: 9.1537e-04 - val_mae: 0.0221 - 109ms/e
poch - 4ms/step
Epoch 27/100
25/25 - 0s - loss: 9.4627e-04 - mae: 0.0223 - val_loss: 0.0011 - val_mae: 0.0251 - 89ms/epoch
- 4ms/step
Epoch 28/100
25/25 - 0s - loss: 0.0011 - mae: 0.0243 - val_loss: 0.0010 - val_mae: 0.0240 - 91ms/epoch - 4m
s/step
Epoch 29/100
25/25 - 0s - loss: 8.5364e-04 - mae: 0.0210 - val_loss: 9.5455e-04 - val_mae: 0.0226 - 127ms/e
poch - 5ms/step
Epoch 30/100
25/25 - 0s - loss: 8.1536e-04 - mae: 0.0208 - val_loss: 9.0813e-04 - val_mae: 0.0219 - 105ms/e
poch - 4ms/step
Epoch 31/100
25/25 - 0s - loss: 8.9445e-04 - mae: 0.0214 - val_loss: 0.0011 - val_mae: 0.0244 - 97ms/epoch
- 4ms/step
Epoch 32/100
25/25 - 0s - loss: 9.8253e-04 - mae: 0.0232 - val_loss: 0.0010 - val_mae: 0.0238 - 98ms/epoch
- 4ms/step
Epoch 33/100
25/25 - 0s - loss: 7.8295e-04 - mae: 0.0197 - val_loss: 8.8375e-04 - val_mae: 0.0212 - 129ms/e
poch - 5ms/step
Epoch 34/100
25/25 - 0s - loss: 7.8200e-04 - mae: 0.0200 - val_loss: 0.0012 - val_mae: 0.0263 - 108ms/epoch
- 4ms/step
Epoch 35/100
25/25 - 0s - loss: 8.2006e-04 - mae: 0.0206 - val_loss: 9.7192e-04 - val_mae: 0.0224 - 95ms/ep
och - 4ms/step
Epoch 36/100
25/25 - 0s - loss: 8.2834e-04 - mae: 0.0206 - val_loss: 9.5710e-04 - val_mae: 0.0219 - 100ms/e
poch - 4ms/step
Epoch 37/100
25/25 - 0s - loss: 7.6678e-04 - mae: 0.0196 - val_loss: 8.8869e-04 - val_mae: 0.0213 - 122ms/e
poch - 5ms/step
Epoch 38/100
25/25 - 0s - loss: 7.3187e-04 - mae: 0.0190 - val_loss: 8.8869e-04 - val_mae: 0.0215 - 157ms/e
poch - 6ms/step

Training SimpleRNN with 2 layer(s) and 50 units per layer...
Epoch 1/100
25/25 - 3s - loss: 0.0597 - mae: 0.1825 - val_loss: 0.0049 - val_mae: 0.0549 - 3s/epoch - 108m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0071 - mae: 0.0652 - val_loss: 0.0037 - val_mae: 0.0513 - 136ms/epoch - 5
ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0030 - mae: 0.0404 - val_loss: 0.0016 - val_mae: 0.0323 - 130ms/epoch - 5
ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0017 - mae: 0.0301 - val_loss: 0.0016 - val_mae: 0.0320 - 124ms/epoch - 5
ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0014 - mae: 0.0272 - val_loss: 0.0012 - val_mae: 0.0274 - 125ms/epoch - 5
ms/step
```

```
Epoch 6/100
25/25 - 0s - loss: 0.0013 - mae: 0.0268 - val_loss: 0.0012 - val_mae: 0.0264 - 127ms/epoch - 5
ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0012 - mae: 0.0247 - val_loss: 0.0012 - val_mae: 0.0276 - 150ms/epoch - 6
ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0012 - mae: 0.0249 - val_loss: 0.0011 - val_mae: 0.0254 - 122ms/epoch - 5
ms/step
Epoch 9/100
25/25 - 0s - loss: 0.0013 - mae: 0.0266 - val_loss: 0.0017 - val_mae: 0.0341 - 123ms/epoch - 5
ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0014 - mae: 0.0269 - val_loss: 0.0010 - val_mae: 0.0240 - 122ms/epoch - 5
ms/step
Epoch 11/100
25/25 - 0s - loss: 0.0012 - mae: 0.0261 - val_loss: 0.0011 - val_mae: 0.0246 - 125ms/epoch - 5
ms/step
Epoch 12/100
25/25 - 0s - loss: 0.0010 - mae: 0.0238 - val_loss: 0.0016 - val_mae: 0.0336 - 133ms/epoch - 5
ms/step
Epoch 13/100
25/25 - 0s - loss: 0.0012 - mae: 0.0261 - val_loss: 9.1991e-04 - val_mae: 0.0232 - 158ms/epoch
- 6ms/step
Epoch 14/100
25/25 - 0s - loss: 9.0863e-04 - mae: 0.0219 - val_loss: 9.7322e-04 - val_mae: 0.0230 - 153ms/e
poch - 6ms/step
Epoch 15/100
25/25 - 0s - loss: 9.1324e-04 - mae: 0.0218 - val_loss: 9.4150e-04 - val_mae: 0.0233 - 125ms/e
poch - 5ms/step
Epoch 16/100
25/25 - 0s - loss: 0.0011 - mae: 0.0246 - val_loss: 9.4763e-04 - val_mae: 0.0227 - 145ms/epoch
- 6ms/step
Epoch 17/100
25/25 - 0s - loss: 0.0011 - mae: 0.0243 - val_loss: 9.2267e-04 - val_mae: 0.0228 - 128ms/epoch
- 5ms/step
Epoch 18/100
25/25 - 0s - loss: 9.2993e-04 - mae: 0.0222 - val_loss: 0.0010 - val_mae: 0.0234 - 132ms/epoch
- 5ms/step

Training SimpleRNN with 2 layer(s) and 100 units per layer...
Epoch 1/100
25/25 - 3s - loss: 0.1116 - mae: 0.2457 - val_loss: 0.0063 - val_mae: 0.0690 - 3s/epoch - 128m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0073 - mae: 0.0683 - val_loss: 0.0031 - val_mae: 0.0472 - 167ms/epoch - 7
ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0026 - mae: 0.0384 - val_loss: 0.0020 - val_mae: 0.0358 - 191ms/epoch - 8
ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0017 - mae: 0.0307 - val_loss: 0.0018 - val_mae: 0.0355 - 158ms/epoch - 6
ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0015 - mae: 0.0283 - val_loss: 0.0016 - val_mae: 0.0326 - 157ms/epoch - 6
ms/step
Epoch 6/100
25/25 - 0s - loss: 0.0014 - mae: 0.0275 - val_loss: 0.0014 - val_mae: 0.0286 - 149ms/epoch - 6
ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0013 - mae: 0.0263 - val_loss: 0.0012 - val_mae: 0.0268 - 156ms/epoch - 6
ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0012 - mae: 0.0248 - val_loss: 0.0012 - val_mae: 0.0275 - 135ms/epoch - 5
ms/step
Epoch 9/100
```

```
25/25 - 0s - loss: 0.0011 - mae: 0.0239 - val_loss: 0.0010 - val_mae: 0.0245 - 137ms/epoch - 5
ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0010 - mae: 0.0230 - val_loss: 0.0010 - val_mae: 0.0240 - 135ms/epoch - 5
ms/step
Epoch 11/100
25/25 - 0s - loss: 0.0011 - mae: 0.0248 - val_loss: 9.7735e-04 - val_mae: 0.0237 - 198ms/epoch
- 8ms/step
Epoch 12/100
25/25 - 0s - loss: 0.0010 - mae: 0.0236 - val_loss: 0.0017 - val_mae: 0.0327 - 140ms/epoch - 6
ms/step
Epoch 13/100
25/25 - 0s - loss: 0.0010 - mae: 0.0234 - val_loss: 9.0474e-04 - val_mae: 0.0231 - 161ms/epoch
- 6ms/step
Epoch 14/100
25/25 - 0s - loss: 0.0010 - mae: 0.0231 - val_loss: 0.0011 - val_mae: 0.0248 - 136ms/epoch - 5
ms/step
Epoch 15/100
25/25 - 0s - loss: 9.4636e-04 - mae: 0.0225 - val_loss: 8.8519e-04 - val_mae: 0.0230 - 136ms/e
poch - 5ms/step
Epoch 16/100
25/25 - 0s - loss: 9.8852e-04 - mae: 0.0228 - val_loss: 0.0012 - val_mae: 0.0269 - 143ms/epoch
- 6ms/step
Epoch 17/100
25/25 - 0s - loss: 8.5935e-04 - mae: 0.0210 - val_loss: 8.4535e-04 - val_mae: 0.0216 - 137ms/e
poch - 5ms/step
Epoch 18/100
25/25 - 0s - loss: 8.3814e-04 - mae: 0.0208 - val_loss: 9.5571e-04 - val_mae: 0.0232 - 151ms/e
poch - 6ms/step
Epoch 19/100
25/25 - 0s - loss: 8.9480e-04 - mae: 0.0221 - val_loss: 0.0010 - val_mae: 0.0255 - 136ms/epoch
- 5ms/step
Epoch 20/100
25/25 - 0s - loss: 9.4080e-04 - mae: 0.0222 - val_loss: 8.1633e-04 - val_mae: 0.0215 - 137ms/e
poch - 5ms/step
Epoch 21/100
25/25 - 0s - loss: 7.4175e-04 - mae: 0.0193 - val_loss: 8.3220e-04 - val_mae: 0.0214 - 137ms/e
poch - 5ms/step
Epoch 22/100
25/25 - 0s - loss: 7.9056e-04 - mae: 0.0206 - val_loss: 8.2706e-04 - val_mae: 0.0213 - 135ms/e
poch - 5ms/step
Epoch 23/100
25/25 - 0s - loss: 8.2147e-04 - mae: 0.0207 - val_loss: 0.0016 - val_mae: 0.0329 - 135ms/epoch
- 5ms/step
Epoch 24/100
25/25 - 0s - loss: 8.1945e-04 - mae: 0.0210 - val_loss: 8.3607e-04 - val_mae: 0.0221 - 137ms/e
poch - 5ms/step
Epoch 25/100
25/25 - 0s - loss: 7.8555e-04 - mae: 0.0204 - val_loss: 8.2435e-04 - val_mae: 0.0212 - 143ms/e
poch - 6ms/step

Training LSTM with 1 layer(s) and 50 units per layer...
Epoch 1/100
25/25 - 4s - loss: 0.0730 - mae: 0.1937 - val_loss: 0.0065 - val_mae: 0.0705 - 4s/epoch - 149m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0045 - mae: 0.0511 - val_loss: 0.0023 - val_mae: 0.0395 - 148ms/epoch - 6
ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0024 - mae: 0.0365 - val_loss: 0.0019 - val_mae: 0.0338 - 132ms/epoch - 5
ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0021 - mae: 0.0324 - val_loss: 0.0018 - val_mae: 0.0318 - 118ms/epoch - 5
ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0020 - mae: 0.0322 - val_loss: 0.0017 - val_mae: 0.0316 - 155ms/epoch - 6
```

```
ms/step
Epoch 6/100
25/25 - 0s - loss: 0.0020 - mae: 0.0322 - val_loss: 0.0017 - val_mae: 0.0319 - 245ms/epoch - 1
0ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0020 - mae: 0.0322 - val_loss: 0.0017 - val_mae: 0.0321 - 127ms/epoch - 5
ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0019 - mae: 0.0315 - val_loss: 0.0017 - val_mae: 0.0315 - 132ms/epoch - 5
ms/step
Epoch 9/100
25/25 - 0s - loss: 0.0019 - mae: 0.0312 - val_loss: 0.0017 - val_mae: 0.0315 - 140ms/epoch - 6
ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0019 - mae: 0.0314 - val_loss: 0.0017 - val_mae: 0.0314 - 147ms/epoch - 6
ms/step
Epoch 11/100
25/25 - 0s - loss: 0.0019 - mae: 0.0309 - val_loss: 0.0017 - val_mae: 0.0315 - 131ms/epoch - 5
ms/step
Epoch 12/100
25/25 - 0s - loss: 0.0018 - mae: 0.0308 - val_loss: 0.0017 - val_mae: 0.0317 - 138ms/epoch - 6
ms/step
Epoch 13/100
25/25 - 0s - loss: 0.0018 - mae: 0.0308 - val_loss: 0.0017 - val_mae: 0.0319 - 119ms/epoch - 5
ms/step
Epoch 14/100
25/25 - 0s - loss: 0.0018 - mae: 0.0304 - val_loss: 0.0016 - val_mae: 0.0314 - 119ms/epoch - 5
ms/step
Epoch 15/100
25/25 - 0s - loss: 0.0018 - mae: 0.0303 - val_loss: 0.0016 - val_mae: 0.0311 - 120ms/epoch - 5
ms/step
Epoch 16/100
25/25 - 0s - loss: 0.0018 - mae: 0.0300 - val_loss: 0.0016 - val_mae: 0.0305 - 117ms/epoch - 5
ms/step
Epoch 17/100
25/25 - 0s - loss: 0.0017 - mae: 0.0297 - val_loss: 0.0016 - val_mae: 0.0310 - 120ms/epoch - 5
ms/step
Epoch 18/100
25/25 - 0s - loss: 0.0017 - mae: 0.0298 - val_loss: 0.0016 - val_mae: 0.0304 - 122ms/epoch - 5
ms/step
Epoch 19/100
25/25 - 0s - loss: 0.0017 - mae: 0.0291 - val_loss: 0.0016 - val_mae: 0.0301 - 120ms/epoch - 5
ms/step
Epoch 20/100
25/25 - 0s - loss: 0.0016 - mae: 0.0290 - val_loss: 0.0018 - val_mae: 0.0314 - 121ms/epoch - 5
ms/step
Epoch 21/100
25/25 - 0s - loss: 0.0016 - mae: 0.0291 - val_loss: 0.0016 - val_mae: 0.0301 - 118ms/epoch - 5
ms/step
Epoch 22/100
25/25 - 0s - loss: 0.0017 - mae: 0.0293 - val_loss: 0.0015 - val_mae: 0.0300 - 119ms/epoch - 5
ms/step
Epoch 23/100
25/25 - 0s - loss: 0.0016 - mae: 0.0290 - val_loss: 0.0015 - val_mae: 0.0309 - 119ms/epoch - 5
ms/step
Epoch 24/100
25/25 - 0s - loss: 0.0015 - mae: 0.0281 - val_loss: 0.0015 - val_mae: 0.0294 - 144ms/epoch - 6
ms/step
Epoch 25/100
25/25 - 0s - loss: 0.0016 - mae: 0.0284 - val_loss: 0.0015 - val_mae: 0.0294 - 155ms/epoch - 6
ms/step
Epoch 26/100
25/25 - 0s - loss: 0.0015 - mae: 0.0282 - val_loss: 0.0015 - val_mae: 0.0299 - 118ms/epoch - 5
ms/step
Epoch 27/100
25/25 - 0s - loss: 0.0015 - mae: 0.0283 - val_loss: 0.0015 - val_mae: 0.0294 - 125ms/epoch - 5
```

```
ms/step
Epoch 28/100
25/25 - 0s - loss: 0.0015 - mae: 0.0272 - val_loss: 0.0014 - val_mae: 0.0289 - 147ms/epoch - 6
ms/step
Epoch 29/100
25/25 - 0s - loss: 0.0014 - mae: 0.0271 - val_loss: 0.0014 - val_mae: 0.0292 - 146ms/epoch - 6
ms/step
Epoch 30/100
25/25 - 0s - loss: 0.0014 - mae: 0.0270 - val_loss: 0.0015 - val_mae: 0.0293 - 119ms/epoch - 5
ms/step
Epoch 31/100
25/25 - 0s - loss: 0.0014 - mae: 0.0270 - val_loss: 0.0016 - val_mae: 0.0314 - 123ms/epoch - 5
ms/step
Epoch 32/100
25/25 - 0s - loss: 0.0014 - mae: 0.0270 - val_loss: 0.0014 - val_mae: 0.0287 - 118ms/epoch - 5
ms/step
Epoch 33/100
25/25 - 0s - loss: 0.0014 - mae: 0.0267 - val_loss: 0.0014 - val_mae: 0.0280 - 119ms/epoch - 5
ms/step
Epoch 34/100
25/25 - 0s - loss: 0.0014 - mae: 0.0271 - val_loss: 0.0013 - val_mae: 0.0281 - 118ms/epoch - 5
ms/step
Epoch 35/100
25/25 - 0s - loss: 0.0014 - mae: 0.0265 - val_loss: 0.0013 - val_mae: 0.0277 - 121ms/epoch - 5
ms/step
Epoch 36/100
25/25 - 0s - loss: 0.0013 - mae: 0.0255 - val_loss: 0.0014 - val_mae: 0.0296 - 121ms/epoch - 5
ms/step
Epoch 37/100
25/25 - 0s - loss: 0.0013 - mae: 0.0260 - val_loss: 0.0014 - val_mae: 0.0281 - 144ms/epoch - 6
ms/step
Epoch 38/100
25/25 - 0s - loss: 0.0012 - mae: 0.0251 - val_loss: 0.0013 - val_mae: 0.0272 - 147ms/epoch - 6
ms/step
Epoch 39/100
25/25 - 0s - loss: 0.0012 - mae: 0.0247 - val_loss: 0.0013 - val_mae: 0.0273 - 118ms/epoch - 5
ms/step
Epoch 40/100
25/25 - 0s - loss: 0.0012 - mae: 0.0247 - val_loss: 0.0013 - val_mae: 0.0269 - 119ms/epoch - 5
ms/step
Epoch 41/100
25/25 - 0s - loss: 0.0012 - mae: 0.0249 - val_loss: 0.0013 - val_mae: 0.0278 - 142ms/epoch - 6
ms/step
Epoch 42/100
25/25 - 0s - loss: 0.0012 - mae: 0.0244 - val_loss: 0.0012 - val_mae: 0.0264 - 150ms/epoch - 6
ms/step
Epoch 43/100
25/25 - 0s - loss: 0.0012 - mae: 0.0242 - val_loss: 0.0014 - val_mae: 0.0276 - 119ms/epoch - 5
ms/step
Epoch 44/100
25/25 - 0s - loss: 0.0012 - mae: 0.0244 - val_loss: 0.0013 - val_mae: 0.0266 - 118ms/epoch - 5
ms/step
Epoch 45/100
25/25 - 0s - loss: 0.0011 - mae: 0.0241 - val_loss: 0.0013 - val_mae: 0.0271 - 121ms/epoch - 5
ms/step
Epoch 46/100
25/25 - 0s - loss: 0.0011 - mae: 0.0235 - val_loss: 0.0014 - val_mae: 0.0286 - 118ms/epoch - 5
ms/step
Epoch 47/100
25/25 - 0s - loss: 0.0011 - mae: 0.0231 - val_loss: 0.0012 - val_mae: 0.0256 - 119ms/epoch - 5
ms/step
Epoch 48/100
25/25 - 0s - loss: 0.0011 - mae: 0.0238 - val_loss: 0.0013 - val_mae: 0.0266 - 117ms/epoch - 5
ms/step
Epoch 49/100
25/25 - 0s - loss: 0.0011 - mae: 0.0235 - val_loss: 0.0012 - val_mae: 0.0253 - 118ms/epoch - 5
```

```
ms/step
Epoch 50/100
25/25 - 0s - loss: 0.0011 - mae: 0.0230 - val_loss: 0.0012 - val_mae: 0.0267 - 118ms/epoch - 5
ms/step
Epoch 51/100
25/25 - 0s - loss: 0.0011 - mae: 0.0235 - val_loss: 0.0012 - val_mae: 0.0264 - 122ms/epoch - 5
ms/step
Epoch 52/100
25/25 - 0s - loss: 0.0011 - mae: 0.0232 - val_loss: 0.0011 - val_mae: 0.0249 - 118ms/epoch - 5
ms/step
Epoch 53/100
25/25 - 0s - loss: 0.0010 - mae: 0.0225 - val_loss: 0.0012 - val_mae: 0.0260 - 119ms/epoch - 5
ms/step
Epoch 54/100
25/25 - 0s - loss: 0.0010 - mae: 0.0232 - val_loss: 0.0014 - val_mae: 0.0298 - 124ms/epoch - 5
ms/step
Epoch 55/100
25/25 - 0s - loss: 0.0011 - mae: 0.0237 - val_loss: 0.0011 - val_mae: 0.0249 - 120ms/epoch - 5
ms/step
Epoch 56/100
25/25 - 0s - loss: 9.8238e-04 - mae: 0.0221 - val_loss: 0.0011 - val_mae: 0.0243 - 138ms/epoch
- 6ms/step
Epoch 57/100
25/25 - 0s - loss: 9.8875e-04 - mae: 0.0228 - val_loss: 0.0011 - val_mae: 0.0244 - 117ms/epoch
- 5ms/step
Epoch 58/100
25/25 - 0s - loss: 9.5973e-04 - mae: 0.0222 - val_loss: 0.0011 - val_mae: 0.0246 - 118ms/epoch
- 5ms/step
Epoch 59/100
25/25 - 0s - loss: 9.6434e-04 - mae: 0.0220 - val_loss: 0.0012 - val_mae: 0.0266 - 167ms/epoch
- 7ms/step
Epoch 60/100
25/25 - 0s - loss: 0.0010 - mae: 0.0227 - val_loss: 0.0014 - val_mae: 0.0288 - 125ms/epoch - 5
ms/step
Epoch 61/100
25/25 - 0s - loss: 9.8519e-04 - mae: 0.0226 - val_loss: 0.0013 - val_mae: 0.0273 - 125ms/epoch
- 5ms/step
Epoch 62/100
25/25 - 0s - loss: 0.0010 - mae: 0.0232 - val_loss: 0.0012 - val_mae: 0.0254 - 122ms/epoch - 5
ms/step

Training LSTM with 2 layer(s) and 50 units per layer...
Epoch 1/100
25/25 - 7s - loss: 0.0384 - mae: 0.1350 - val_loss: 0.0088 - val_mae: 0.0702 - 7s/epoch - 275m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0041 - mae: 0.0479 - val_loss: 0.0032 - val_mae: 0.0431 - 254ms/epoch - 1
0ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0027 - mae: 0.0377 - val_loss: 0.0021 - val_mae: 0.0351 - 315ms/epoch - 1
3ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0023 - mae: 0.0345 - val_loss: 0.0020 - val_mae: 0.0339 - 213ms/epoch - 9
ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0023 - mae: 0.0343 - val_loss: 0.0019 - val_mae: 0.0334 - 273ms/epoch - 1
1ms/step
Epoch 6/100
25/25 - 0s - loss: 0.0024 - mae: 0.0350 - val_loss: 0.0019 - val_mae: 0.0329 - 279ms/epoch - 1
1ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0022 - mae: 0.0338 - val_loss: 0.0018 - val_mae: 0.0325 - 301ms/epoch - 1
2ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0022 - mae: 0.0336 - val_loss: 0.0018 - val_mae: 0.0327 - 229ms/epoch - 9
ms/step
```

```
Epoch 9/100
25/25 - 0s - loss: 0.0021 - mae: 0.0331 - val_loss: 0.0018 - val_mae: 0.0322 - 234ms/epoch - 9
ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0021 - mae: 0.0329 - val_loss: 0.0021 - val_mae: 0.0342 - 230ms/epoch - 9
ms/step
Epoch 11/100
25/25 - 0s - loss: 0.0022 - mae: 0.0335 - val_loss: 0.0018 - val_mae: 0.0334 - 288ms/epoch - 1
2ms/step
Epoch 12/100
25/25 - 0s - loss: 0.0021 - mae: 0.0338 - val_loss: 0.0019 - val_mae: 0.0324 - 231ms/epoch - 9
ms/step
Epoch 13/100
25/25 - 0s - loss: 0.0020 - mae: 0.0321 - val_loss: 0.0017 - val_mae: 0.0316 - 221ms/epoch - 9
ms/step
Epoch 14/100
25/25 - 0s - loss: 0.0020 - mae: 0.0327 - val_loss: 0.0020 - val_mae: 0.0359 - 211ms/epoch - 8
ms/step
Epoch 15/100
25/25 - 0s - loss: 0.0021 - mae: 0.0333 - val_loss: 0.0017 - val_mae: 0.0314 - 215ms/epoch - 9
ms/step
Epoch 16/100
25/25 - 0s - loss: 0.0019 - mae: 0.0311 - val_loss: 0.0017 - val_mae: 0.0320 - 208ms/epoch - 8
ms/step
Epoch 17/100
25/25 - 0s - loss: 0.0019 - mae: 0.0316 - val_loss: 0.0016 - val_mae: 0.0308 - 211ms/epoch - 8
ms/step
Epoch 18/100
25/25 - 0s - loss: 0.0019 - mae: 0.0310 - val_loss: 0.0016 - val_mae: 0.0315 - 210ms/epoch - 8
ms/step
Epoch 19/100
25/25 - 0s - loss: 0.0018 - mae: 0.0301 - val_loss: 0.0016 - val_mae: 0.0308 - 207ms/epoch - 8
ms/step
Epoch 20/100
25/25 - 0s - loss: 0.0018 - mae: 0.0306 - val_loss: 0.0018 - val_mae: 0.0318 - 212ms/epoch - 8
ms/step
Epoch 21/100
25/25 - 0s - loss: 0.0017 - mae: 0.0296 - val_loss: 0.0016 - val_mae: 0.0300 - 206ms/epoch - 8
ms/step
Epoch 22/100
25/25 - 0s - loss: 0.0017 - mae: 0.0296 - val_loss: 0.0018 - val_mae: 0.0315 - 209ms/epoch - 8
ms/step
Epoch 23/100
25/25 - 0s - loss: 0.0017 - mae: 0.0295 - val_loss: 0.0015 - val_mae: 0.0299 - 217ms/epoch - 9
ms/step
Epoch 24/100
25/25 - 0s - loss: 0.0016 - mae: 0.0282 - val_loss: 0.0015 - val_mae: 0.0298 - 211ms/epoch - 8
ms/step
Epoch 25/100
25/25 - 0s - loss: 0.0015 - mae: 0.0278 - val_loss: 0.0017 - val_mae: 0.0329 - 208ms/epoch - 8
ms/step
Epoch 26/100
25/25 - 0s - loss: 0.0015 - mae: 0.0277 - val_loss: 0.0015 - val_mae: 0.0292 - 207ms/epoch - 8
ms/step
Epoch 27/100
25/25 - 0s - loss: 0.0015 - mae: 0.0273 - val_loss: 0.0015 - val_mae: 0.0292 - 210ms/epoch - 8
ms/step
Epoch 28/100
25/25 - 0s - loss: 0.0014 - mae: 0.0274 - val_loss: 0.0016 - val_mae: 0.0291 - 205ms/epoch - 8
ms/step
Epoch 29/100
25/25 - 0s - loss: 0.0014 - mae: 0.0267 - val_loss: 0.0015 - val_mae: 0.0304 - 209ms/epoch - 8
ms/step
Epoch 30/100
25/25 - 0s - loss: 0.0013 - mae: 0.0264 - val_loss: 0.0016 - val_mae: 0.0298 - 233ms/epoch - 9
ms/step
```

```
Epoch 31/100
25/25 - 0s - loss: 0.0014 - mae: 0.0264 - val_loss: 0.0014 - val_mae: 0.0284 - 227ms/epoch - 9
ms/step
Epoch 32/100
25/25 - 0s - loss: 0.0013 - mae: 0.0263 - val_loss: 0.0018 - val_mae: 0.0314 - 221ms/epoch - 9
ms/step
Epoch 33/100
25/25 - 0s - loss: 0.0014 - mae: 0.0273 - val_loss: 0.0014 - val_mae: 0.0280 - 207ms/epoch - 8
ms/step
Epoch 34/100
25/25 - 0s - loss: 0.0013 - mae: 0.0260 - val_loss: 0.0014 - val_mae: 0.0272 - 209ms/epoch - 8
ms/step
Epoch 35/100
25/25 - 0s - loss: 0.0012 - mae: 0.0250 - val_loss: 0.0013 - val_mae: 0.0267 - 231ms/epoch - 9
ms/step
Epoch 36/100
25/25 - 0s - loss: 0.0012 - mae: 0.0247 - val_loss: 0.0013 - val_mae: 0.0268 - 211ms/epoch - 8
ms/step
Epoch 37/100
25/25 - 0s - loss: 0.0012 - mae: 0.0247 - val_loss: 0.0013 - val_mae: 0.0265 - 216ms/epoch - 9
ms/step
Epoch 38/100
25/25 - 0s - loss: 0.0013 - mae: 0.0266 - val_loss: 0.0013 - val_mae: 0.0271 - 202ms/epoch - 8
ms/step
Epoch 39/100
25/25 - 0s - loss: 0.0012 - mae: 0.0242 - val_loss: 0.0013 - val_mae: 0.0266 - 207ms/epoch - 8
ms/step
Epoch 40/100
25/25 - 0s - loss: 0.0012 - mae: 0.0249 - val_loss: 0.0013 - val_mae: 0.0274 - 218ms/epoch - 9
ms/step
Epoch 41/100
25/25 - 0s - loss: 0.0012 - mae: 0.0254 - val_loss: 0.0014 - val_mae: 0.0282 - 197ms/epoch - 8
ms/step
Epoch 42/100
25/25 - 0s - loss: 0.0013 - mae: 0.0271 - val_loss: 0.0012 - val_mae: 0.0261 - 199ms/epoch - 8
ms/step
Epoch 43/100
25/25 - 0s - loss: 0.0011 - mae: 0.0239 - val_loss: 0.0012 - val_mae: 0.0259 - 200ms/epoch - 8
ms/step
Epoch 44/100
25/25 - 0s - loss: 0.0011 - mae: 0.0235 - val_loss: 0.0013 - val_mae: 0.0261 - 196ms/epoch - 8
ms/step
Epoch 45/100
25/25 - 0s - loss: 0.0011 - mae: 0.0233 - val_loss: 0.0012 - val_mae: 0.0257 - 200ms/epoch - 8
ms/step
Epoch 46/100
25/25 - 0s - loss: 0.0011 - mae: 0.0245 - val_loss: 0.0013 - val_mae: 0.0267 - 244ms/epoch - 1
0ms/step
Epoch 47/100
25/25 - 0s - loss: 0.0011 - mae: 0.0236 - val_loss: 0.0013 - val_mae: 0.0266 - 212ms/epoch - 8
ms/step
Epoch 48/100
25/25 - 0s - loss: 0.0011 - mae: 0.0234 - val_loss: 0.0012 - val_mae: 0.0259 - 211ms/epoch - 8
ms/step

Training LSTM with 2 layer(s) and 100 units per layer...
Epoch 1/100
25/25 - 9s - loss: 0.0326 - mae: 0.1137 - val_loss: 0.0033 - val_mae: 0.0489 - 9s/epoch - 359m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0031 - mae: 0.0403 - val_loss: 0.0019 - val_mae: 0.0342 - 258ms/epoch - 1
0ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0023 - mae: 0.0339 - val_loss: 0.0019 - val_mae: 0.0323 - 246ms/epoch - 1
0ms/step
Epoch 4/100
```

```
25/25 - 0s - loss: 0.0022 - mae: 0.0333 - val_loss: 0.0017 - val_mae: 0.0316 - 256ms/epoch - 1
0ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0022 - mae: 0.0344 - val_loss: 0.0017 - val_mae: 0.0323 - 250ms/epoch - 1
0ms/step
Epoch 6/100
25/25 - 0s - loss: 0.0022 - mae: 0.0338 - val_loss: 0.0018 - val_mae: 0.0315 - 248ms/epoch - 1
0ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0021 - mae: 0.0330 - val_loss: 0.0018 - val_mae: 0.0316 - 321ms/epoch - 1
3ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0020 - mae: 0.0316 - val_loss: 0.0016 - val_mae: 0.0312 - 283ms/epoch - 1
1ms/step
Epoch 9/100
25/25 - 0s - loss: 0.0019 - mae: 0.0311 - val_loss: 0.0016 - val_mae: 0.0312 - 299ms/epoch - 1
2ms/step
Epoch 10/100
25/25 - 1s - loss: 0.0019 - mae: 0.0312 - val_loss: 0.0017 - val_mae: 0.0305 - 709ms/epoch - 2
8ms/step
Epoch 11/100
25/25 - 0s - loss: 0.0019 - mae: 0.0322 - val_loss: 0.0023 - val_mae: 0.0353 - 440ms/epoch - 1
8ms/step
Epoch 12/100
25/25 - 0s - loss: 0.0020 - mae: 0.0325 - val_loss: 0.0018 - val_mae: 0.0310 - 316ms/epoch - 1
3ms/step
Epoch 13/100
25/25 - 0s - loss: 0.0017 - mae: 0.0293 - val_loss: 0.0016 - val_mae: 0.0313 - 322ms/epoch - 1
3ms/step
Epoch 14/100
25/25 - 0s - loss: 0.0017 - mae: 0.0295 - val_loss: 0.0015 - val_mae: 0.0299 - 275ms/epoch - 1
1ms/step
Epoch 15/100
25/25 - 0s - loss: 0.0016 - mae: 0.0288 - val_loss: 0.0015 - val_mae: 0.0293 - 445ms/epoch - 1
8ms/step
Epoch 16/100
25/25 - 0s - loss: 0.0017 - mae: 0.0301 - val_loss: 0.0018 - val_mae: 0.0345 - 461ms/epoch - 1
8ms/step
Epoch 17/100
25/25 - 0s - loss: 0.0017 - mae: 0.0296 - val_loss: 0.0018 - val_mae: 0.0316 - 340ms/epoch - 1
4ms/step
Epoch 18/100
25/25 - 0s - loss: 0.0017 - mae: 0.0300 - val_loss: 0.0015 - val_mae: 0.0303 - 365ms/epoch - 1
5ms/step
Epoch 19/100
25/25 - 0s - loss: 0.0016 - mae: 0.0281 - val_loss: 0.0016 - val_mae: 0.0312 - 443ms/epoch - 1
8ms/step
Epoch 20/100
25/25 - 0s - loss: 0.0016 - mae: 0.0287 - val_loss: 0.0014 - val_mae: 0.0287 - 356ms/epoch - 1
4ms/step
Epoch 21/100
25/25 - 0s - loss: 0.0015 - mae: 0.0276 - val_loss: 0.0019 - val_mae: 0.0319 - 381ms/epoch - 1
5ms/step
Epoch 22/100
25/25 - 0s - loss: 0.0014 - mae: 0.0266 - val_loss: 0.0014 - val_mae: 0.0292 - 360ms/epoch - 1
4ms/step
Epoch 23/100
25/25 - 0s - loss: 0.0013 - mae: 0.0260 - val_loss: 0.0014 - val_mae: 0.0274 - 443ms/epoch - 1
8ms/step
Epoch 24/100
25/25 - 1s - loss: 0.0013 - mae: 0.0252 - val_loss: 0.0015 - val_mae: 0.0299 - 555ms/epoch - 2
2ms/step
Epoch 25/100
25/25 - 0s - loss: 0.0014 - mae: 0.0274 - val_loss: 0.0015 - val_mae: 0.0287 - 363ms/epoch - 1
5ms/step
Epoch 26/100
```

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25/25 - 0s - loss: 0.0015 - mae: 0.0282 - val_loss: 0.0013 - val_mae: 0.0269 - 310ms/epoch - 1
2ms/step
Epoch 27/100
25/25 - 0s - loss: 0.0012 - mae: 0.0247 - val_loss: 0.0013 - val_mae: 0.0275 - 481ms/epoch - 1
9ms/step
Epoch 28/100
25/25 - 0s - loss: 0.0011 - mae: 0.0239 - val_loss: 0.0013 - val_mae: 0.0260 - 491ms/epoch - 2
0ms/step
Epoch 29/100
25/25 - 0s - loss: 0.0011 - mae: 0.0232 - val_loss: 0.0015 - val_mae: 0.0282 - 324ms/epoch - 1
3ms/step
Epoch 30/100
25/25 - 0s - loss: 0.0011 - mae: 0.0249 - val_loss: 0.0013 - val_mae: 0.0268 - 303ms/epoch - 1
2ms/step
Epoch 31/100
25/25 - 0s - loss: 0.0011 - mae: 0.0235 - val_loss: 0.0012 - val_mae: 0.0253 - 289ms/epoch - 1
2ms/step
Epoch 32/100
25/25 - 0s - loss: 0.0010 - mae: 0.0232 - val_loss: 0.0014 - val_mae: 0.0276 - 267ms/epoch - 1
1ms/step
Epoch 33/100
25/25 - 0s - loss: 0.0011 - mae: 0.0250 - val_loss: 0.0011 - val_mae: 0.0250 - 295ms/epoch - 1
2ms/step
Epoch 34/100
25/25 - 0s - loss: 0.0011 - mae: 0.0235 - val_loss: 0.0011 - val_mae: 0.0247 - 270ms/epoch - 1
1ms/step
Epoch 35/100
25/25 - 0s - loss: 0.0011 - mae: 0.0233 - val_loss: 0.0011 - val_mae: 0.0247 - 256ms/epoch - 1
0ms/step
Epoch 36/100
25/25 - 0s - loss: 0.0011 - mae: 0.0251 - val_loss: 0.0012 - val_mae: 0.0267 - 266ms/epoch - 1
1ms/step
Epoch 37/100
25/25 - 0s - loss: 9.8995e-04 - mae: 0.0227 - val_loss: 0.0011 - val_mae: 0.0249 - 303ms/epoch
- 12ms/step
Epoch 38/100
25/25 - 0s - loss: 9.6357e-04 - mae: 0.0220 - val_loss: 0.0010 - val_mae: 0.0236 - 302ms/epoch
- 12ms/step
Epoch 39/100
25/25 - 0s - loss: 9.9493e-04 - mae: 0.0227 - val_loss: 0.0014 - val_mae: 0.0283 - 271ms/epoch
- 11ms/step
Epoch 40/100
25/25 - 0s - loss: 9.2257e-04 - mae: 0.0217 - val_loss: 0.0010 - val_mae: 0.0234 - 249ms/epoch
- 10ms/step
Epoch 41/100
25/25 - 0s - loss: 8.8863e-04 - mae: 0.0213 - val_loss: 0.0014 - val_mae: 0.0289 - 259ms/epoch
- 10ms/step
Epoch 42/100
25/25 - 0s - loss: 9.7682e-04 - mae: 0.0222 - val_loss: 0.0010 - val_mae: 0.0238 - 248ms/epoch
- 10ms/step
Epoch 43/100
25/25 - 0s - loss: 9.1007e-04 - mae: 0.0220 - val_loss: 0.0010 - val_mae: 0.0230 - 269ms/epoch
- 11ms/step
Epoch 44/100
25/25 - 0s - loss: 8.5621e-04 - mae: 0.0209 - val_loss: 0.0011 - val_mae: 0.0245 - 254ms/epoch
- 10ms/step
Epoch 45/100
25/25 - 0s - loss: 8.3326e-04 - mae: 0.0205 - val_loss: 0.0010 - val_mae: 0.0238 - 261ms/epoch
- 10ms/step
Epoch 46/100
25/25 - 0s - loss: 8.5387e-04 - mae: 0.0212 - val_loss: 9.5924e-04 - val_mae: 0.0226 - 249ms/e
poch - 10ms/step
Epoch 47/100
25/25 - 0s - loss: 8.1566e-04 - mae: 0.0204 - val_loss: 9.2297e-04 - val_mae: 0.0221 - 249ms/e
poch - 10ms/step
Epoch 48/100
```

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25/25 - 0s - loss: 7.9063e-04 - mae: 0.0198 - val_loss: 0.0010 - val_mae: 0.0231 - 249ms/epoch
- 10ms/step
Epoch 49/100
25/25 - 0s - loss: 8.5701e-04 - mae: 0.0210 - val_loss: 8.9396e-04 - val_mae: 0.0218 - 258ms/e
poch - 10ms/step
Epoch 50/100
25/25 - 0s - loss: 8.4364e-04 - mae: 0.0208 - val_loss: 0.0010 - val_mae: 0.0236 - 246ms/epoch
- 10ms/step
Epoch 51/100
25/25 - 0s - loss: 8.4783e-04 - mae: 0.0210 - val_loss: 9.0482e-04 - val_mae: 0.0215 - 247ms/e
poch - 10ms/step
Epoch 52/100
25/25 - 0s - loss: 7.8123e-04 - mae: 0.0198 - val_loss: 8.8358e-04 - val_mae: 0.0215 - 255ms/e
poch - 10ms/step
Epoch 53/100
25/25 - 0s - loss: 8.1734e-04 - mae: 0.0206 - val_loss: 0.0013 - val_mae: 0.0276 - 276ms/epoch
- 11ms/step
Epoch 54/100
25/25 - 0s - loss: 8.0439e-04 - mae: 0.0205 - val_loss: 8.8728e-04 - val_mae: 0.0218 - 253ms/e
poch - 10ms/step
Epoch 55/100
25/25 - 0s - loss: 7.9834e-04 - mae: 0.0201 - val_loss: 8.7826e-04 - val_mae: 0.0213 - 249ms/e
poch - 10ms/step
Epoch 56/100
25/25 - 0s - loss: 7.7497e-04 - mae: 0.0196 - val_loss: 8.5459e-04 - val_mae: 0.0211 - 251ms/e
poch - 10ms/step
Epoch 57/100
25/25 - 0s - loss: 7.5363e-04 - mae: 0.0193 - val_loss: 8.7601e-04 - val_mae: 0.0217 - 290ms/e
poch - 12ms/step
Epoch 58/100
25/25 - 0s - loss: 7.7940e-04 - mae: 0.0197 - val_loss: 8.9503e-04 - val_mae: 0.0217 - 246ms/e
poch - 10ms/step
Epoch 59/100
25/25 - 0s - loss: 7.7433e-04 - mae: 0.0196 - val_loss: 0.0012 - val_mae: 0.0259 - 252ms/epoch
- 10ms/step
Epoch 60/100
25/25 - 0s - loss: 8.6799e-04 - mae: 0.0215 - val_loss: 0.0012 - val_mae: 0.0264 - 254ms/epoch
- 10ms/step
Epoch 61/100
25/25 - 0s - loss: 8.3836e-04 - mae: 0.0204 - val_loss: 8.7827e-04 - val_mae: 0.0214 - 254ms/e
poch - 10ms/step

Training GRU with 1 layer(s) and 50 units per layer...
Epoch 1/100
25/25 - 4s - loss: 0.0727 - mae: 0.2005 - val_loss: 0.0110 - val_mae: 0.0911 - 4s/epoch - 169m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0063 - mae: 0.0645 - val_loss: 0.0027 - val_mae: 0.0446 - 130ms/epoch - 5
ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0021 - mae: 0.0349 - val_loss: 0.0015 - val_mae: 0.0301 - 135ms/epoch - 5
ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0013 - mae: 0.0259 - val_loss: 0.0013 - val_mae: 0.0270 - 152ms/epoch - 6
ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0012 - mae: 0.0242 - val_loss: 0.0013 - val_mae: 0.0265 - 151ms/epoch - 6
ms/step
Epoch 6/100
25/25 - 0s - loss: 0.0012 - mae: 0.0243 - val_loss: 0.0012 - val_mae: 0.0261 - 151ms/epoch - 6
ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0011 - mae: 0.0237 - val_loss: 0.0012 - val_mae: 0.0256 - 137ms/epoch - 5
ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0011 - mae: 0.0232 - val_loss: 0.0012 - val_mae: 0.0254 - 133ms/epoch - 5
```

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ms/step
Epoch 9/100
25/25 - 0s - loss: 0.0011 - mae: 0.0231 - val_loss: 0.0011 - val_mae: 0.0249 - 134ms/epoch - 5
ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0010 - mae: 0.0227 - val_loss: 0.0011 - val_mae: 0.0246 - 142ms/epoch - 6
ms/step
Epoch 11/100
25/25 - 0s - loss: 0.0010 - mae: 0.0227 - val_loss: 0.0011 - val_mae: 0.0244 - 184ms/epoch - 7
ms/step
Epoch 12/100
25/25 - 0s - loss: 9.8353e-04 - mae: 0.0222 - val_loss: 0.0011 - val_mae: 0.0243 - 146ms/epoch
- 6ms/step
Epoch 13/100
25/25 - 0s - loss: 9.5847e-04 - mae: 0.0222 - val_loss: 0.0011 - val_mae: 0.0243 - 145ms/epoch
- 6ms/step
Epoch 14/100
25/25 - 0s - loss: 9.3567e-04 - mae: 0.0216 - val_loss: 0.0010 - val_mae: 0.0237 - 150ms/epoch
- 6ms/step
Epoch 15/100
25/25 - 0s - loss: 9.1419e-04 - mae: 0.0215 - val_loss: 0.0010 - val_mae: 0.0237 - 157ms/epoch
- 6ms/step
Epoch 16/100
25/25 - 0s - loss: 9.0642e-04 - mae: 0.0213 - val_loss: 0.0010 - val_mae: 0.0233 - 148ms/epoch
- 6ms/step
Epoch 17/100
25/25 - 0s - loss: 8.9197e-04 - mae: 0.0213 - val_loss: 0.0010 - val_mae: 0.0238 - 148ms/epoch
- 6ms/step
Epoch 18/100
25/25 - 0s - loss: 8.7028e-04 - mae: 0.0209 - val_loss: 0.0010 - val_mae: 0.0232 - 148ms/epoch
- 6ms/step
Epoch 19/100
25/25 - 0s - loss: 8.7142e-04 - mae: 0.0209 - val_loss: 0.0010 - val_mae: 0.0230 - 132ms/epoch
- 5ms/step
Epoch 20/100
25/25 - 0s - loss: 8.5659e-04 - mae: 0.0207 - val_loss: 9.9100e-04 - val_mae: 0.0228 - 132ms/e
poch - 5ms/step
Epoch 21/100
25/25 - 0s - loss: 8.7876e-04 - mae: 0.0211 - val_loss: 9.9725e-04 - val_mae: 0.0231 - 133ms/e
poch - 5ms/step
Epoch 22/100
25/25 - 0s - loss: 8.5238e-04 - mae: 0.0206 - val_loss: 9.8968e-04 - val_mae: 0.0230 - 148ms/e
poch - 6ms/step
Epoch 23/100
25/25 - 0s - loss: 8.5923e-04 - mae: 0.0207 - val_loss: 0.0010 - val_mae: 0.0237 - 136ms/epoch
- 5ms/step
Epoch 24/100
25/25 - 0s - loss: 8.7048e-04 - mae: 0.0210 - val_loss: 9.6614e-04 - val_mae: 0.0225 - 129ms/e
poch - 5ms/step
Epoch 25/100
25/25 - 0s - loss: 8.2512e-04 - mae: 0.0204 - val_loss: 9.7066e-04 - val_mae: 0.0224 - 137ms/e
poch - 5ms/step
Epoch 26/100
25/25 - 0s - loss: 8.3871e-04 - mae: 0.0207 - val_loss: 0.0011 - val_mae: 0.0243 - 130ms/epoch
- 5ms/step
Epoch 27/100
25/25 - 0s - loss: 8.1806e-04 - mae: 0.0202 - val_loss: 9.6892e-04 - val_mae: 0.0223 - 130ms/e
poch - 5ms/step
Epoch 28/100
25/25 - 0s - loss: 8.0130e-04 - mae: 0.0198 - val_loss: 9.5018e-04 - val_mae: 0.0223 - 132ms/e
poch - 5ms/step
Epoch 29/100
25/25 - 0s - loss: 8.0200e-04 - mae: 0.0200 - val_loss: 9.4569e-04 - val_mae: 0.0222 - 140ms/e
poch - 6ms/step
Epoch 30/100
25/25 - 0s - loss: 7.9545e-04 - mae: 0.0197 - val_loss: 9.5012e-04 - val_mae: 0.0224 - 150ms/e
```

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poch - 6ms/step
Epoch 31/100
25/25 - 0s - loss: 7.7907e-04 - mae: 0.0196 - val_loss: 9.3675e-04 - val_mae: 0.0221 - 153ms/e
poch - 6ms/step
Epoch 32/100
25/25 - 0s - loss: 8.5894e-04 - mae: 0.0205 - val_loss: 9.4043e-04 - val_mae: 0.0221 - 132ms/e
poch - 5ms/step
Epoch 33/100
25/25 - 0s - loss: 7.8029e-04 - mae: 0.0196 - val_loss: 9.2507e-04 - val_mae: 0.0220 - 132ms/e
poch - 5ms/step
Epoch 34/100
25/25 - 0s - loss: 7.9010e-04 - mae: 0.0196 - val_loss: 9.2505e-04 - val_mae: 0.0219 - 129ms/e
poch - 5ms/step
Epoch 35/100
25/25 - 0s - loss: 7.7382e-04 - mae: 0.0195 - val_loss: 9.3040e-04 - val_mae: 0.0218 - 131ms/e
poch - 5ms/step
Epoch 36/100
25/25 - 0s - loss: 7.6096e-04 - mae: 0.0194 - val_loss: 9.2042e-04 - val_mae: 0.0219 - 130ms/e
poch - 5ms/step
Epoch 37/100
25/25 - 0s - loss: 7.6114e-04 - mae: 0.0194 - val_loss: 9.3432e-04 - val_mae: 0.0222 - 128ms/e
poch - 5ms/step
Epoch 38/100
25/25 - 0s - loss: 7.8005e-04 - mae: 0.0199 - val_loss: 9.3162e-04 - val_mae: 0.0222 - 131ms/e
poch - 5ms/step
Epoch 39/100
25/25 - 0s - loss: 7.5528e-04 - mae: 0.0193 - val_loss: 9.1993e-04 - val_mae: 0.0219 - 129ms/e
poch - 5ms/step
Epoch 40/100
25/25 - 0s - loss: 7.6303e-04 - mae: 0.0194 - val_loss: 9.1752e-04 - val_mae: 0.0217 - 129ms/e
poch - 5ms/step
Epoch 41/100
25/25 - 0s - loss: 7.5412e-04 - mae: 0.0192 - val_loss: 9.2127e-04 - val_mae: 0.0217 - 128ms/e
poch - 5ms/step
Epoch 42/100
25/25 - 0s - loss: 7.4563e-04 - mae: 0.0192 - val_loss: 9.0080e-04 - val_mae: 0.0216 - 128ms/e
poch - 5ms/step
Epoch 43/100
25/25 - 0s - loss: 7.4479e-04 - mae: 0.0190 - val_loss: 9.3521e-04 - val_mae: 0.0218 - 128ms/e
poch - 5ms/step
Epoch 44/100
25/25 - 0s - loss: 7.6945e-04 - mae: 0.0197 - val_loss: 9.3368e-04 - val_mae: 0.0218 - 130ms/e
poch - 5ms/step
Epoch 45/100
25/25 - 0s - loss: 7.5717e-04 - mae: 0.0191 - val_loss: 8.9805e-04 - val_mae: 0.0214 - 130ms/e
poch - 5ms/step
Epoch 46/100
25/25 - 0s - loss: 7.5770e-04 - mae: 0.0194 - val_loss: 8.9357e-04 - val_mae: 0.0214 - 130ms/e
poch - 5ms/step
Epoch 47/100
25/25 - 0s - loss: 7.4193e-04 - mae: 0.0190 - val_loss: 8.9286e-04 - val_mae: 0.0214 - 130ms/e
poch - 5ms/step
Epoch 48/100
25/25 - 0s - loss: 7.4881e-04 - mae: 0.0191 - val_loss: 9.7153e-04 - val_mae: 0.0230 - 130ms/e
poch - 5ms/step
Epoch 49/100
25/25 - 0s - loss: 7.3683e-04 - mae: 0.0188 - val_loss: 9.1202e-04 - val_mae: 0.0219 - 132ms/e
poch - 5ms/step
Epoch 50/100
25/25 - 0s - loss: 7.9081e-04 - mae: 0.0196 - val_loss: 0.0011 - val_mae: 0.0240 - 129ms/epoch
- 5ms/step
Epoch 51/100
25/25 - 0s - loss: 7.4780e-04 - mae: 0.0190 - val_loss: 8.8766e-04 - val_mae: 0.0213 - 130ms/e
poch - 5ms/step
Epoch 52/100
25/25 - 0s - loss: 7.2647e-04 - mae: 0.0187 - val_loss: 8.8062e-04 - val_mae: 0.0211 - 130ms/e
```

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poch - 5ms/step
Epoch 53/100
25/25 - 0s - loss: 7.1608e-04 - mae: 0.0187 - val_loss: 8.7783e-04 - val_mae: 0.0212 - 129ms/e
poch - 5ms/step
Epoch 54/100
25/25 - 0s - loss: 7.4025e-04 - mae: 0.0189 - val_loss: 8.7533e-04 - val_mae: 0.0211 - 129ms/e
poch - 5ms/step
Epoch 55/100
25/25 - 0s - loss: 7.3421e-04 - mae: 0.0188 - val_loss: 8.7368e-04 - val_mae: 0.0211 - 129ms/e
poch - 5ms/step
Epoch 56/100
25/25 - 0s - loss: 7.4303e-04 - mae: 0.0191 - val_loss: 8.7061e-04 - val_mae: 0.0212 - 131ms/e
poch - 5ms/step
Epoch 57/100
25/25 - 0s - loss: 7.5211e-04 - mae: 0.0191 - val_loss: 8.7339e-04 - val_mae: 0.0210 - 127ms/e
poch - 5ms/step
Epoch 58/100
25/25 - 0s - loss: 7.1595e-04 - mae: 0.0187 - val_loss: 8.7763e-04 - val_mae: 0.0213 - 128ms/e
poch - 5ms/step
Epoch 59/100
25/25 - 0s - loss: 7.2808e-04 - mae: 0.0187 - val_loss: 8.6154e-04 - val_mae: 0.0209 - 129ms/e
poch - 5ms/step
Epoch 60/100
25/25 - 0s - loss: 7.2769e-04 - mae: 0.0190 - val_loss: 9.5639e-04 - val_mae: 0.0227 - 129ms/e
poch - 5ms/step
Epoch 61/100
25/25 - 0s - loss: 8.0910e-04 - mae: 0.0201 - val_loss: 8.9901e-04 - val_mae: 0.0217 - 128ms/e
poch - 5ms/step
Epoch 62/100
25/25 - 0s - loss: 7.1172e-04 - mae: 0.0185 - val_loss: 8.5808e-04 - val_mae: 0.0208 - 131ms/e
poch - 5ms/step
Epoch 63/100
25/25 - 0s - loss: 7.1758e-04 - mae: 0.0187 - val_loss: 8.6818e-04 - val_mae: 0.0208 - 129ms/e
poch - 5ms/step
Epoch 64/100
25/25 - 0s - loss: 7.0864e-04 - mae: 0.0184 - val_loss: 8.9979e-04 - val_mae: 0.0218 - 130ms/e
poch - 5ms/step
Epoch 65/100
25/25 - 0s - loss: 7.3743e-04 - mae: 0.0188 - val_loss: 8.8979e-04 - val_mae: 0.0214 - 129ms/e
poch - 5ms/step
Epoch 66/100
25/25 - 0s - loss: 7.0281e-04 - mae: 0.0184 - val_loss: 8.5654e-04 - val_mae: 0.0208 - 130ms/e
poch - 5ms/step
Epoch 67/100
25/25 - 0s - loss: 7.1997e-04 - mae: 0.0187 - val_loss: 8.9473e-04 - val_mae: 0.0217 - 128ms/e
poch - 5ms/step
Epoch 68/100
25/25 - 0s - loss: 7.4337e-04 - mae: 0.0189 - val_loss: 8.4802e-04 - val_mae: 0.0207 - 130ms/e
poch - 5ms/step
Epoch 69/100
25/25 - 0s - loss: 7.2578e-04 - mae: 0.0187 - val_loss: 8.6113e-04 - val_mae: 0.0207 - 127ms/e
poch - 5ms/step
Epoch 70/100
25/25 - 0s - loss: 6.9385e-04 - mae: 0.0182 - val_loss: 8.5067e-04 - val_mae: 0.0207 - 127ms/e
poch - 5ms/step
Epoch 71/100
25/25 - 0s - loss: 7.0429e-04 - mae: 0.0182 - val_loss: 8.4840e-04 - val_mae: 0.0207 - 130ms/e
poch - 5ms/step
Epoch 72/100
25/25 - 0s - loss: 7.2315e-04 - mae: 0.0186 - val_loss: 8.5129e-04 - val_mae: 0.0207 - 128ms/e
poch - 5ms/step
Epoch 73/100
25/25 - 0s - loss: 6.9254e-04 - mae: 0.0181 - val_loss: 8.5079e-04 - val_mae: 0.0207 - 132ms/e
poch - 5ms/step

Training GRU with 2 layer(s) and 50 units per layer...
```

```
Epoch 1/100
25/25 - 6s - loss: 0.0273 - mae: 0.1188 - val_loss: 0.0058 - val_mae: 0.0575 - 6s/epoch - 233m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0025 - mae: 0.0378 - val_loss: 0.0016 - val_mae: 0.0299 - 251ms/epoch - 1
0ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0014 - mae: 0.0271 - val_loss: 0.0012 - val_mae: 0.0259 - 235ms/epoch - 9
ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0014 - mae: 0.0263 - val_loss: 0.0012 - val_mae: 0.0271 - 225ms/epoch - 9
ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0013 - mae: 0.0253 - val_loss: 0.0012 - val_mae: 0.0256 - 245ms/epoch - 1
0ms/step
Epoch 6/100
25/25 - 0s - loss: 0.0012 - mae: 0.0246 - val_loss: 0.0012 - val_mae: 0.0258 - 245ms/epoch - 1
0ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0012 - mae: 0.0242 - val_loss: 0.0011 - val_mae: 0.0258 - 248ms/epoch - 1
0ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0011 - mae: 0.0240 - val_loss: 0.0012 - val_mae: 0.0260 - 254ms/epoch - 1
0ms/step
Epoch 9/100
25/25 - 0s - loss: 0.0011 - mae: 0.0235 - val_loss: 0.0011 - val_mae: 0.0257 - 252ms/epoch - 1
0ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0011 - mae: 0.0234 - val_loss: 0.0011 - val_mae: 0.0256 - 240ms/epoch - 1
0ms/step
Epoch 11/100
25/25 - 0s - loss: 0.0011 - mae: 0.0229 - val_loss: 0.0011 - val_mae: 0.0243 - 224ms/epoch - 9
ms/step
Epoch 12/100
25/25 - 0s - loss: 0.0011 - mae: 0.0236 - val_loss: 0.0011 - val_mae: 0.0240 - 243ms/epoch - 1
0ms/step
Epoch 13/100
25/25 - 0s - loss: 0.0010 - mae: 0.0229 - val_loss: 0.0011 - val_mae: 0.0243 - 222ms/epoch - 9
ms/step
Epoch 14/100
25/25 - 0s - loss: 9.3723e-04 - mae: 0.0217 - val_loss: 0.0010 - val_mae: 0.0235 - 225ms/epoch
- 9ms/step
Epoch 15/100
25/25 - 0s - loss: 9.3842e-04 - mae: 0.0216 - val_loss: 0.0011 - val_mae: 0.0238 - 222ms/epoch
- 9ms/step
Epoch 16/100
25/25 - 0s - loss: 8.9928e-04 - mae: 0.0211 - val_loss: 9.8154e-04 - val_mae: 0.0228 - 249ms/e
poch - 10ms/step
Epoch 17/100
25/25 - 0s - loss: 9.0042e-04 - mae: 0.0214 - val_loss: 9.7688e-04 - val_mae: 0.0226 - 249ms/e
poch - 10ms/step
Epoch 18/100
25/25 - 0s - loss: 9.6346e-04 - mae: 0.0225 - val_loss: 0.0012 - val_mae: 0.0247 - 236ms/epoch
- 9ms/step
Epoch 19/100
25/25 - 0s - loss: 8.8901e-04 - mae: 0.0213 - val_loss: 9.7753e-04 - val_mae: 0.0225 - 220ms/e
poch - 9ms/step
Epoch 20/100
25/25 - 0s - loss: 8.5573e-04 - mae: 0.0205 - val_loss: 9.3193e-04 - val_mae: 0.0221 - 220ms/e
poch - 9ms/step
Epoch 21/100
25/25 - 0s - loss: 8.6614e-04 - mae: 0.0210 - val_loss: 9.9103e-04 - val_mae: 0.0233 - 221ms/e
poch - 9ms/step
Epoch 22/100
25/25 - 0s - loss: 7.9607e-04 - mae: 0.0198 - val_loss: 8.9595e-04 - val_mae: 0.0217 - 224ms/e
poch - 9ms/step
```

```
Epoch 23/100
25/25 - 0s - loss: 8.3187e-04 - mae: 0.0204 - val_loss: 9.9485e-04 - val_mae: 0.0231 - 222ms/e
poch - 9ms/step
Epoch 24/100
25/25 - 0s - loss: 8.5972e-04 - mae: 0.0207 - val_loss: 9.3801e-04 - val_mae: 0.0219 - 217ms/e
poch - 9ms/step
Epoch 25/100
25/25 - 0s - loss: 8.0077e-04 - mae: 0.0200 - val_loss: 0.0012 - val_mae: 0.0252 - 219ms/epoch
- 9ms/step
Epoch 26/100
25/25 - 0s - loss: 8.8526e-04 - mae: 0.0209 - val_loss: 9.3738e-04 - val_mae: 0.0226 - 217ms/e
poch - 9ms/step
Epoch 27/100
25/25 - 0s - loss: 7.6402e-04 - mae: 0.0193 - val_loss: 0.0010 - val_mae: 0.0235 - 221ms/epoch
- 9ms/step

Training GRU with 2 layer(s) and 100 units per layer...
Epoch 1/100
25/25 - 6s - loss: 0.0153 - mae: 0.0880 - val_loss: 0.0034 - val_mae: 0.0502 - 6s/epoch - 222m
s/step
Epoch 2/100
25/25 - 0s - loss: 0.0018 - mae: 0.0313 - val_loss: 0.0017 - val_mae: 0.0299 - 256ms/epoch - 1
0ms/step
Epoch 3/100
25/25 - 0s - loss: 0.0013 - mae: 0.0255 - val_loss: 0.0013 - val_mae: 0.0273 - 255ms/epoch - 1
0ms/step
Epoch 4/100
25/25 - 0s - loss: 0.0012 - mae: 0.0246 - val_loss: 0.0013 - val_mae: 0.0278 - 252ms/epoch - 1
0ms/step
Epoch 5/100
25/25 - 0s - loss: 0.0012 - mae: 0.0246 - val_loss: 0.0012 - val_mae: 0.0259 - 254ms/epoch - 1
0ms/step
Epoch 6/100
25/25 - 0s - loss: 0.0011 - mae: 0.0236 - val_loss: 0.0012 - val_mae: 0.0257 - 252ms/epoch - 1
0ms/step
Epoch 7/100
25/25 - 0s - loss: 0.0011 - mae: 0.0234 - val_loss: 0.0012 - val_mae: 0.0253 - 255ms/epoch - 1
0ms/step
Epoch 8/100
25/25 - 0s - loss: 0.0010 - mae: 0.0231 - val_loss: 0.0011 - val_mae: 0.0248 - 268ms/epoch - 1
1ms/step
Epoch 9/100
25/25 - 0s - loss: 0.0010 - mae: 0.0230 - val_loss: 0.0013 - val_mae: 0.0286 - 253ms/epoch - 1
0ms/step
Epoch 10/100
25/25 - 0s - loss: 0.0010 - mae: 0.0231 - val_loss: 0.0011 - val_mae: 0.0245 - 252ms/epoch - 1
0ms/step
Epoch 11/100
25/25 - 0s - loss: 9.4755e-04 - mae: 0.0216 - val_loss: 0.0011 - val_mae: 0.0242 - 255ms/epoch
- 10ms/step
Epoch 12/100
25/25 - 0s - loss: 9.0876e-04 - mae: 0.0215 - val_loss: 0.0011 - val_mae: 0.0250 - 253ms/epoch
- 10ms/step
Epoch 13/100
25/25 - 0s - loss: 9.8228e-04 - mae: 0.0229 - val_loss: 0.0010 - val_mae: 0.0233 - 262ms/epoch
- 10ms/step
Epoch 14/100
25/25 - 0s - loss: 8.8387e-04 - mae: 0.0210 - val_loss: 0.0010 - val_mae: 0.0239 - 297ms/epoch
- 12ms/step
Epoch 15/100
25/25 - 0s - loss: 8.5912e-04 - mae: 0.0206 - val_loss: 0.0010 - val_mae: 0.0227 - 283ms/epoch
- 11ms/step
Epoch 16/100
25/25 - 0s - loss: 8.3808e-04 - mae: 0.0208 - val_loss: 9.3781e-04 - val_mae: 0.0222 - 264ms/e
poch - 11ms/step
Epoch 17/100
```

```
25/25 - 0s - loss: 8.5918e-04 - mae: 0.0209 - val_loss: 9.3518e-04 - val_mae: 0.0223 - 288ms/e
poch - 12ms/step
Epoch 18/100
25/25 - 0s - loss: 7.9766e-04 - mae: 0.0200 - val_loss: 0.0011 - val_mae: 0.0245 - 298ms/epoch
- 12ms/step
Epoch 19/100
25/25 - 0s - loss: 8.3111e-04 - mae: 0.0202 - val_loss: 9.1341e-04 - val_mae: 0.0215 - 300ms/e
poch - 12ms/step
Epoch 20/100
25/25 - 0s - loss: 7.5856e-04 - mae: 0.0193 - val_loss: 8.7641e-04 - val_mae: 0.0213 - 305ms/e
poch - 12ms/step
Epoch 21/100
25/25 - 0s - loss: 8.0116e-04 - mae: 0.0201 - val_loss: 9.0687e-04 - val_mae: 0.0216 - 317ms/e
poch - 13ms/step
Epoch 22/100
25/25 - 0s - loss: 7.7053e-04 - mae: 0.0196 - val_loss: 8.7158e-04 - val_mae: 0.0210 - 315ms/e
poch - 13ms/step
Epoch 23/100
25/25 - 0s - loss: 7.6250e-04 - mae: 0.0196 - val_loss: 0.0012 - val_mae: 0.0272 - 329ms/epoch
- 13ms/step
Epoch 24/100
25/25 - 0s - loss: 8.1878e-04 - mae: 0.0205 - val_loss: 0.0011 - val_mae: 0.0253 - 300ms/epoch
- 12ms/step
Epoch 25/100
25/25 - 0s - loss: 7.8916e-04 - mae: 0.0199 - val_loss: 8.6486e-04 - val_mae: 0.0210 - 257ms/e
poch - 10ms/step
Epoch 26/100
25/25 - 0s - loss: 7.3924e-04 - mae: 0.0191 - val_loss: 9.0855e-04 - val_mae: 0.0214 - 252ms/e
poch - 10ms/step
Epoch 27/100
25/25 - 0s - loss: 8.3136e-04 - mae: 0.0204 - val_loss: 0.0011 - val_mae: 0.0249 - 287ms/epoch
- 11ms/step
Epoch 28/100
25/25 - 0s - loss: 8.4128e-04 - mae: 0.0210 - val_loss: 8.2883e-04 - val_mae: 0.0205 - 256ms/e
poch - 10ms/step
Epoch 29/100
25/25 - 0s - loss: 7.9054e-04 - mae: 0.0197 - val_loss: 8.3260e-04 - val_mae: 0.0203 - 253ms/e
poch - 10ms/step
Epoch 30/100
25/25 - 0s - loss: 7.1677e-04 - mae: 0.0188 - val_loss: 8.3773e-04 - val_mae: 0.0204 - 251ms/e
poch - 10ms/step
Epoch 31/100
25/25 - 0s - loss: 6.9848e-04 - mae: 0.0186 - val_loss: 9.0427e-04 - val_mae: 0.0215 - 261ms/e
poch - 10ms/step
Epoch 32/100
25/25 - 0s - loss: 6.8402e-04 - mae: 0.0180 - val_loss: 8.5987e-04 - val_mae: 0.0211 - 254ms/e
poch - 10ms/step
Epoch 33/100
25/25 - 0s - loss: 6.8799e-04 - mae: 0.0183 - val_loss: 8.5723e-04 - val_mae: 0.0213 - 257ms/e
poch - 10ms/step
```

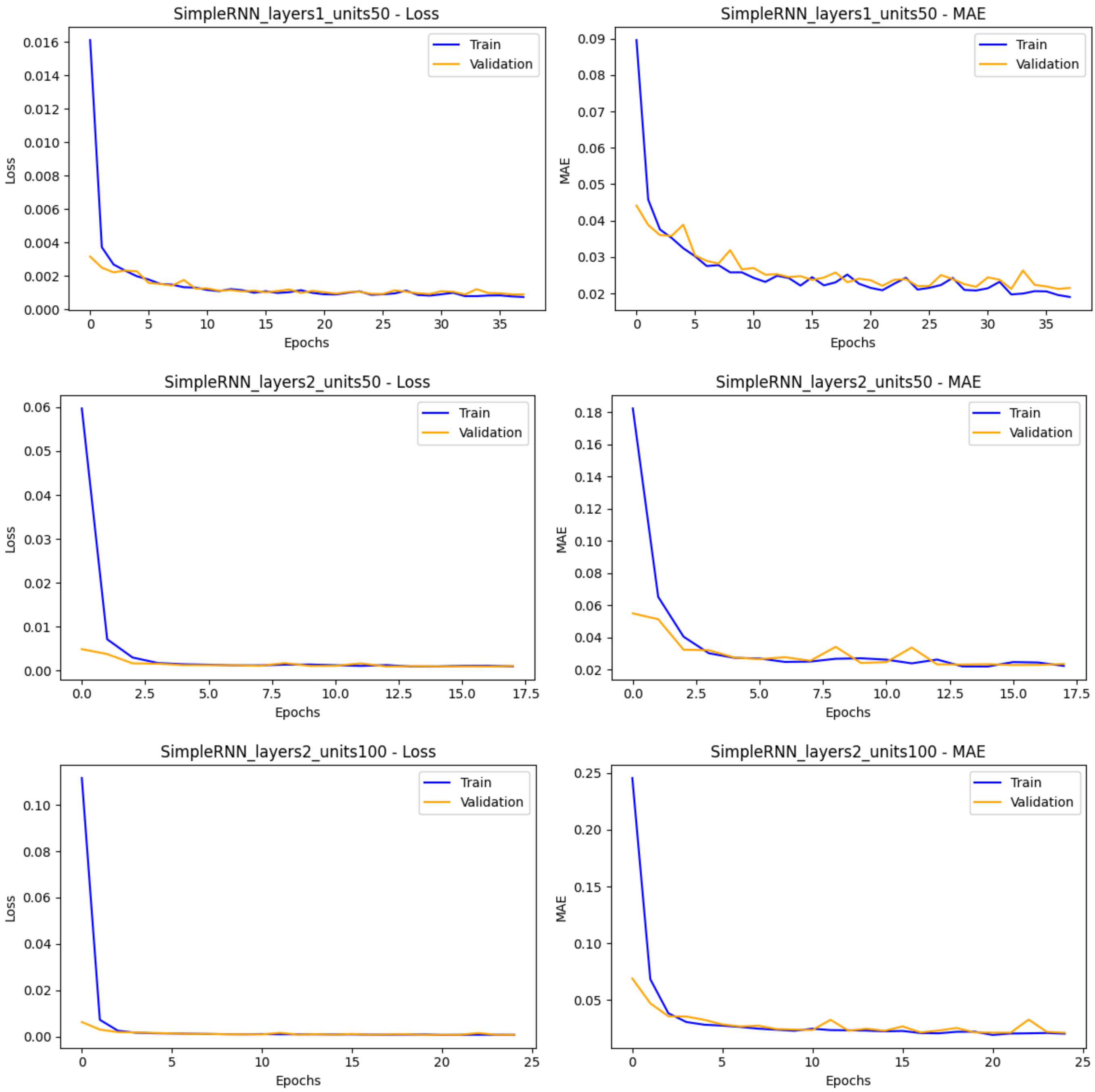
Крок 4: Прогнозування та візуалізація результатів

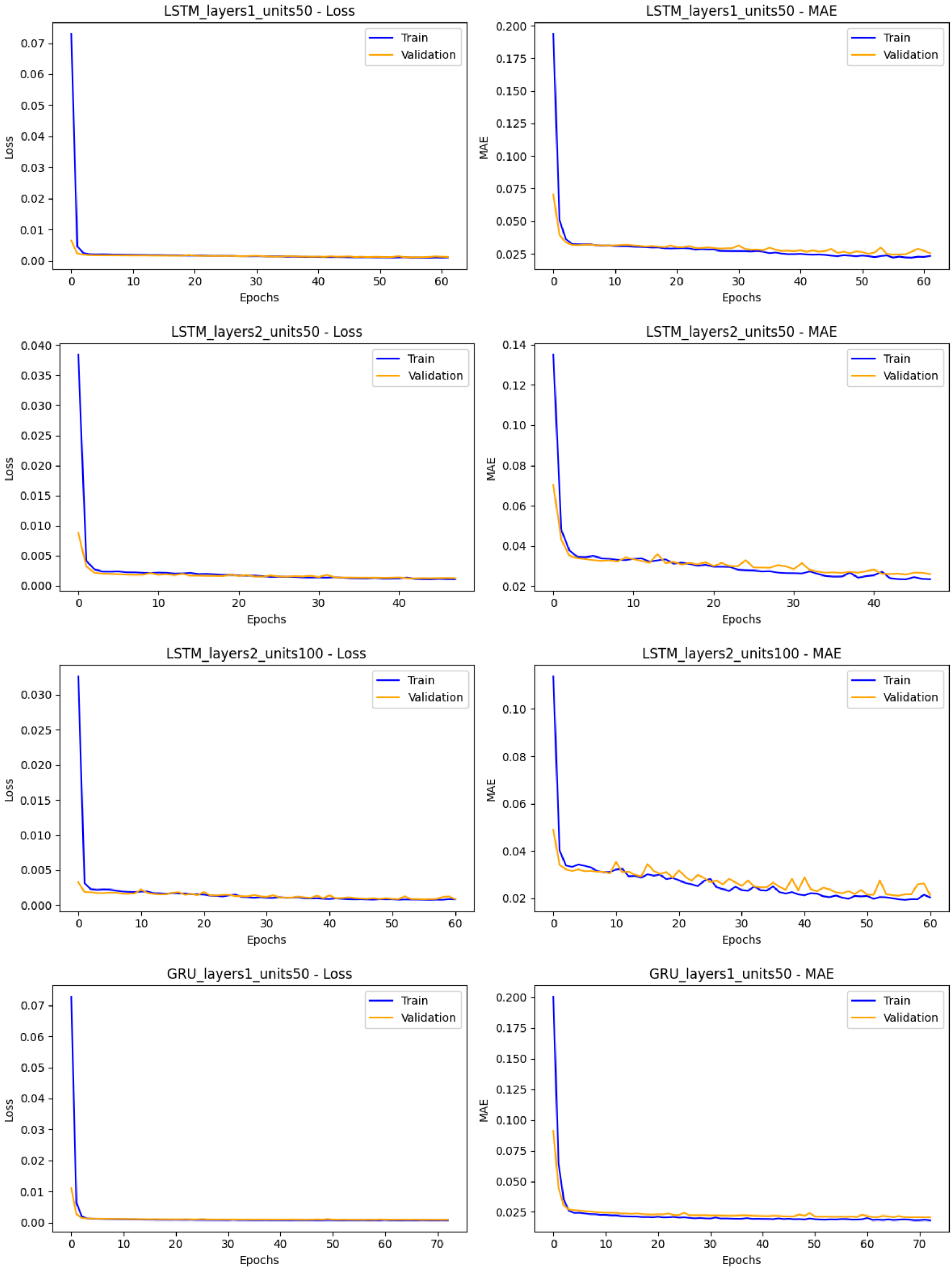
In [15]:
```
# Графіки history для однієї моделі (Loss, Mae)
def plot_history(history_dict, title):
    fig, axes = plt.subplots(1, 2, figsize=(12, 4))

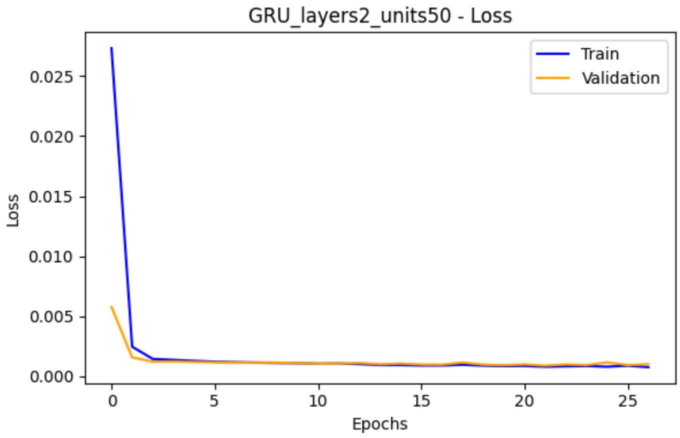
    # Loss
    axes[0].plot(history_dict['loss'], label='Train', color='blue')
    axes[0].plot(history_dict['val_loss'], label='Validation', color='orange')
    axes[0].set_title(f'{title} - Loss')
    axes[0].set_xlabel('Epochs')
    axes[0].set_ylabel('Loss')
    axes[0].legend()
```

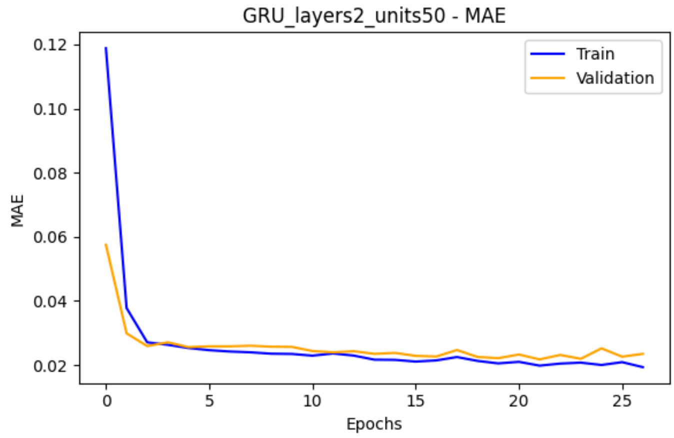
```python
    # Mae
    axes[1].plot(history_dict['mae'], label='Train', color='blue')
    axes[1].plot(history_dict['val_mae'], label='Validation', color='orange')
    axes[1].set_title(f'{title} - MAE')
    axes[1].set_xlabel('Epochs')
    axes[1].set_ylabel('MAE')
    axes[1].legend()

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

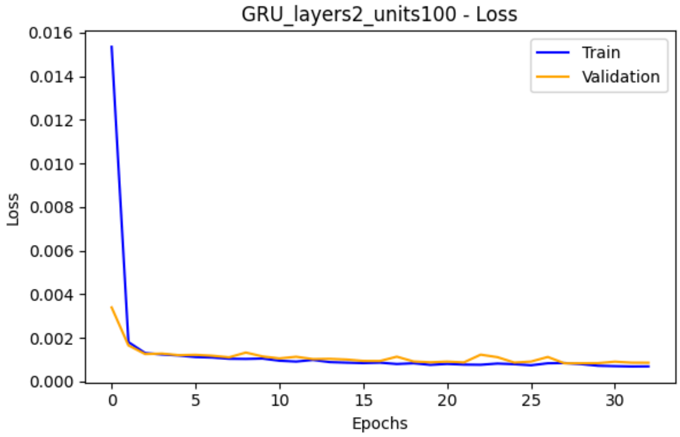
In [16]:
```python
for name, history_dict in results.items():
    plot_history(history_dict, title=name)
```

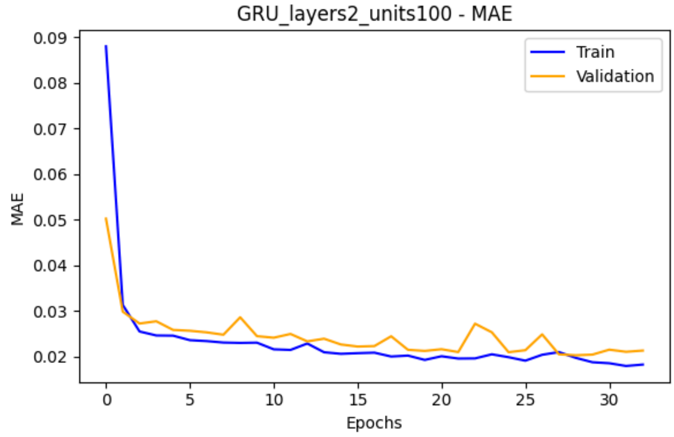



LSTM_layers1_units50 - Loss
LSTM_layers1_units50 - MAE
LSTM_layers2_units50 - Loss
LSTM_layers2_units50 - MAE
LSTM_layers2_units100 - Loss
LSTM_layers2_units100 - MAE
GRU_layers1_units50 - Loss
GRU_layers1_units50 - MAE
Train
Validation
Loss
MAE
Epochs



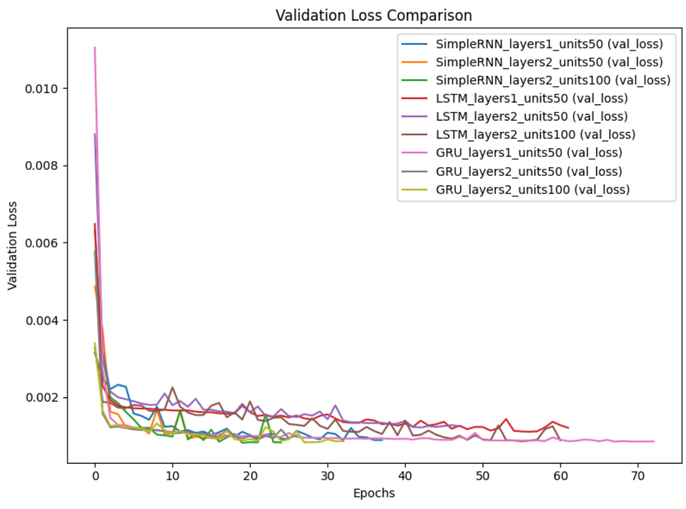


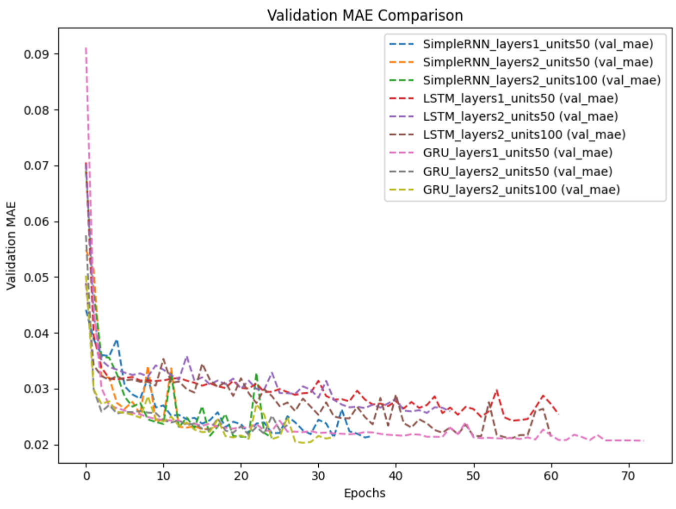




In [18]:

```python
# Створення підграфіків
fig, axes = plt.subplots(1, 2, figsize=(16, 6))  # 1 рядок, 2 графіки

# Графік для validation loss
for key, history in results.items():
    axes[0].plot(history['val_loss'], label=f"{key} (val_loss)")
axes[0].set_title('Validation Loss Comparison')
axes[0].set_xlabel('Epochs')
axes[0].set_ylabel('Validation Loss')
axes[0].legend()

# Графік для validation MAE
for key, history in results.items():
    axes[1].plot(history['val_mae'], '--', label=f"{key} (val_mae)")
axes[1].set_title('Validation MAE Comparison')
axes[1].set_xlabel('Epochs')
axes[1].set_ylabel('Validation MAE')
axes[1].legend()

# Відображення графіків
plt.tight_layout()
plt.show()
```





Hold-Out валідація

In [19]:
```
# Передбачення та оцінка
metrics_results = {}

for model_name, model in trained_models.items():
    y_pred = model.predict(X_test)

    # Масштабування назад
    y_test_original = scaler.inverse_transform(
        np.concatenate([X_test[:, -1, :], y_test.reshape(-1, 1)], axis=1)
    )[:, -1]
    y_pred_original = scaler.inverse_transform(
        np.concatenate([X_test[:, -1, :], y_pred.reshape(-1, 1)], axis=1)
    )[:, -1]

    # Обчислення метрик
    metrics = calculate_metrics(y_test_original, y_pred_original)
    metrics_results[model_name] = metrics
```

```
7/7 [==============================] - 0s 2ms/step
7/7 [==============================] - 0s 2ms/step
7/7 [==============================] - 0s 3ms/step
7/7 [==============================] - 1s 3ms/step
7/7 [==============================] - 1s 2ms/step
7/7 [==============================] - 1s 4ms/step
7/7 [==============================] - 1s 4ms/step
7/7 [==============================] - 1s 3ms/step
7/7 [==============================] - 1s 4ms/step
```

In [20]:
```
# Таблиця результатів
holdout_results = pd.DataFrame([
    {"Model": name, **metrics}
    for name, metrics in metrics_results.items()
])

holdout_results
```

Out[20]:

	Model	MSE	RMSE	MAE	MAPE	R2 Score
0	SimpleRNN_layers1_units50	185.224791	13.609731	9.725657	0.023242	0.984202
1	SimpleRNN_layers2_units50	192.803161	13.885358	10.608896	0.025879	0.983556
2	SimpleRNN_layers2_units100	171.093695	13.080279	9.855910	0.023942	0.985408
3	LSTM_layers1_units50	231.182620	15.204691	11.162238	0.027188	0.980283
4	LSTM_layers2_units50	254.165463	15.942568	11.874604	0.029180	0.978323
5	LSTM_layers2_units100	179.113248	13.383320	9.674530	0.023420	0.984724
6	GRU_layers1_units50	177.735877	13.331762	9.494313	0.022983	0.984841
7	GRU_layers2_units50	187.782322	13.703369	9.952121	0.024298	0.983984
8	GRU_layers2_units100	173.715323	13.180111	9.392318	0.022834	0.985184

K-Fold крос-валідація

In [21]:
```
# K-Fold конфігурація
k_folds = 5
kf = KFold(n_splits=k_folds, shuffle=True, random_state=42)

# Крос-валідація
```

```python
def cross_validate_model(model_type, num_layers, units, X, y, kf):
    fold_metrics = []

    for fold, (train_idx, val_idx) in enumerate(kf.split(X)):
        print(f"  Fold {fold + 1}/{k_folds}")

        X_train_fold, X_val_fold = X[train_idx], X[val_idx]
        y_train_fold, y_val_fold = y[train_idx], y[val_idx]

        # Клонування моделі
        model_copy = create_rnn_model(
            model_type=model_type,
            input_shape=(X.shape[1], X.shape[2]),
            num_layers=num_layers,
            units=units
        )

        model_copy.compile(optimizer='adam', loss='mse', metrics=['mae'])

        # Тренування моделі з early stopping
        model_copy.fit(
            X_train_fold, y_train_fold,
            epochs=100,
            batch_size=32,
            validation_data=(X_val_fold, y_val_fold),
            verbose=0,
            callbacks=[early_stopping]
        )

        y_pred = model_copy.predict(X_val_fold)

        # Масштабування назад
        y_val_fold_original = scaler.inverse_transform(
            np.concatenate([X_val_fold[:, -1, :], y_val_fold.reshape(-1, 1)], axis=1)
        )[:, -1]
        y_pred_original = scaler.inverse_transform(
            np.concatenate([X_val_fold[:, -1, :], y_pred.reshape(-1, 1)], axis=1)
        )[:, -1]

        # Обчислення метрик
        metrics = calculate_metrics(y_val_fold_original, y_pred_original)
        fold_metrics.append(metrics)

    # Середнє значення метрик
    avg_metrics = {key: np.mean([fold[key] for fold in fold_metrics]) for key in fold_metrics

    return avg_metrics
```

In [22]:

```python
# Оцінка моделей за K-Fold
metrics_kfold_results = {}

for config in model_configs:
    model_type = config['type']
    num_layers = config['layers']
    units = config['units']

    print(f"\nK-Fold Evaluation for {model_type} with {num_layers} layer(s) and {units} units
    avg_metrics = cross_validate_model(model_type, num_layers, units, X_train, y_train, kf)
    key = f"{model_type}_layers{num_layers}_units{units}"
    metrics_kfold_results[key] = avg_metrics
```

```
K-Fold Evaluation for SimpleRNN with 1 layer(s) and 50 units per layer...
  Fold 1/5
5/5 [==============================] - 0s 2ms/step
  Fold 2/5
5/5 [==============================] - 0s 2ms/step
  Fold 3/5
5/5 [==============================] - 0s 2ms/step
  Fold 4/5
5/5 [==============================] - 0s 1ms/step
  Fold 5/5
5/5 [==============================] - 0s 2ms/step

K-Fold Evaluation for SimpleRNN with 2 layer(s) and 50 units per layer...
  Fold 1/5
5/5 [==============================] - 0s 2ms/step
  Fold 2/5
5/5 [==============================] - 0s 5ms/step
  Fold 3/5
5/5 [==============================] - 0s 2ms/step
  Fold 4/5
5/5 [==============================] - 0s 2ms/step
  Fold 5/5
5/5 [==============================] - 0s 2ms/step

K-Fold Evaluation for SimpleRNN with 2 layer(s) and 100 units per layer...
  Fold 1/5
5/5 [==============================] - 0s 4ms/step
  Fold 2/5
5/5 [==============================] - 0s 2ms/step
  Fold 3/5
5/5 [==============================] - 0s 2ms/step
  Fold 4/5
5/5 [==============================] - 0s 3ms/step
  Fold 5/5
5/5 [==============================] - 0s 3ms/step

K-Fold Evaluation for LSTM with 1 layer(s) and 50 units per layer...
  Fold 1/5
5/5 [==============================] - 1s 2ms/step
  Fold 2/5
5/5 [==============================] - 1s 2ms/step
  Fold 3/5
5/5 [==============================] - 1s 2ms/step
  Fold 4/5
5/5 [==============================] - 1s 2ms/step
  Fold 5/5
5/5 [==============================] - 1s 2ms/step

K-Fold Evaluation for LSTM with 2 layer(s) and 50 units per layer...
  Fold 1/5
5/5 [==============================] - 1s 3ms/step
  Fold 2/5
5/5 [==============================] - 1s 3ms/step
  Fold 3/5
5/5 [==============================] - 1s 3ms/step
  Fold 4/5
5/5 [==============================] - 1s 5ms/step
  Fold 5/5
5/5 [==============================] - 1s 3ms/step

K-Fold Evaluation for LSTM with 2 layer(s) and 100 units per layer...
  Fold 1/5
5/5 [==============================] - 1s 5ms/step
  Fold 2/5
5/5 [==============================] - 1s 3ms/step
  Fold 3/5
```

```
5/5 [==============================] - 1s 3ms/step
  Fold 4/5
5/5 [==============================] - 1s 4ms/step
  Fold 5/5
5/5 [==============================] - 1s 3ms/step

K-Fold Evaluation for GRU with 1 layer(s) and 50 units per layer...
  Fold 1/5
5/5 [==============================] - 0s 2ms/step
  Fold 2/5
5/5 [==============================] - 0s 2ms/step
  Fold 3/5
5/5 [==============================] - 0s 2ms/step
  Fold 4/5
5/5 [==============================] - 0s 2ms/step
  Fold 5/5
5/5 [==============================] - 0s 2ms/step

K-Fold Evaluation for GRU with 2 layer(s) and 50 units per layer...
  Fold 1/5
5/5 [==============================] - 1s 4ms/step
  Fold 2/5
5/5 [==============================] - 1s 3ms/step
  Fold 3/5
5/5 [==============================] - 1s 3ms/step
  Fold 4/5
5/5 [==============================] - 1s 3ms/step
  Fold 5/5
5/5 [==============================] - 1s 4ms/step

K-Fold Evaluation for GRU with 2 layer(s) and 100 units per layer...
  Fold 1/5
5/5 [==============================] - 1s 7ms/step
  Fold 2/5
5/5 [==============================] - 1s 4ms/step
  Fold 3/5
5/5 [==============================] - 1s 4ms/step
  Fold 4/5
5/5 [==============================] - 1s 3ms/step
  Fold 5/5
5/5 [==============================] - 1s 4ms/step
```

In [23]:

```
# Таблиця результатів K-Fold
kfold_results_table = pd.DataFrame([
    {"Model": name, **metrics}
    for name, metrics in metrics_kfold_results.items()
])

kfold_results_table
```

Out[23]:

	Model	MSE	RMSE	MAE	MAPE	R2 Score
0	SimpleRNN_layers1_units50	190.298960	13.529176	9.711182	0.023967	0.983211
1	SimpleRNN_layers2_units50	179.175170	13.171594	9.440649	0.023328	0.984187
2	SimpleRNN_layers2_units100	171.328400	13.014206	9.287868	0.023161	0.984976
3	LSTM_layers1_units50	190.770239	13.640555	9.741704	0.024185	0.983413
4	LSTM_layers2_units50	253.410957	15.401208	11.070845	0.027551	0.978359
5	LSTM_layers2_units100	180.970096	13.286261	9.438707	0.023585	0.984199
6	GRU_layers1_units50	154.954739	12.324526	8.761772	0.021705	0.986429
7	GRU_layers2_units50	151.622451	12.163998	8.587721	0.021347	0.986736
8	GRU_layers2_units100	153.328595	12.267450	8.729803	0.021744	0.986556

In [24]:

```
# Об'єднання таблиць Hold-out і K-Fold
combined_results = holdout_results.copy()
combined_results.columns = ["Model"] + [f"{col} (Hold-out)" for col in combined_results.colum

kfold_results_table.columns = ["Model"] + [f"{col} (K-Fold)" for col in kfold_results_table.c

# Об'єднання по моделі
final_results = pd.merge(combined_results, kfold_results_table, on="Model")

# Сортування колонок, крім "Model"
sorted_columns = ["Model"] + sorted([col for col in final_results.columns if col != "Model"])
final_results = final_results[sorted_columns]

# Закруглення числових колонок до 3 знаків після коми
numerical_columns = final_results.select_dtypes(include=['float', 'int']).columns
final_results[numerical_columns] = final_results[numerical_columns].round(3)

final_results[sorted_columns]
```

Out[24]:

	Model	MAE (Hold-out)	MAE (K-Fold)	MAPE (Hold-out)	MAPE (K-Fold)	MSE (Hold-out)	MSE (K-Fold)	R2 Score (Hold-out)	R2 Score (K-Fold)	RMSE (Hold-out)
0	SimpleRNN_layers1_units50	9.726	9.711	0.023	0.024	185.225	190.299	0.984	0.983	13.610
1	SimpleRNN_layers2_units50	10.609	9.441	0.026	0.023	192.803	179.175	0.984	0.984	13.885
2	SimpleRNN_layers2_units100	9.856	9.288	0.024	0.023	171.094	171.328	0.985	0.985	13.080
3	LSTM_layers1_units50	11.162	9.742	0.027	0.024	231.183	190.770	0.980	0.983	15.205
4	LSTM_layers2_units50	11.875	11.071	0.029	0.028	254.165	253.411	0.978	0.978	15.943
5	LSTM_layers2_units100	9.675	9.439	0.023	0.024	179.113	180.970	0.985	0.984	13.383
6	GRU_layers1_units50	9.494	8.762	0.023	0.022	177.736	154.955	0.985	0.986	13.332
7	GRU_layers2_units50	9.952	8.588	0.024	0.021	187.782	151.622	0.984	0.987	13.703
8	GRU_layers2_units100	9.392	8.730	0.023	0.022	173.715	153.329	0.985	0.987	13.180

In [25]:

```
# Об'єднання таблиць Hold-out і K-Fold
combined_results1 = holdout_results.copy()
combined_results1.columns = ["Model"] + [f"{col} (Hold-out)" for col in combined_results.colu
```

```python
combined_results2 = kfold_results_table.copy()
combined_results2.columns = ["Model"] + [f"{col} (K-Fold)" for col in combined_results2.colum

# Об'єднання по моделі
final_results = pd.merge(combined_results, kfold_results_table, on="Model")

# Сортування колонок, крім "Model"
sorted_columns = ["Model"] + sorted([col for col in final_results.columns if col != "Model"])
final_results = final_results[sorted_columns]

final_results
```

Out[25]:

	Model	MAE (Hold-out)	MAE (K-Fold)	MAPE (Hold-out)	MAPE (K-Fold)	MSE (Hold-out)	MSE (K-Fold)	Sc (Ho o
0	SimpleRNN_layers1_units50	9.725657	9.711182	0.023242	0.023967	185.224791	190.298960	0.9842
1	SimpleRNN_layers2_units50	10.608896	9.440649	0.025879	0.023328	192.803161	179.175170	0.9835
2	SimpleRNN_layers2_units100	9.855910	9.287868	0.023942	0.023161	171.093695	171.328400	0.9854
3	LSTM_layers1_units50	11.162238	9.741704	0.027188	0.024185	231.182620	190.770239	0.9802
4	LSTM_layers2_units50	11.874604	11.070845	0.029180	0.027551	254.165463	253.410957	0.9783
5	LSTM_layers2_units100	9.674530	9.438707	0.023420	0.023585	179.113248	180.970096	0.9847
6	GRU_layers1_units50	9.494313	8.761772	0.022983	0.021705	177.735877	154.954739	0.9848
7	GRU_layers2_units50	9.952121	8.587721	0.024298	0.021347	187.782322	151.622451	0.9839
8	GRU_layers2_units100	9.392318	8.729803	0.022834	0.021744	173.715323	153.328595	0.9851

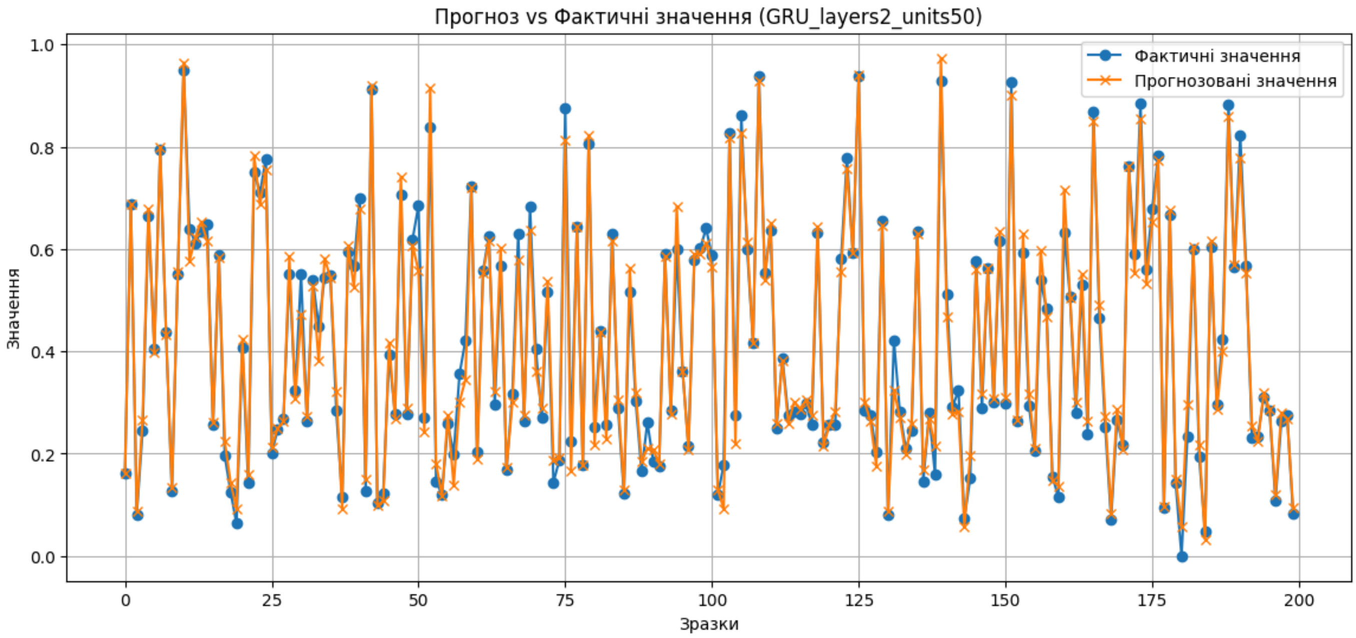
In [26]:

```python
# Знаходимо модель з найменшим MSE (K-Fold)
best_model_name = final_results.loc[final_results["MSE (K-Fold)"].idxmin(), "Model"]
best_model = trained_models[best_model_name]

# Прогноз для тестового набору
y_pred_best = best_model.predict(X_test)
```

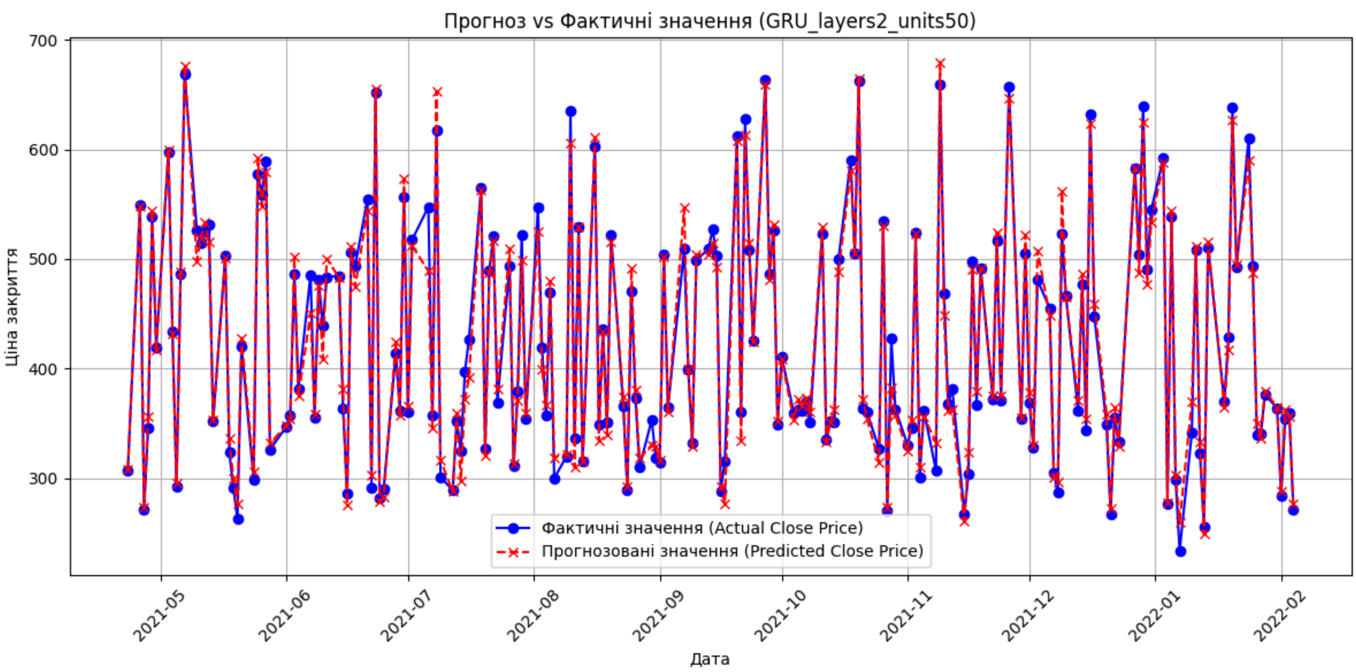
```
7/7 [==============================] - 0s 3ms/step
```

In [27]:

```python
# Масштабування назад для фактичних значень
y_test_original = scaler.inverse_transform(
    np.concatenate([X_test[:, -1, :], y_test.reshape(-1, 1)], axis=1)
)[:, -1]

# Масштабування назад для прогнозованих значень
y_pred_best_original = scaler.inverse_transform(
    np.concatenate([X_test[:, -1, :], y_pred_best.reshape(-1, 1)], axis=1)
)[:, -1]

# Побудова графіку
plt.figure(figsize=(14, 6))
plt.plot(y_test, label="Фактичні значення", marker='o')
plt.plot(y_pred_best, label="Прогнозовані значення", marker='x')
plt.title(f"Прогноз vs Фактичні значення ({best_model_name})")
plt.xlabel("Зразки")
plt.ylabel("Значення")
plt.legend()
plt.grid(True)
plt.show()
```



In [28]:
```python
# Відновлення масштабів тільки для 'Close'
y_test_rescaled = scaler.inverse_transform(
    np.hstack((np.zeros((len(y_test), scaled_data.shape[1] - 1)), y_test.reshape(-1, 1)))
)[:, -1]

y_pred_rescaled = scaler.inverse_transform(
    np.hstack((np.zeros((len(y_pred_best), scaled_data.shape[1] - 1)), y_pred_best.reshape(-1
)[:, -1]

# Дати для тестового набору
test_dates = pd.to_datetime(data['Date']).iloc[-len(y_test):]

# Побудова графіку
plt.figure(figsize=(12, 6))
plt.plot(test_dates, y_test_rescaled, label="Фактичні значення (Actual Close Price)", marker=
plt.plot(test_dates, y_pred_rescaled, label="Прогнозовані значення (Predicted Close Price)", 
plt.title(f"Прогноз vs Фактичні значення ({best_model_name})")
plt.xlabel("Дата")
plt.ylabel("Ціна закриття")
plt.legend()
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Глибина історії (look_back)

In [29]:
```
def experiment_with_look_back(look_back_values, model_config, data, scaler):
    results = {}

    for look_back in look_back_values:
        print(f"\nТестування з look_back={look_back}...")

        # Масштабування даних
        scaled_data = scaler.fit_transform(data[['Open', 'High', 'Low', 'Volume', 'Close']].v

        # Формування послідовностей
        X, y = [], []
        for i in range(len(scaled_data) - look_back):
            X.append(scaled_data[i:i + look_back, :-1])  # Всі ознаки, окрім 'Close'
            y.append(scaled_data[i + look_back, -1])    # Цільова змінна – 'Close'
        X, y = np.array(X), np.array(y)

        # Розділення на тренувальні та тестові набори
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state

        # Створення моделі
        model = create_rnn_model(
            model_type=model_config['type'],
            input_shape=(look_back, X_train.shape[2]),
            num_layers=model_config['layers'],
            units=model_config['units']
        )

        # Навчання моделі
        history = model.fit(
            X_train, y_train,
            epochs=100,
            batch_size=32,
            validation_data=(X_test, y_test),
            verbose=0,
            callbacks=[early_stopping]
        )

        # Прогнозування
        y_pred = model.predict(X_test)

        # Масштабування назад
        y_test_original = scaler.inverse_transform(
            np.concatenate([X_test[:, -1, :], y_test.reshape(-1, 1)], axis=1)
        )[:, -1]

        y_pred_original = scaler.inverse_transform(
            np.concatenate([X_test[:, -1, :], y_pred.reshape(-1, 1)], axis=1)
        )[:, -1]

        # Оцінка моделі
        metrics = calculate_metrics(y_test_original, y_pred_original)

        # Збереження результатів
        results[look_back] = metrics

    return results
```

In [30]:
```
# Визначення параметрів експерименту
look_back_values = [5, 10, 15, 20, 30, 50, 100, 500]
model_config = {
    'type': 'SimpleRNN',
    'layers': 1,
```

```
    'units': 50
}

# Запуск експерименту
look_back_results = experiment_with_look_back(look_back_values, model_config, data, scaler)
```

```
Тестування з look_back=5...
7/7 [==============================] - 0s 1ms/step

Тестування з look_back=10...
7/7 [==============================] - 0s 2ms/step

Тестування з look_back=15...
7/7 [==============================] - 0s 2ms/step

Тестування з look_back=20...
7/7 [==============================] - 0s 2ms/step

Тестування з look_back=30...
7/7 [==============================] - 0s 2ms/step

Тестування з look_back=50...
6/6 [==============================] - 0s 3ms/step

Тестування з look_back=100...
6/6 [==============================] - 0s 10ms/step

Тестування з look_back=500...
4/4 [==============================] - 0s 16ms/step
```

In [31]:

```
# Таблиця результатів
look_back_results_table = pd.DataFrame.from_dict(look_back_results, orient='index')
look_back_results_table.index.name = 'look_back'
look_back_results_table.reset_index(inplace=True)

look_back_results_table
```

Out[31]:

	look_back	MSE	RMSE	MAE	MAPE	R2 Score
0	5	142.494700	11.937114	7.865797	0.019424	0.988396
1	10	173.877576	13.186265	9.321431	0.022489	0.985170
2	15	176.211897	13.274483	10.074320	0.024079	0.984953
3	20	156.240298	12.499612	9.230627	0.022773	0.986211
4	30	221.330972	14.877196	9.441981	0.022557	0.978814
5	50	216.012053	14.697349	10.041104	0.023402	0.981099
6	100	172.343378	13.127962	9.741260	0.024555	0.984941
7	500	173.717029	13.180176	9.864816	0.020003	0.973615

Частина 2: Генерація тексту

Крок 1: Імпорт бібліотек

In [32]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import string, os
import re
```

```python
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Embedding, LSTM, GRU, Dense
from tensorflow.keras.callbacks import EarlyStopping
```

Крок 2: Підготовка текстових даних

In [33]:
```python
data2 = pd.read_csv('en_songs.csv')
data2.head()
```

Out[33]:

	Artist	Title	Lyrics
0	Taylor Swift	cardigan	Vintage tee, brand new phone\nHigh heels on co...
1	Taylor Swift	exile	I can see you standing, honey\nWith his arms a...
2	Taylor Swift	Lover	We could leave the Christmas lights up 'til Ja...
3	Taylor Swift	the 1	I'm doing good, I'm on some new shit\nBeen say...
4	Taylor Swift	Look What You Made Me Do	I don't like your little games\nDon't like you...

In [34]:
```python
df_lyrics = data2[['Lyrics']]
df_lyrics.head()
```

Out[34]:

	Lyrics
0	Vintage tee, brand new phone\nHigh heels on co...
1	I can see you standing, honey\nWith his arms a...
2	We could leave the Christmas lights up 'til Ja...
3	I'm doing good, I'm on some new shit\nBeen say...
4	I don't like your little games\nDon't like you...

In [36]:
```python
df_lyrics.loc[:, 'Number_of_words'] = df_lyrics['Lyrics'].apply(lambda x: len(str(x).split()))
df_lyrics.head()
```

Out[36]:

	Lyrics	Number_of_words
0	Vintage tee, brand new phone\nHigh heels on co...	337
1	I can see you standing, honey\nWith his arms a...	459
2	We could leave the Christmas lights up 'til Ja...	259
3	I'm doing good, I'm on some new shit\nBeen say...	308
4	I don't like your little games\nDon't like you...	558

In [37]:
```python
df_lyrics['Number_of_words'].describe()
```

```
Out[37]: count     745.000000
         mean      276.260403
         std       129.230505
         min         1.000000
         25%       189.000000
         50%       255.000000
         75%       340.000000
         max      1386.000000
         Name: Number_of_words, dtype: float64
```

```
In [38]: df_lyrics = df_lyrics[df_lyrics['Number_of_words'] > 5]
```

```
In [39]: df_lyrics['Number_of_words'].describe()
```

```
Out[39]: count     744.000000
         mean      276.630376
         std       128.922021
         min        23.000000
         25%       189.000000
         50%       255.500000
         75%       340.000000
         max      1386.000000
         Name: Number_of_words, dtype: float64
```

```
In [40]: df_lyrics_5 = df_lyrics.sample(n=5, random_state=42)
```

```
In [41]: df_lyrics_5['Number_of_words'].describe()
```

```
Out[41]: count      5.000000
         mean     291.400000
         std       56.100802
         min      208.000000
         25%      271.000000
         50%      298.000000
         75%      325.000000
         max      355.000000
         Name: Number_of_words, dtype: float64
```

```
In [42]: def clean_text(text):
             # text = text.lower()
             text = re.sub("[^A-Za-z0-9'\.\?!\n ]", "", text)
             text = text.replace('\n', ' ')
             text = re.sub(" +", " ", text)
             return text.strip()

         df_lyrics_5['Cleaned_Lyrics'] = df_lyrics['Lyrics'].apply(clean_text)
         df_lyrics_5
```

Out[42]:

	Lyrics	Number_of_words	Cleaned_Lyrics
609	Today, while the blossoms still cling to the v...	208	Today while the blossoms still cling to the vi...
539	I could take the high road\nBut I know that I'...	298	I could take the high road But I know that I'm...
695	It's getting late, have you seen my mates?\nMa...	325	It's getting late have you seen my mates? Ma t...
350	I'm so gone\nAnyone could see that I'm wasted\...	271	I'm so gone Anyone could see that I'm wasted Y...
174	Time - He's waiting in the wings\nHe speaks of...	355	Time He's waiting in the wings He speaks of se...

In [43]:
```
# Перевірити на наявність певного патерну
noise_pattern = r'\bhistory24embedshare\b|\burlcopyembedcopy\b'
noise_count = df_lyrics_5['Cleaned_Lyrics'].str.contains(noise_pattern, regex=True).sum()
print(f"Кількість знайдених патернів: {noise_count}")

# Видалити цей патерн
if noise_count > 0:
    df_lyrics_5['Cleaned_Lyrics'] = df_lyrics_5['Cleaned_Lyrics'].apply(
        lambda x: re.sub(noise_pattern, '', x)
    )
    print("Видалено шуми")
else:
    print("Шуми не знайдені")
```

```
Кількість знайдених патернів: 0
Шуми не знайдені
```

In [44]:
```
# Об'єднання очищених текстів пісень для токенізації
text = ' '.join(df_lyrics_5['Cleaned_Lyrics'].tolist())
print("Довжина тексту: ", len(text))
```

```
Довжина тексту:  7113
```

In [45]:
```
# Токенізація
tokenizer = Tokenizer()  # Ліміт (num_words=100)
tokenizer.fit_on_texts([text])
total_words = len(tokenizer.word_index) + 1
```

In [46]:
```
# Створення послідовностей
input_sequences = []
for line in text.split('.'):  # Поділ за реченнями для отримання осмислених послідовностей
    token_list = tokenizer.texts_to_sequences([line])[0]
    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[:i+1]
        input_sequences.append(n_gram_sequence)
```

In [47]:
```
# Падінг послідовностей
max_sequence_len = max([len(x) for x in input_sequences])
input_sequences = pad_sequences(input_sequences, maxlen=max_sequence_len, padding='pre')
```

In [48]:
```
# Поділ на вхідні та вихідні дані
X, y = input_sequences[:, :-1], input_sequences[:, -1]
y = tf.keras.utils.to_categorical(y, num_classes=len(tokenizer.word_index) + 1)
```

Крок 3: Створення та навчання моделі

In [49]:
```
# Функція для створення моделі на основі конфігурації
def create_text_generation_model(total_words, max_sequence_len, embedding_dim, rnn_type, num_
    model = Sequential()
    model.add(Embedding(total_words, embedding_dim, input_length=max_sequence_len - 1))

    RNN_LAYER = {'LSTM': LSTM, 'GRU': GRU}[rnn_type]

    # Додавання рекурентних шарів
    for i in range(num_layers):
        is_last_layer = (i == num_layers - 1)
        model.add(RNN_LAYER(units_per_layer, return_sequences=not is_last_layer))

    # Додавання вихідного шару
    model.add(Dense(total_words, activation='softmax'))
    return model
```

In [50]:
```
# Визначення конфігурацій моделей
model_configs = [
    {'rnn_type': 'LSTM', 'embedding_dim': 100, 'num_layers': 1, 'units_per_layer': 150, 'epoc
    {'rnn_type': 'LSTM', 'embedding_dim': 200, 'num_layers': 2, 'units_per_layer': 100, 'epoc
    {'rnn_type': 'GRU',  'embedding_dim': 150, 'num_layers': 1, 'units_per_layer': 200, 'epoc
    {'rnn_type': 'GRU',  'embedding_dim': 100, 'num_layers': 2, 'units_per_layer': 150, 'epoc
]
```

In [51]:
```
early_stopping = EarlyStopping(monitor='loss', patience=5, restore_best_weights=True)
```

In [52]:
```
trained_models = {}

for config in model_configs:
    print(f"\nTraining {config['rnn_type']} model with {config['num_layers']} layer(s), "
          f"{config['units_per_layer']} units/layer, embedding size {config['embedding_dim']}

    # Створення та компіляція моделі
    model = create_text_generation_model(
        total_words=total_words,
        max_sequence_len=max_sequence_len,
        embedding_dim=config['embedding_dim'],
        rnn_type=config['rnn_type'],
        num_layers=config['num_layers'],
        units_per_layer=config['units_per_layer']
    )
    model.compile(loss='categorical_crossentropy', optimizer='adam')

    # Навчання моделі
    history = model.fit(
        X, y,
        epochs=config['epochs'],
        batch_size=32,
        verbose=1,
        callbacks=[early_stopping]
    )

    # Збереження моделі та історії навчання
    key = f"{config['rnn_type']}_layers{config['num_layers']}_units{config['units_per_layer']
    trained_models[key] = (model, history)
```

```
Training LSTM model with 1 layer(s), 150 units/layer, embedding size 100...
Epoch 1/30
46/46 [==============================] - 37s 712ms/step - loss: 5.5938
Epoch 2/30
46/46 [==============================] - 36s 790ms/step - loss: 5.0483
Epoch 3/30
46/46 [==============================] - 36s 776ms/step - loss: 4.7478
Epoch 4/30
46/46 [==============================] - 36s 776ms/step - loss: 4.4989
Epoch 5/30
46/46 [==============================] - 39s 850ms/step - loss: 4.2495
Epoch 6/30
46/46 [==============================] - 39s 841ms/step - loss: 4.0294
Epoch 7/30
46/46 [==============================] - 40s 866ms/step - loss: 3.7583
Epoch 8/30
46/46 [==============================] - 34s 741ms/step - loss: 3.4994
Epoch 9/30
46/46 [==============================] - 34s 738ms/step - loss: 3.2249
Epoch 10/30
46/46 [==============================] - 34s 744ms/step - loss: 2.9584
Epoch 11/30
46/46 [==============================] - 34s 737ms/step - loss: 2.7017
Epoch 12/30
46/46 [==============================] - 34s 735ms/step - loss: 2.4832
Epoch 13/30
46/46 [==============================] - 34s 736ms/step - loss: 2.2356
Epoch 14/30
46/46 [==============================] - 36s 779ms/step - loss: 2.0845
Epoch 15/30
46/46 [==============================] - 35s 755ms/step - loss: 1.8522
Epoch 16/30
46/46 [==============================] - 39s 827ms/step - loss: 1.6667
Epoch 17/30
46/46 [==============================] - 35s 751ms/step - loss: 1.5150
Epoch 18/30
46/46 [==============================] - 34s 746ms/step - loss: 1.3632
Epoch 19/30
46/46 [==============================] - 34s 744ms/step - loss: 1.2327
Epoch 20/30
46/46 [==============================] - 34s 750ms/step - loss: 1.1177
Epoch 21/30
46/46 [==============================] - 35s 766ms/step - loss: 1.0093
Epoch 22/30
46/46 [==============================] - 35s 759ms/step - loss: 0.9216
Epoch 23/30
46/46 [==============================] - 35s 762ms/step - loss: 0.8234
Epoch 24/30
46/46 [==============================] - 36s 773ms/step - loss: 0.7502
Epoch 25/30
46/46 [==============================] - 35s 758ms/step - loss: 0.6774
Epoch 26/30
46/46 [==============================] - 35s 765ms/step - loss: 0.6131
Epoch 27/30
46/46 [==============================] - 38s 827ms/step - loss: 0.5696
Epoch 28/30
46/46 [==============================] - 37s 805ms/step - loss: 0.5109
Epoch 29/30
46/46 [==============================] - 35s 759ms/step - loss: 0.4627
Epoch 30/30
46/46 [==============================] - 35s 765ms/step - loss: 0.4262

Training LSTM model with 2 layer(s), 100 units/layer, embedding size 200...
Epoch 1/40
46/46 [==============================] - 59s 1s/step - loss: 5.5275
Epoch 2/40
```

```
46/46 [==============================] - 54s 1s/step - loss: 4.9863
Epoch 3/40
46/46 [==============================] - 54s 1s/step - loss: 4.7660
Epoch 4/40
46/46 [==============================] - 54s 1s/step - loss: 4.6039
Epoch 5/40
46/46 [==============================] - 55s 1s/step - loss: 4.4332
Epoch 6/40
46/46 [==============================] - 54s 1s/step - loss: 4.2782
Epoch 7/40
46/46 [==============================] - 57s 1s/step - loss: 4.1343
Epoch 8/40
46/46 [==============================] - 61s 1s/step - loss: 3.9752
Epoch 9/40
46/46 [==============================] - 57s 1s/step - loss: 3.8150
Epoch 10/40
46/46 [==============================] - 55s 1s/step - loss: 3.6624
Epoch 11/40
46/46 [==============================] - 55s 1s/step - loss: 3.5192
Epoch 12/40
46/46 [==============================] - 56s 1s/step - loss: 3.3889
Epoch 13/40
46/46 [==============================] - 56s 1s/step - loss: 3.2620
Epoch 14/40
46/46 [==============================] - 57s 1s/step - loss: 3.1423
Epoch 15/40
46/46 [==============================] - 57s 1s/step - loss: 3.0098
Epoch 16/40
46/46 [==============================] - 58s 1s/step - loss: 2.9024
Epoch 17/40
46/46 [==============================] - 57s 1s/step - loss: 2.7870
Epoch 18/40
46/46 [==============================] - 59s 1s/step - loss: 2.6742
Epoch 19/40
46/46 [==============================] - 59s 1s/step - loss: 2.5785
Epoch 20/40
46/46 [==============================] - 66s 1s/step - loss: 2.4862
Epoch 21/40
46/46 [==============================] - 58s 1s/step - loss: 2.3710
Epoch 22/40
46/46 [==============================] - 58s 1s/step - loss: 2.3690
Epoch 23/40
46/46 [==============================] - 57s 1s/step - loss: 2.2532
Epoch 24/40
46/46 [==============================] - 56s 1s/step - loss: 2.1684
Epoch 25/40
46/46 [==============================] - 68s 1s/step - loss: 2.0572
Epoch 26/40
46/46 [==============================] - 65s 1s/step - loss: 1.9565
Epoch 27/40
46/46 [==============================] - 72s 2s/step - loss: 1.8697
Epoch 28/40
46/46 [==============================] - 68s 1s/step - loss: 1.7795
Epoch 29/40
46/46 [==============================] - 68s 1s/step - loss: 1.7121
Epoch 30/40
46/46 [==============================] - 64s 1s/step - loss: 1.6308
Epoch 31/40
46/46 [==============================] - 67s 1s/step - loss: 1.5629
Epoch 32/40
46/46 [==============================] - 69s 1s/step - loss: 1.4941
Epoch 33/40
46/46 [==============================] - 64s 1s/step - loss: 1.4292
Epoch 34/40
46/46 [==============================] - 68s 1s/step - loss: 1.3609
Epoch 35/40
```

```
46/46 [==============================] - 78s 2s/step - loss: 1.2980
Epoch 36/40
46/46 [==============================] - 66s 1s/step - loss: 1.2383
Epoch 37/40
46/46 [==============================] - 91s 2s/step - loss: 1.2086
Epoch 38/40
46/46 [==============================] - 61s 1s/step - loss: 1.1496
Epoch 39/40
46/46 [==============================] - 73s 2s/step - loss: 1.0932
Epoch 40/40
46/46 [==============================] - 59s 1s/step - loss: 1.0298

Training GRU model with 1 layer(s), 200 units/layer, embedding size 150...
Epoch 1/50
46/46 [==============================] - 48s 971ms/step - loss: 5.5266
Epoch 2/50
46/46 [==============================] - 45s 978ms/step - loss: 4.7674
Epoch 3/50
46/46 [==============================] - 44s 966ms/step - loss: 4.4203
Epoch 4/50
46/46 [==============================] - 48s 1s/step - loss: 4.0337
Epoch 5/50
46/46 [==============================] - 49s 1s/step - loss: 3.5134
Epoch 6/50
46/46 [==============================] - 49s 1s/step - loss: 2.9711
Epoch 7/50
46/46 [==============================] - 47s 1s/step - loss: 2.4983
Epoch 8/50
46/46 [==============================] - 53s 1s/step - loss: 2.0914
Epoch 9/50
46/46 [==============================] - 49s 1s/step - loss: 1.7330
Epoch 10/50
46/46 [==============================] - 49s 1s/step - loss: 1.4180
Epoch 11/50
46/46 [==============================] - 49s 1s/step - loss: 1.1456
Epoch 12/50
46/46 [==============================] - 52s 1s/step - loss: 0.9125
Epoch 13/50
46/46 [==============================] - 48s 1s/step - loss: 0.7207
Epoch 14/50
46/46 [==============================] - 49s 1s/step - loss: 0.5689
Epoch 15/50
46/46 [==============================] - 49s 1s/step - loss: 0.4431
Epoch 16/50
46/46 [==============================] - 51s 1s/step - loss: 0.3559
Epoch 17/50
46/46 [==============================] - 51s 1s/step - loss: 0.2936
Epoch 18/50
46/46 [==============================] - 50s 1s/step - loss: 0.2468
Epoch 19/50
46/46 [==============================] - 43s 941ms/step - loss: 0.2122
Epoch 20/50
46/46 [==============================] - 43s 937ms/step - loss: 0.1868
Epoch 21/50
46/46 [==============================] - 52s 1s/step - loss: 0.1676
Epoch 22/50
46/46 [==============================] - 55s 1s/step - loss: 0.1492
Epoch 23/50
46/46 [==============================] - 63s 1s/step - loss: 0.1393
Epoch 24/50
46/46 [==============================] - 50s 1s/step - loss: 0.1344
Epoch 25/50
46/46 [==============================] - 45s 992ms/step - loss: 0.1286
Epoch 26/50
46/46 [==============================] - 41s 890ms/step - loss: 0.1172
Epoch 27/50
```

```
46/46 [==============================] - 41s 899ms/step - loss: 0.1107
Epoch 28/50
46/46 [==============================] - 42s 907ms/step - loss: 0.1088
Epoch 29/50
46/46 [==============================] - 41s 896ms/step - loss: 0.1033
Epoch 30/50
46/46 [==============================] - 42s 903ms/step - loss: 0.0997
Epoch 31/50
46/46 [==============================] - 41s 885ms/step - loss: 0.0973
Epoch 32/50
46/46 [==============================] - 42s 911ms/step - loss: 0.0933
Epoch 33/50
46/46 [==============================] - 41s 896ms/step - loss: 0.0952
Epoch 34/50
46/46 [==============================] - 41s 892ms/step - loss: 0.0886
Epoch 35/50
46/46 [==============================] - 41s 902ms/step - loss: 0.0889
Epoch 36/50
46/46 [==============================] - 41s 888ms/step - loss: 0.0868
Epoch 37/50
46/46 [==============================] - 42s 905ms/step - loss: 0.0875
Epoch 38/50
46/46 [==============================] - 41s 891ms/step - loss: 0.0817
Epoch 39/50
46/46 [==============================] - 42s 913ms/step - loss: 0.0816
Epoch 40/50
46/46 [==============================] - 41s 900ms/step - loss: 0.0817
Epoch 41/50
46/46 [==============================] - 41s 897ms/step - loss: 0.0807
Epoch 42/50
46/46 [==============================] - 41s 898ms/step - loss: 0.0782
Epoch 43/50
46/46 [==============================] - 40s 878ms/step - loss: 0.0816
Epoch 44/50
46/46 [==============================] - 41s 891ms/step - loss: 0.0784
Epoch 45/50
46/46 [==============================] - 40s 879ms/step - loss: 0.0759
Epoch 46/50
46/46 [==============================] - 41s 895ms/step - loss: 0.0734
Epoch 47/50
46/46 [==============================] - 41s 885ms/step - loss: 0.0747
Epoch 48/50
46/46 [==============================] - 41s 883ms/step - loss: 0.0761
Epoch 49/50
46/46 [==============================] - 41s 889ms/step - loss: 0.0718
Epoch 50/50
46/46 [==============================] - 40s 878ms/step - loss: 0.0730

Training GRU model with 2 layer(s), 150 units/layer, embedding size 100...
Epoch 1/30
46/46 [==============================] - 66s 1s/step - loss: 5.4469
Epoch 2/30
46/46 [==============================] - 61s 1s/step - loss: 4.8879
Epoch 3/30
46/46 [==============================] - 64s 1s/step - loss: 4.5949
Epoch 4/30
46/46 [==============================] - 61s 1s/step - loss: 4.3092
Epoch 5/30
46/46 [==============================] - 61s 1s/step - loss: 4.0030
Epoch 6/30
46/46 [==============================] - 61s 1s/step - loss: 3.6429
Epoch 7/30
46/46 [==============================] - 62s 1s/step - loss: 3.2960
Epoch 8/30
46/46 [==============================] - 62s 1s/step - loss: 2.9400
Epoch 9/30
```

```
46/46 [==============================] - 62s 1s/step - loss: 2.6587
Epoch 10/30
46/46 [==============================] - 62s 1s/step - loss: 2.3604
Epoch 11/30
46/46 [==============================] - 65s 1s/step - loss: 2.1005
Epoch 12/30
46/46 [==============================] - 62s 1s/step - loss: 1.8402
Epoch 13/30
46/46 [==============================] - 62s 1s/step - loss: 1.6311
Epoch 14/30
46/46 [==============================] - 61s 1s/step - loss: 1.4483
Epoch 15/30
46/46 [==============================] - 62s 1s/step - loss: 1.2845
Epoch 16/30
46/46 [==============================] - 62s 1s/step - loss: 1.1390
Epoch 17/30
46/46 [==============================] - 63s 1s/step - loss: 1.0106
Epoch 18/30
46/46 [==============================] - 63s 1s/step - loss: 0.8935
Epoch 19/30
46/46 [==============================] - 63s 1s/step - loss: 0.8009
Epoch 20/30
46/46 [==============================] - 63s 1s/step - loss: 0.6921
Epoch 21/30
46/46 [==============================] - 63s 1s/step - loss: 0.6078
Epoch 22/30
46/46 [==============================] - 63s 1s/step - loss: 0.5491
Epoch 23/30
46/46 [==============================] - 63s 1s/step - loss: 0.4790
Epoch 24/30
46/46 [==============================] - 64s 1s/step - loss: 0.4217
Epoch 25/30
46/46 [==============================] - 63s 1s/step - loss: 0.3799
Epoch 26/30
46/46 [==============================] - 64s 1s/step - loss: 0.3418
Epoch 27/30
46/46 [==============================] - 64s 1s/step - loss: 0.3061
Epoch 28/30
46/46 [==============================] - 64s 1s/step - loss: 0.2761
Epoch 29/30
46/46 [==============================] - 64s 1s/step - loss: 0.2533
Epoch 30/30
46/46 [==============================] - 64s 1s/step - loss: 0.2349
```

In [53]:

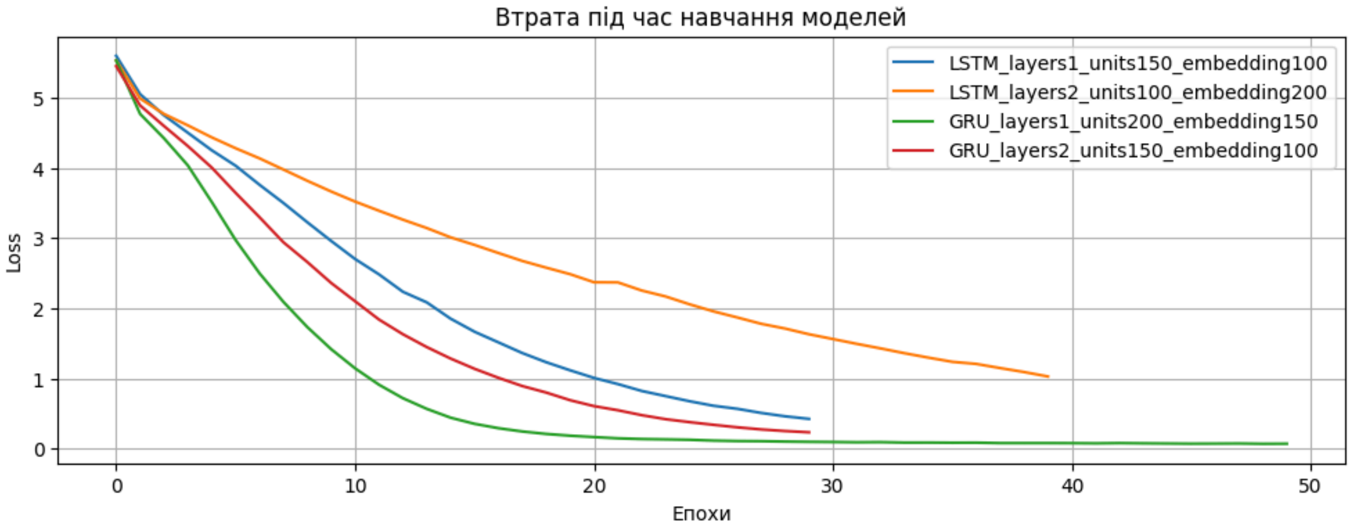
```python
for key, (model, history) in trained_models.items():
    print(f"\nModel: {key}")
    print(f"History keys: {list(history.history.keys())}")
```

```
Model: LSTM_layers1_units150_embedding100
History keys: ['loss']

Model: LSTM_layers2_units100_embedding200
History keys: ['loss']

Model: GRU_layers1_units200_embedding150
History keys: ['loss']

Model: GRU_layers2_units150_embedding100
History keys: ['loss']
```

In [54]:

```python
# Візуалізація втрати
plt.figure(figsize=(12, 4))
for key, (model, history) in trained_models.items():
    plt.plot(history.history['loss'], label=f"{key}")

plt.title("Втрата під час навчання моделей")
```

```python
plt.xlabel("Епохи")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
```



In [55]:
```python
# Генерація тексту на основі початкового тексту та конфігурації моделі
def generate_text(seed_text, next_words, model, max_sequence_len, tokenizer):
    for _ in range(next_words):
        # Токенізація початкового тексту
        token_list = tokenizer.texts_to_sequences([seed_text])[0]

        # Доповнення токенізованої послідовності до потрібної довжини
        token_list = pad_sequences([token_list], maxlen=max_sequence_len-1, padding='pre')

        # Прогнозування наступного слова на основі токенів
        predicted = model.predict(token_list, verbose=0)
        predicted_word_index = np.argmax(predicted, axis=1)

        # Перетворення індексу в слово за допомогою словника токенізатора
        predicted_word = tokenizer.index_word.get(predicted_word_index[0], '')

        # Додавання спрогнозованого слова до початкового тексту
        seed_text += " " + predicted_word

    return seed_text
```

Крок 4: Генерація тексту

In [56]:
```python
# Генерація тексту для кількох моделей
def generate_text_for_models(seed_text, next_words, trained_models, max_sequence_len, tokeniz
    results = []

    # Прохід по всіх навчених моделях
    for model_key, (model, _) in trained_models.items():
        # Генерація тексту за допомогою моделі
        generated_text = generate_text(seed_text, next_words, model, max_sequence_len, tokeni

        # Збереження моделі та згенерованого тексту
        results.append([model_key, generated_text])

    # Створення таблиці результатів
    df = pd.DataFrame(results, columns=["Model", "Generated Text"])
    return df
```

In [57]:
```python
# Налаштування
next_words = 50
```

```
max_sequence_len = max([len(x) for x in input_sequences])
pd.set_option('display.max_colwidth', None)
```

In [58]:
```
df = generate_text_for_models("And the sky is grey", next_words, trained_models, max_sequence_
df
```

Out[58]:

	Model	Generated Text
0	LSTM_layers1_units150_embedding100	And the sky is grey you're you're and i'll left your coat behind take your the up is hard but is hateful i had so many dreams i had so many breakthroughs but you my love were kind but love has left you dreamless the door to dreams was closed your park was real and
1	LSTM_layers2_units100_embedding200	And the sky is grey you're you're you'll you'll and you'll who and who am i on by now we should be on by now we should be on by now we li li li li li li li li li li li li li li li li li li li li li li li
2	GRU_layers1_units200_embedding150	And the sky is grey blossoms still cling to the vine i'll taste your strawberries i'll drink your sweet wine a million tomorrows shall all pass away 'ere i forget all the joy that is mine today i could take the high road but i know that i'm goin' low i'm a bani'm a bandito
3	GRU_layers2_units150_embedding100	And the sky is grey story i'll laugh and i'll cry and i'll sing today while the blossoms still cling to the vine i'll taste your strawberries i'll drink your sweet wine a million tomorrows shall all pass away 'ere i forget all the joy that is mine today i could take the high road

In [59]:
```
df = generate_text_for_models("I'm afraid of", next_words, trained_models, max_sequence_len, 
df
```

Out[59]:

	Model	Generated Text
0	LSTM_layers1_units150_embedding100	I'm afraid of while the blossoms still cling to the vine i'll taste your strawberries i'll drink your sweet wine a million tomorrows shall all pass away 'ere i forget all the joy that is mine today i can't be contented with yesterday's glory i can't live on promises winter to spring today
1	LSTM_layers2_units100_embedding200	I'm afraid of be by goddamn you're you'll you'll and you'll and who if if i want on on now it on now it it on now lay it on me now lay it all on me now lay it all on me now lay it all on me now lay it all
2	GRU_layers1_units200_embedding150	I'm afraid of be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on
3	GRU_layers2_units150_embedding100	I'm afraid of today i'll the sing i'll cry and i'll sing today while the blossoms still cling to the vine i'll taste your strawberries i'll drink your sweet wine a million tomorrows shall all pass away 'ere i forget all the joy that is mine today i could take the high road

In [60]:
```
next_words = 100
```

In [61]:
```
df = generate_text_for_models("I wish you", next_words, trained_models, max_sequence_len, tok
df
```

Out[61]:

	Model	Generated Text
0	LSTM_layers1_units150_embedding100	I wish you should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by
1	LSTM_layers2_units100_embedding200	I wish you goddamn goddamn looking old freeze to catch a catch it to your cold your vain your vain me me out who who all i all so all oh baby baby will all all on on now on now it on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on
2	GRU_layers1_units200_embedding150	I wish you live on a piece of paper honey mmm put it in my coat before i go hidden in a place you know i'll find it oh ohh later when i'm sitting all alone let me in everything starts at your skin so new your love's always finding me out who am i kidding if all my defences come down oh baby yeah will you lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now lay it all on me now
3	GRU_layers2_units150_embedding100	I wish you on promises winter to spring today is my moment now is my story i'll laugh and i'll cry and i'll sing today while the blossoms still cling to the vine i'll taste your strawberries i'll drink your sweet wine a million tomorrows shall all pass away 'ere i forget all the joy that is mine today i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could take the high road but i

In [62]:

```
df = generate_text_for_models("I love the", next_words, trained_models, max_sequence_len, tok
df
```

Out[62]:

	Model	Generated Text
0	LSTM_layers1_units150_embedding100	I love the goddamn you're looking old you'll freeze and catch a cold 'cause you've left your coat behind take your time breaking up is hard but keeping dark is hateful i had so many dreams i had so many breakthroughs but you my love were kind but love has left you dreamless the door to dreams was closed your park was real and dreamless perhaps you're smiling now smiling through this darkness but all i have to give is guilt for dreaming we should be on by now we should be on by now we should be on by now we should
1	LSTM_layers2_units100_embedding200	I love the you're you'll you'll you'll and i'll who i sing today while the blossoms still cling to the vine i'll taste your strawberries i'll drink your sweet wine a million tomorrows shall all pass away 'ere i forget all the joy that is mine today i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could
2	GRU_layers1_units200_embedding150	I love the sniper in the brain regurgitating drain incestuous and vain and many other last names well i look at my watch it says 925 and i think oh god i'm still alive to be i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could take the high road but i know that i'm goin' low i'm a bani'm a bandito i could take the high road but i know that i'm goin' low
3	GRU_layers2_units150_embedding100	I love the proof could you on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on

In [63]:

```
df = generate_text_for_models("Love is", next_words, trained_models, max_sequence_len, tokeni
df
```

Out[63]:

	Model	Generated Text
0	LSTM_layers1_units150_embedding100	Love is goddamn you're looking old you'll freeze and catch a cold 'cause you've left your coat behind take your time breaking up is hard but keeping dark is hateful i had so many dreams i had so many breakthroughs but you my love were kind but love has left you dreamless the door to dreams was closed your park was real and dreamless perhaps you're smiling now smiling through this darkness but all i have to give is guilt for dreaming we should be on by now we should be on by now we should be on by now we should
1	LSTM_layers2_units100_embedding200	Love is be be goddamn goddamn looking old freeze to catch to catch a cold it and and vain and many last last look of well of at and other other says and 925 and i think i time i alive regurgitating incestuous and vain and many last names it i think i watch you says and 925 and i think i god i'm still still still to to to fear's a rival or close relative to truth either way it helps to hear these words bounce off of the the softest echo time is is my dark my dark my old
2	GRU_layers1_units200_embedding150	Love is you know i'll be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be on by now we should be
3	GRU_layers2_units150_embedding100	Love is you're you're you're freeze and red it's you'll catch a cold 'cause you've left your coat behind take your time breaking up is hard but keeping dark is hateful i had so many dreams i had so many breakthroughs but you my love were kind but love has left you dreamless the door to dreams was closed your park was real and dreamless perhaps you're smiling now smiling through this darkness but all i have to give is guilt for dreaming we should be on by now we should be on by now we should be on by now we

Додатково: збереження моделей (+hist) після навчання

In [64]:

```
save_dir = "saved_models"
os.makedirs(save_dir, exist_ok=True)

for key, (model, history) in trained_models.items():
    model_path = os.path.join(save_dir, f"{key}.h5")
    model.save(model_path)
    print(f"Модель {key} збережена - {model_path}")
```

```
Модель LSTM_layers1_units150_embedding100 збережена - saved_models\LSTM_layers1_units150_embed
ding100.h5
Модель LSTM_layers2_units100_embedding200 збережена - saved_models\LSTM_layers2_units100_embed
ding200.h5
Модель GRU_layers1_units200_embedding150 збережена - saved_models\GRU_layers1_units200_embeddi
ng150.h5
Модель GRU_layers2_units150_embedding100 збережена - saved_models\GRU_layers2_units150_embeddi
ng100.h5
```

```
from tensorflow.keras.models import load_model

save_dir = "saved_models"

loaded_models = {}
for key in os.listdir(save_dir):
    if key.endswith(".h5"):
```

```
        model_path = os.path.join(save_dir, key)
        loaded_models[key] = load_model(model_path)
        print(f"Моделы завантажені з {model_path}")
```

In [66]:
```
import json

for key, (model, history) in trained_models.items():
    history_path = os.path.join(save_dir, f"{key}_history.json")
    with open(history_path, "w") as f:
        json.dump(history.history, f)
    print(f"History для {key} збережена - {history_path}")
```

```
History для LSTM_layers1_units150_embedding100 збережена - saved_models\LSTM_layers1_units150_embedding100_history.json
History для LSTM_layers2_units100_embedding200 збережена - saved_models\LSTM_layers2_units100_embedding200_history.json
History для GRU_layers1_units200_embedding150 збережена - saved_models\GRU_layers1_units200_embedding150_history.json
History для GRU_layers2_units150_embedding100 збережена - saved_models\GRU_layers2_units150_embedding100_history.json
```

```
loaded_histories = {}
for key in os.listdir(save_dir):
    if key.endswith("_history.json"):
        history_path = os.path.join(save_dir, key)
        with open(history_path, "r") as f:
            loaded_histories[key] = json.load(f)
        print(f"Завантажені history з {history_path}")
```

Висновки

У ході виконання лабораторної роботи було виконано два завдання.

У межах першого завдання було здійснено прогнозування часових рядів на прикладі цін закриття акцій Netflix. Для аналізу використовувалися історичні дані, що включали змінні, як-от ціни відкриття, максимум, мінімум, обсяг торгів, та основну цільову змінну — ціну закриття. Було реалізовано підготовку даних, включно з масштабуванням та формуванням вхідних послідовностей для моделей RNN.

Застосовано та порівняно архітектури SimpleRNN, LSTM і GRU із варіаціями кількості шарів та нейронів, а також експериментовано з глибиною історії (look_back). Для оцінки продуктивності моделей використовувалися метрики MSE, RMSE, MAE, MAPE та коефіцієнт детермінації R^2. Навчання моделей проводилося із застосуванням механізмів ранньої зупинки та валідації результатів за допомогою методів Hold-Out та K-Fold крос-валідації.

Результати показали, що моделі GRU із двома шарами та 100 нейронами мали найкращу продуктивність, демонструючи найнижчі значення помилок і найвищий R^2. Використання K-Fold крос-валідації підтвердило стабільність моделей GRU, тоді як LSTM виявили трохи більшу варіативність. Побудовано графіки прогнозованих і фактичних значень, які наочно демонструють точність передбачення. Реалізований підхід підтвердив ефективність RNN для прогнозування часових рядів, особливо для даних зі складними патернами, що включають довготривалі залежності.

У рамках другого завдання реалізовано генерацію тексту пісень із використанням рекурентних нейронних мереж (RNN), включаючи архітектури LSTM та GRU. Для аналізу та генерації тексту виконано попередню обробку даних, що включала токенізацію, формування послідовностей (nграмів), падінг та кодування міток. Дані були підготовлені у форматі, придатному для навчання моделей машинного навчання.

Для навчання використовувалися кастомізовані моделі, створені на основі рекурентних шарів із можливістю варіювання кількості шарів, нейронів, та розмірності вбудованого шару. Навчання моделей проводилося з оптимізацією параметрів на основі функції втрат categorical_crossentropy та механізму ранньої зупинки (EarlyStopping).

Архітектура GRU показала себе ефективнішою для задачі генерації тексту, демонструючи стабільні результати з меншим часом навчання у порівнянні з LSTM. Найкращі результати були досягнуті моделлю GRU із двома шарами та 150 нейронами у кожному шарі. Ця модель генерувала текст, що логічно відповідав контексту, та мала високий рівень когерентності. Збільшення розмірності векторного представлення (Embedding) до 150 покращило якість генерації, проте потребувало більше обчислювальних ресурсів. Використання K-Fold крос-валідації підтвердило стабільність моделей GRU, тоді як LSTM виявили дещо більшу варіативність результатів.

Використання різних початкових фраз для генерації тексту показало, що GRU краще адаптується до семантики контексту, тоді як LSTM частіше генерувала повторювані або менш логічні послідовності.