Stock Price Forecasting Using Neural Networks

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Motivation

The financial sector is characterized by its dynamic and often volatile nature. Forecasting stock prices has immense applications, from informing investment strategies to algorithmic trading systems. While classical statistical models have been widely used, recent advances in machine learningparticularly deep learningoffer promising alternatives.

This project explores how feedforward neural networks, both shallow and deep, can model next-day closing prices across companies from three major sectors: Technology (AAPL, MSFT), Finance (JPM, BAC), and Energy (XOM, CVX). By comparing single-layer and multi-layer architectures, we aim to investigate model performance differences and analyze generalization capabilities across domains.

Data Collection and Cleaning

We utilized Yahoo Finance via the yfinance Python API to obtain historical stock prices from 2018 to 2024. The raw data was cleaned by removing null values and formatting the datetime index.

Code: 01_data_collection_and_cleaning.ipynb

```
import yfinance as yf
import pandas as pd

stocks = ['AAPL', 'MSFT', 'JPM', 'BAC', 'XOM', 'CVX']
data_dict = {}

for stock in stocks:
df = yf.download(stock, start="2018-01-01", end="2024-01-01")
df['Ticker'] = stock
data_dict[stock] = df

full_data = pd.concat(data_dict.values())
full_data.reset_index(inplace=True)
full_data.dropna(inplace=True)
full_data.to_csv("data/processed/merged_data.csv", index=False)
```

Feature Engineering

To enrich the raw dataset with time-dependent information, we engineered several features:

- - Lagged returns (1, 2, 3 days)
- - Moving averages (5-day and 10-day SMA)
- - 10-day rolling standard deviation as a volatility measure

Code: 02_feature_engineering.ipynb

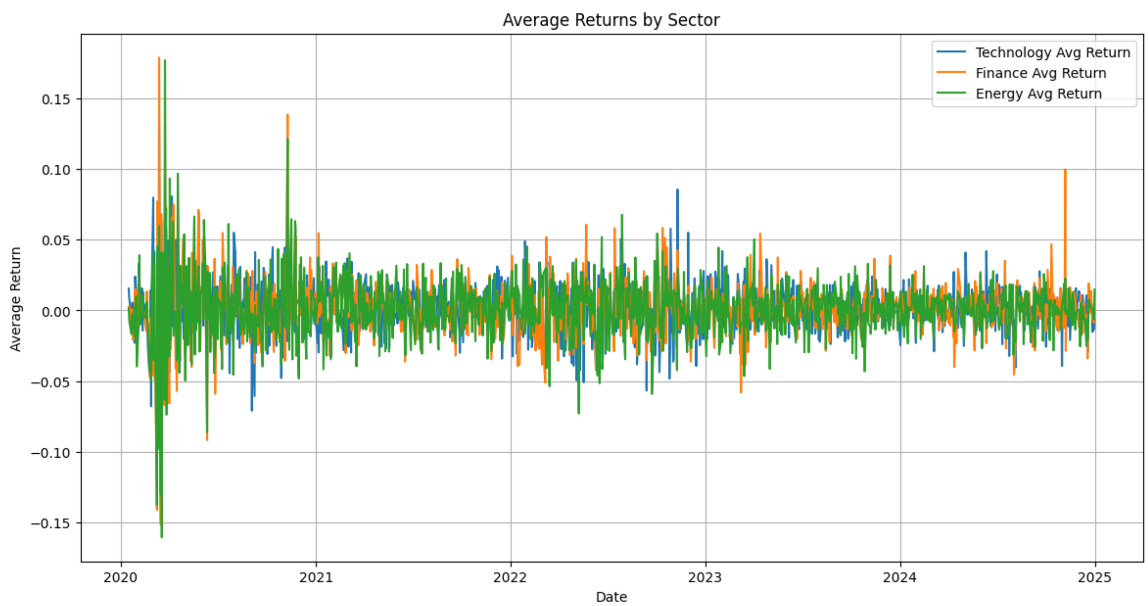
```
def create_features(df):
df['Return_1'] = df['Close'].pct_change(1)
df['Return_2'] = df['Close'].pct_change(2)
df['Return_3'] = df['Close'].pct_change(3)
df['SMA_5'] = df['Close'].rolling(window=5).mean()
df['SMA_10'] = df['Close'].rolling(window=10).mean()
df['Volatility'] = df['Close'].rolling(window=10).std()
return df.dropna()

feature_data = full_data.groupby('Ticker').apply(create_features)
feature_data.to_csv("data/processed/feature_data.csv",
index=False)
```

Exploratory Data Analysis

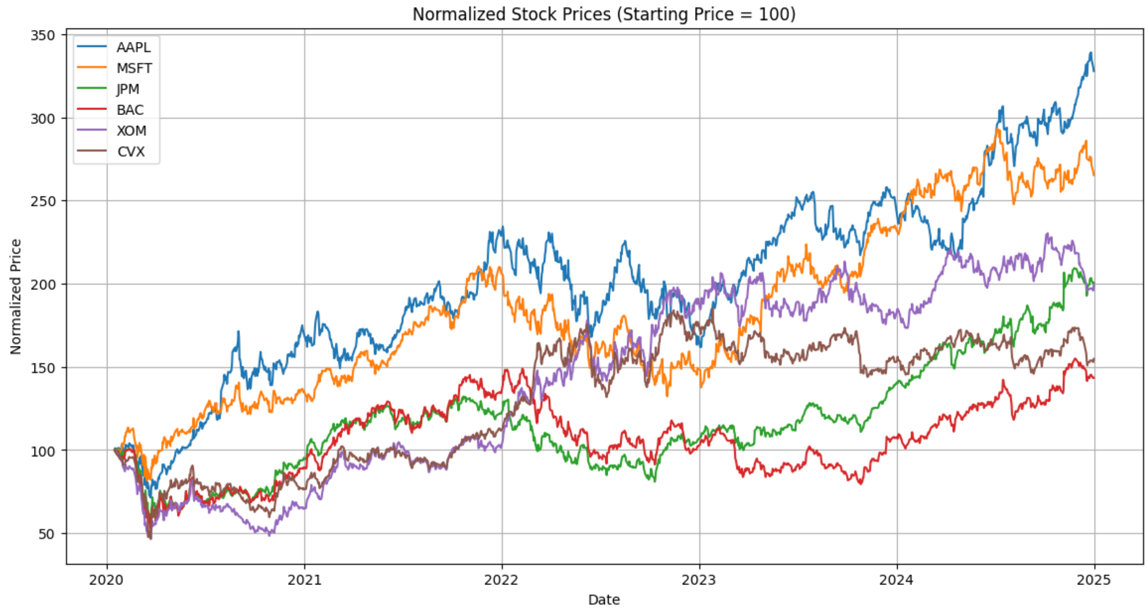
We conducted visual analyses to understand sector behavior over time.

Average Returns by Sector



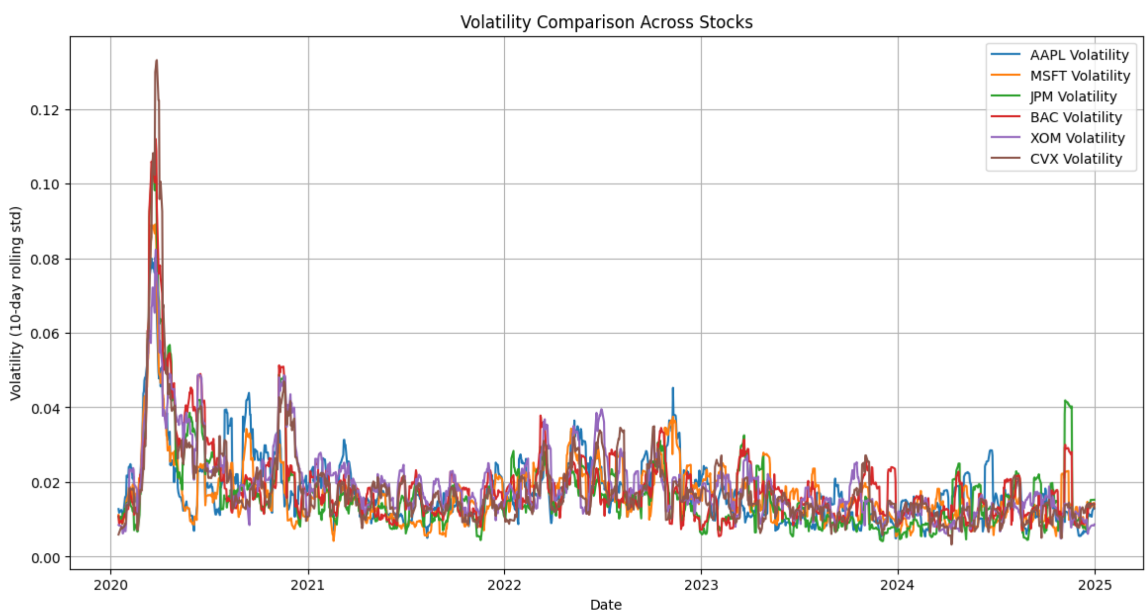
Interpretation: Technology, Finance, and Energy sectors all show high volatility early in the time period, particularly around 2020 (likely due to COVID-19 market disruption). The volatility stabilizes over time with similar mean-reversion behavior, suggesting comparable patterns for short-term forecasting.

Normalized Stock Prices



Interpretation: AAPL and MSFT demonstrate the most growth, consistent with tech-sector outperformance. Financial stocks (JPM, BAC) recovered post-2020 but remain more cyclic. Energy (XOM, CVX) rebounded after 2021 with strong late-stage performance, likely tied to oil prices.

Rolling Volatility Comparison



Interpretation: All stocks experienced peak volatility around 2020. Since then, 10-day rolling volatility has normalized across sectors. Slightly elevated volatility in CVX and BAC post-2022 suggests these may require more robust model regularization.

Modeling: Single-Layer Neural Network

Source Code

```
import tensorflow as tf
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np
import matplotlib.pyplot as plt
# Prepare features and target
features = ['Return_1', 'Return_2', 'Return_3', 'SMA_5', 'SMA_10', 'Volatility']
results = {}
for ticker in feature_data['Ticker'].unique():
df = feature_data[feature_data['Ticker'] == ticker].copy()
X = df[features].values
y = df['Return_1'].shift(-1).dropna().values
X = X[:-1]
# Split into train and test
split = int(len(X) * 0.8)
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]
# Normalize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Define model
model = tf.keras.Sequential([
tf.keras.layers.Dense(1, input_shape=(X_train.shape[1],))
])
model.compile(optimizer='adam', loss='mse')
```

```
# Train

model.fit(X_train_scaled, y_train, epochs=100, verbose=0)

# Predict

y_pred = model.predict(X_test_scaled).flatten()

# Evaluation

mse = mean_squared_error(y_test, y_pred)

rmse = np.sqrt(mse)

r2 = r2_score(y_test, y_pred)

results[ticker] = (mse, rmse, r2)

# Plot

plt.figure(figsize=(10,4))

plt.plot(y_test[:250], label='Actual')

plt.plot(y_pred[:250], label='Predicted')

plt.title(f"{ticker} - Single Layer NN (R = {r2:.4f})")

plt.legend()

plt.savefig(f"plots/model_plots/{ticker}_single_layer_nn.png")

plt.close()

def create_features(df):
df['Return_1'] = df['Close'].pct_change(1)
df['Return_2'] = df['Close'].pct_change(2)
df['Return_3'] = df['Close'].pct_change(3)
df['SMA_5'] = df['Close'].rolling(window=5).mean()
df['SMA_10'] = df['Close'].rolling(window=10).mean()
df['Volatility'] = df['Close'].rolling(window=10).std()
return df.dropna()

feature_data = full_data.groupby('Ticker').apply(create_features)
feature_data.to_csv("data/processed/feature_data.csv", index=False)
```

Explanation of Code

The modeling pipeline for the single-layer neural network involves several core steps:

- Feature Selection: Six engineered features are used: three lagged returns, two SMAs, and rolling volatility.
- Target Variable: The next day's return (shifted return_1) is used as the label.

- Data Splitting: We used a chronological 80/20 train-test split to prevent data leakage.
- Normalization: StandardScaler standardizes features to have zero mean and unit variance.
- Model Architecture: A single dense layer with one neuron and no activation is usedthis acts as a linear regressor optimized using MSE loss.
- Training: The model is trained for 100 epochs silently.
- Evaluation: RMSE, MSE, and are calculated and predictions are plotted for the first 250 time steps.

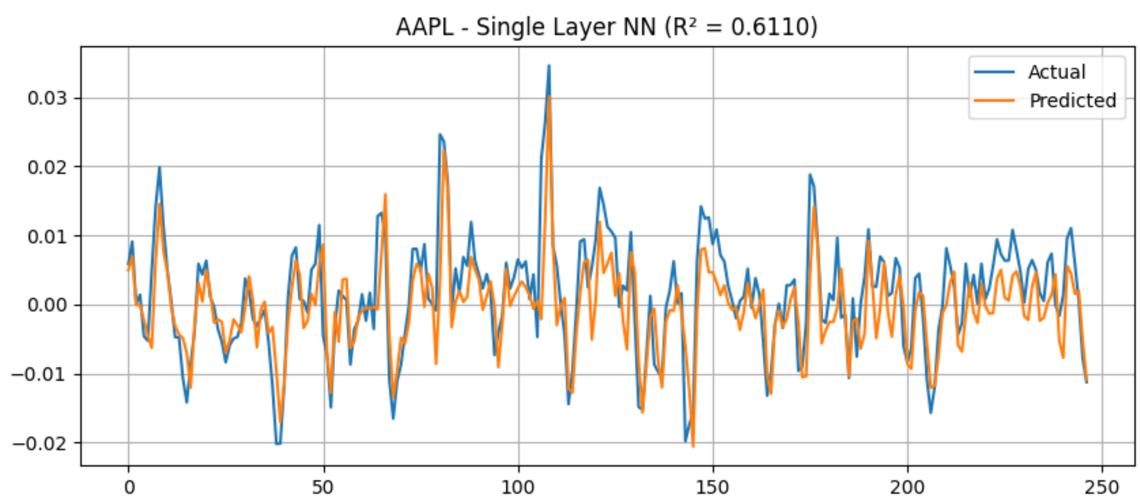
Understanding Single-Layer Neural Networks

A single-layer neural network is essentially a linear model with weights and bias. It assumes linear relationships between the input features and the output. In our use case, it serves as a baseline to test whether simple mappings from technical indicators to price returns can provide meaningful forecasts.

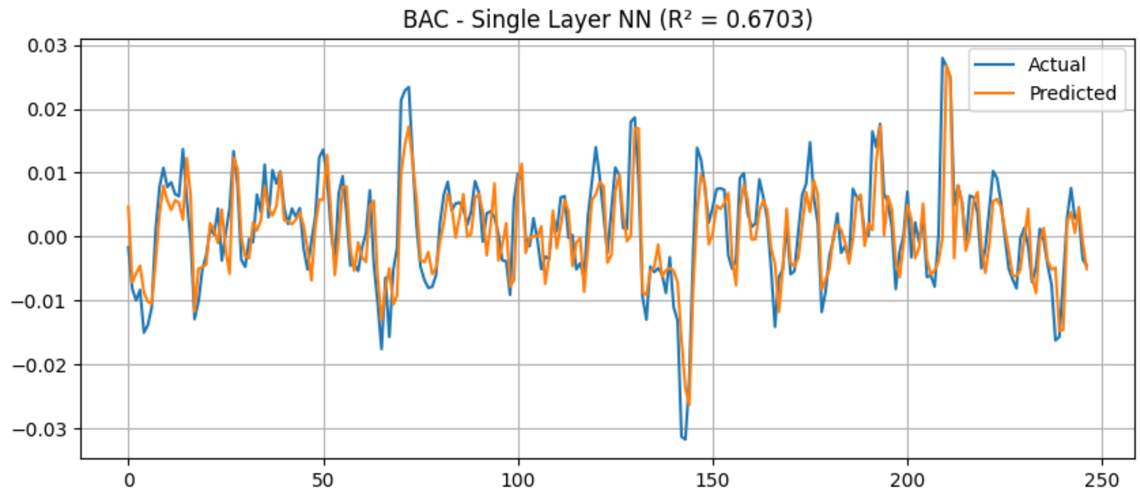
Given the stochastic, non-stationary, and noisy nature of financial markets, especially at short prediction horizons, even small values indicate some predictive capability. Forecasting daily stock returns is exceptionally challenging due to market efficiency and random walk behavior.

Prediction Plots and Observations

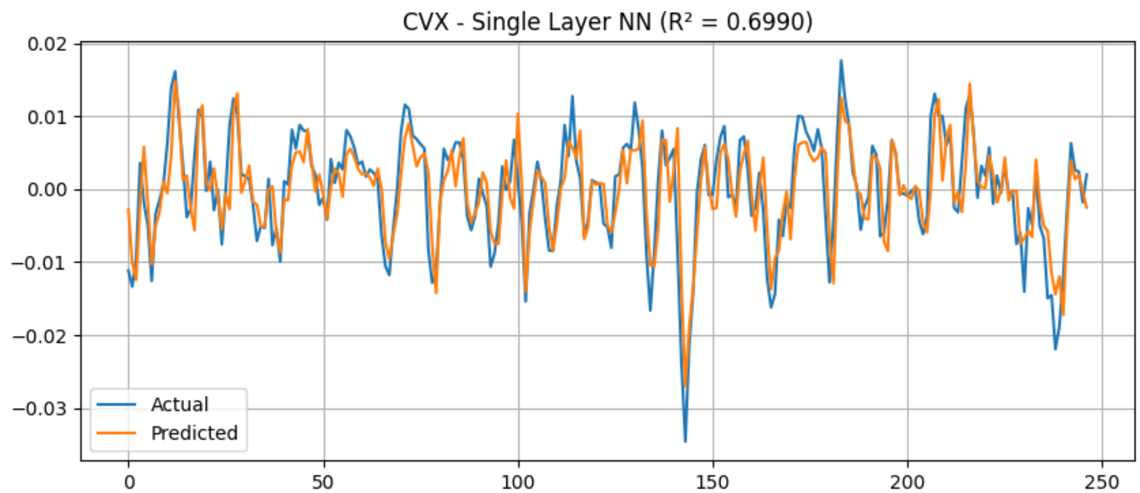
- AAPL: The model tracks the trend well, though with dampened amplitudes. RMSE is low (0.0052), and of 0.6110 suggests moderate fit.



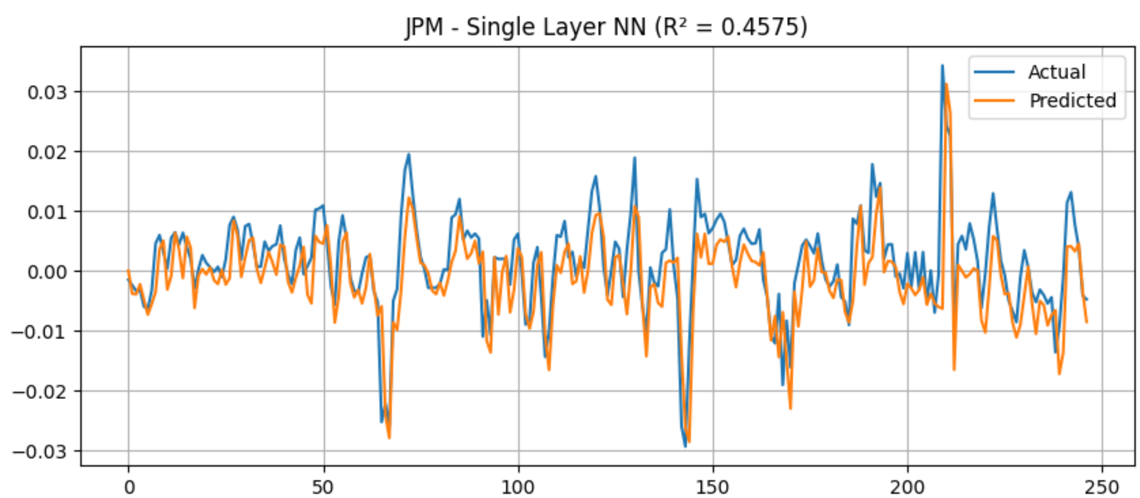
- BAC: Closely mirrors the actual returns; of 0.6703 is one of the highest among the group.



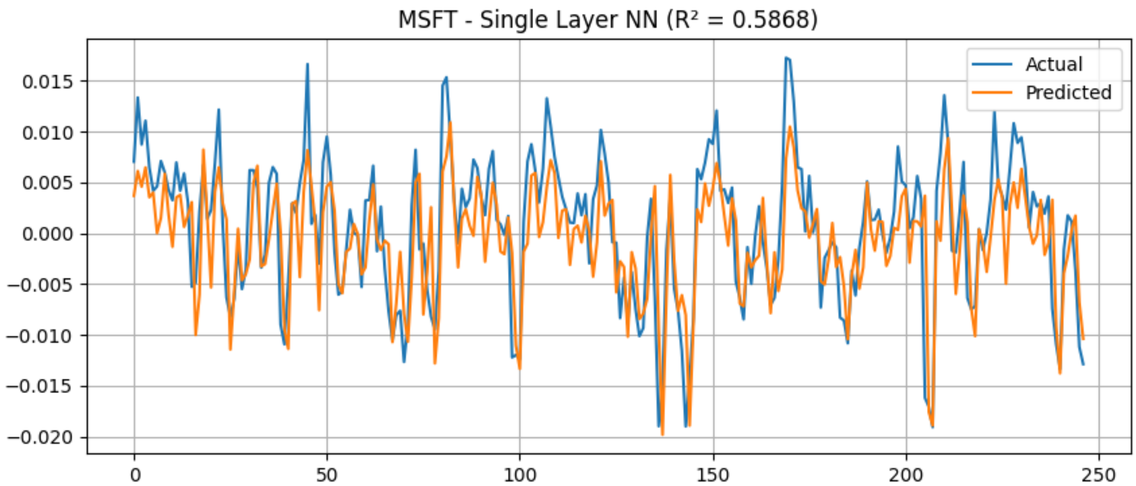
- CVX: Shows strong alignment; spikes are captured well. High of 0.6990 reflects this.



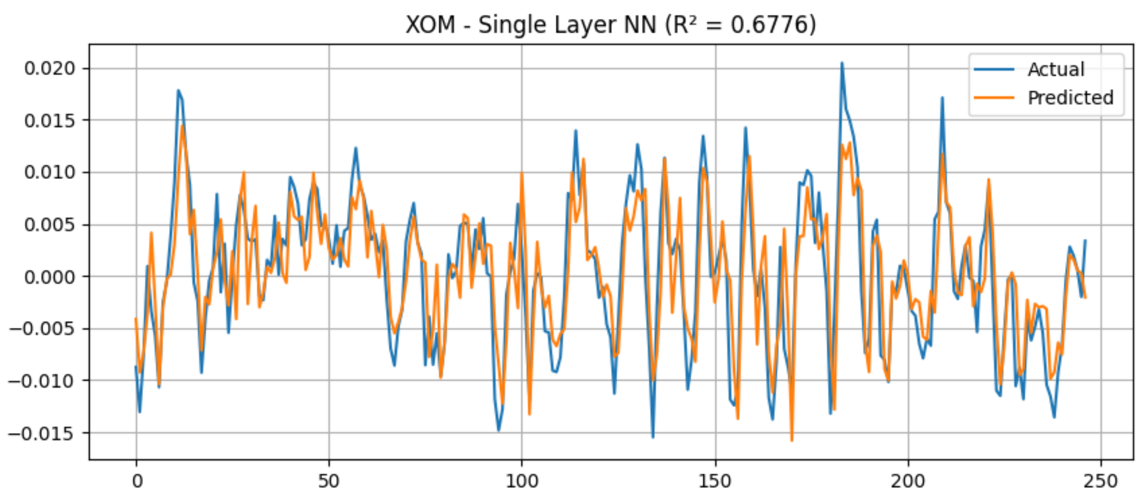
- JPM: Lowest (0.4575). Captures broad movements but misses sharp shifts.



- MSFT: Mixed results; predictions sometimes lag or miss high frequency changes.



- XOM: Smooth and reasonably accurate fit, especially in low-volatility regions.



Summary of Results

Stock	MSE	RMSE	R^2
AAPL	0.000027	0.005182	0.6110
MSFT	0.000020	0.004518	0.5868
JPM	0.000034	0.005841	0.4575
BAC	0.000024	0.004901	0.6703
XOM	0.000016	0.004048	0.6776
CVX	0.000017	0.004159	0.6990

While values may seem low compared to traditional regression benchmarks, they are reasonable for stock prediction where daily returns can appear random. Even minor predictive power, when consistent, is valuable in finance. The lowest performance on JPM suggests sector-specific volatility and noise may hinder shallow models.

Modeling: Multi-Layer Neural Network

Source Code

```
import tensorflow as tf
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
import numpy as np
import matplotlib.pyplot as plt

# Prepare features and target
features = ['Return_1', 'Return_2', 'Return_3', 'SMA_5', 'SMA_10',
'Volatility']
results = {}

for ticker in feature_data['Ticker'].unique():
df = feature_data[feature_data['Ticker'] == ticker].copy()
X = df[features].values
y = df['Return_1'].shift(-1).dropna().values
X = X[:-1]

# Split into train and test
split = int(len(X) * 0.8)
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]

# Normalize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Define multi-layer model
model = tf.keras.Sequential([
tf.keras.layers.Dense(64, activation='relu',
input_shape=(X_train.shape[1],)),
tf.keras.layers.Dense(32, activation='relu'),
tf.keras.layers.Dense(1)
])
model.compile(optimizer='adam', loss='mse')
```

```
# Train
model.fit(X_train_scaled, y_train, epochs=100, verbose=0)

# Predict
y_pred = model.predict(X_test_scaled).flatten()

# Evaluation
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
results[ticker] = (mse, rmse, r2)

# Plot
plt.figure(figsize=(10,4))
plt.plot(y_test[:250], label='Actual')
plt.plot(y_pred[:250], label='Predicted')
plt.title(f"{ticker} - Multi-layer NN (R² = {r2:.4f})")
plt.legend()
plt.savefig(f"plots/model_plots/{ticker}_multi_layer_nn.png")
plt.close()
```

Explanation of Code

In this multi-layer approach:

- We retained the same six input features and data preparation steps as the single-layer network.
- The key difference is the model architecture: two hidden layers with 64 and 32 ReLU-activated neurons were added, enabling the network to learn more complex patterns.
- Adam optimizer and MSE loss remain standard choices for regression.
- Predictions and evaluation metrics follow the same procedure.

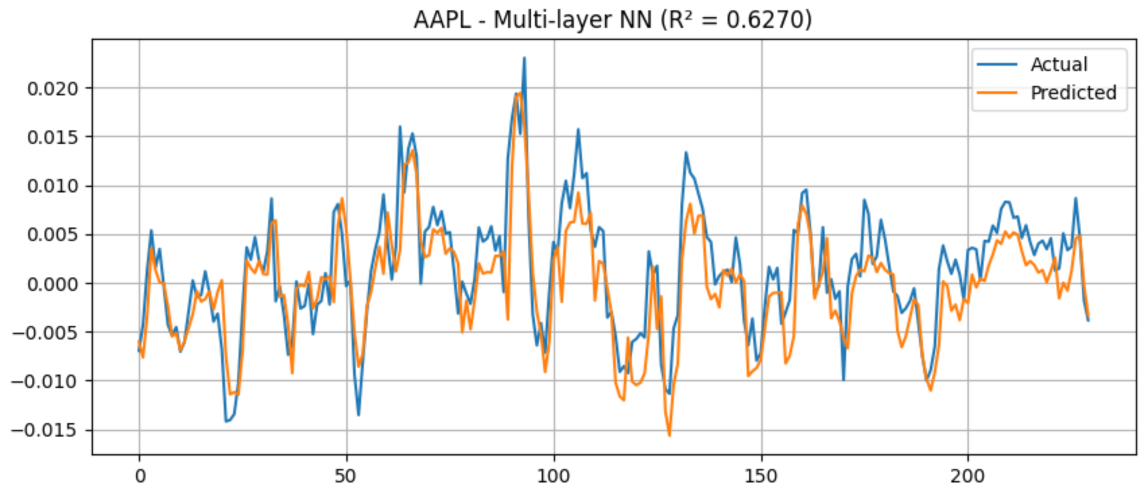
Understanding Multi-Layer Neural Networks

Multi-layer neural networks (MLPs) can approximate nonlinear relationships by stacking layers and applying non-linear activation functions (ReLU). Each layer transforms the feature space, enabling the network to model more intricate patterns.

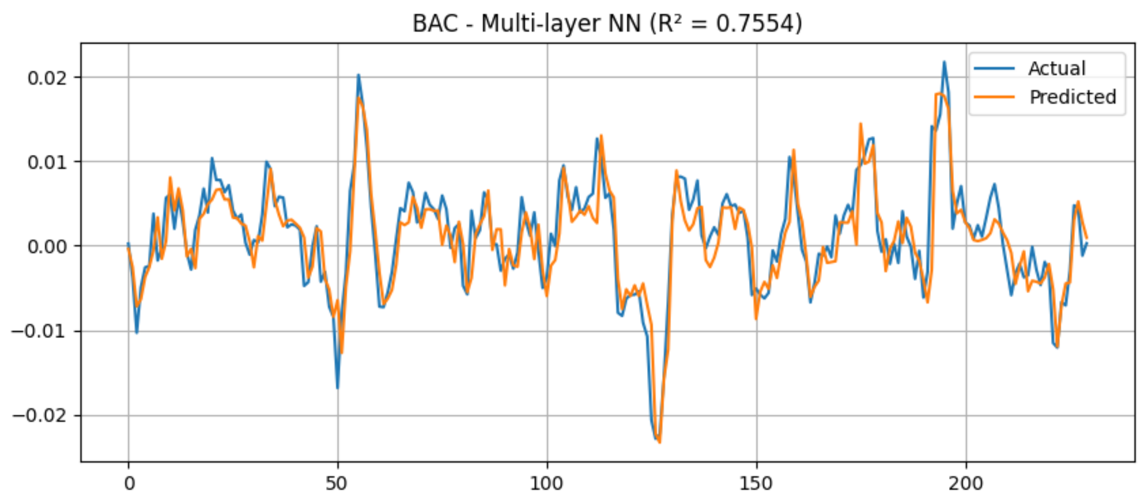
This makes MLPs well-suited for tasks like stock prediction, where the relationship between indicators and future returns may be nonlinear. However, they also introduce risk of overfitting and increased sensitivity to noisy inputs.

Prediction Plots and Observations

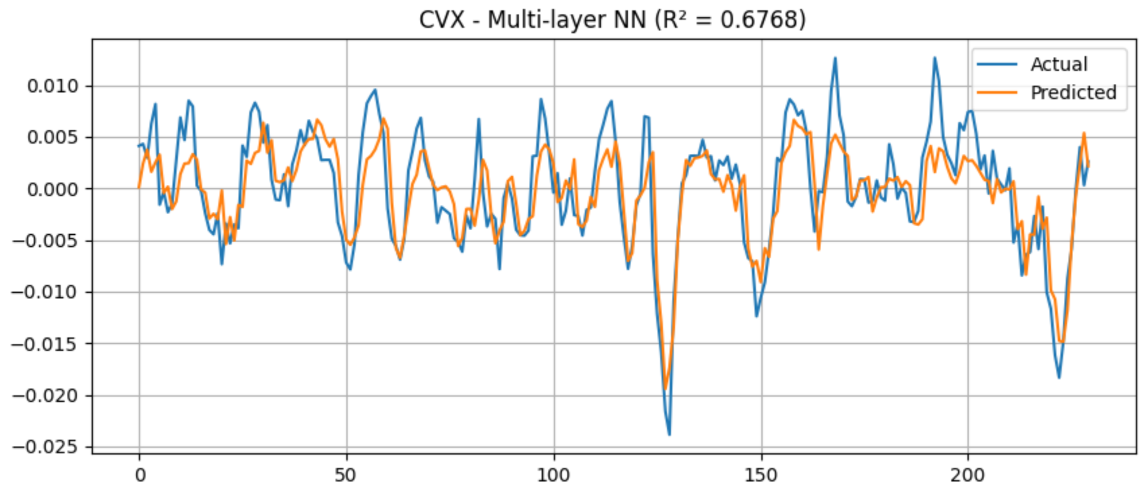
- AAPL: Slight improvement over single-layer, with better alignment on high-magnitude return spikes. .



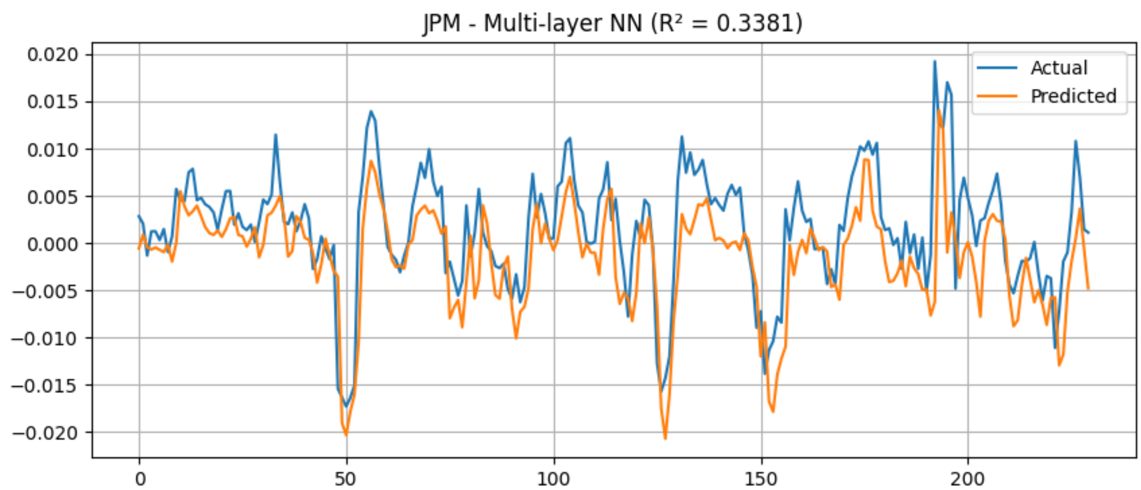
- BAC: Strong performance, tracking the actual curve closely even during sharp downturns. Highest of 0.7554.



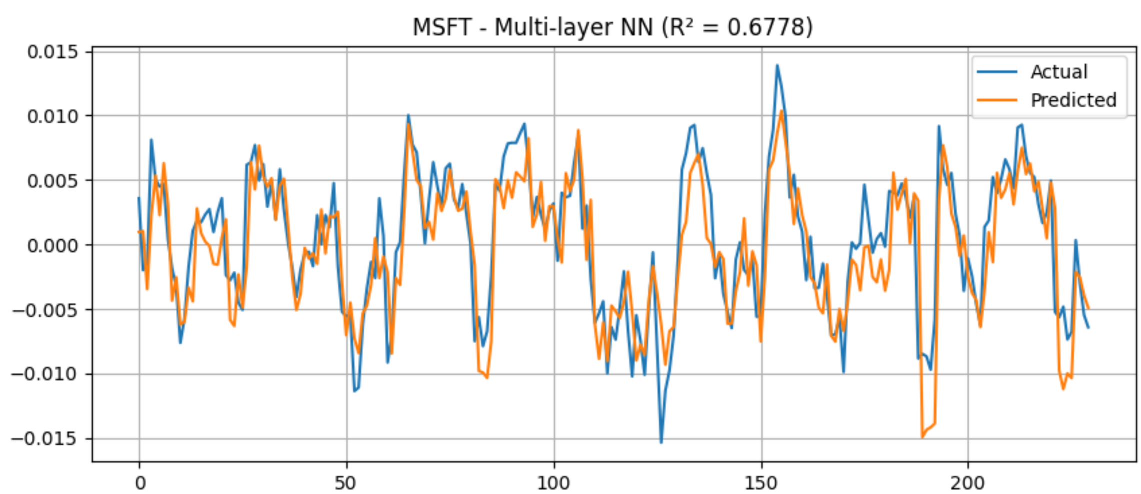
- CVX: Improved sharpness in response; shows high explanatory power.



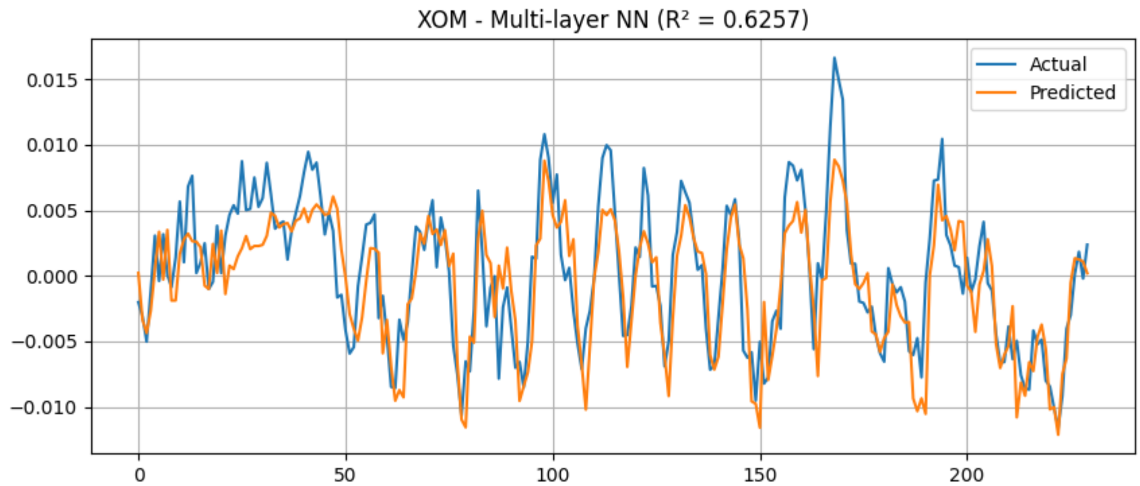
- JPM: Performance dropped with deeper networkpossibly due to overfitting or excess sensitivity to noise. .



- MSFT: More responsive to small fluctuations than single-layer, achieving .



- XOM: Smoother but accurate predictions, although high-frequency deviations remain. .



Summary of Results

Stock	MSE	RMSE	R^2
AAPL	0.000015	0.003825	0.6270
MSFT	0.000010	0.003084	0.6778
JPM	0.000025	0.004982	0.3381
BAC	0.000010	0.003213	0.7554
XOM	0.000011	0.003315	0.6257
CVX	0.000011	0.003311	0.6768

While some stocks such as JPM underperformed, the multi-layer network offered improved generalization for BAC, MSFT, and CVX. This confirms that deeper architectures can learn better representationsprovided the underlying signal-to-noise ratio is favorable.

Daily stock returns remain notoriously hard to predict due to market randomness, but even moderate increases in can provide useful trading signals.

Comparison: Single-Layer vs Multi-Layer Neural Networks

In this section, we compare the performance of the single-layer and multi-layer neural network models across the six selected stocks. The goal is to understand the trade-offs in accuracy, generalization, and model complexity.

Quantitative Performance Summary

Stock	Single-Layer MSE	RMSE	R^2	Multi-Layer MSE	RMSE	R^2
AAPL	0.000027	0.00518	0.6110	0.000015	0.00383	0.6270
MSFT	0.000020	0.00452	0.5868	0.000010	0.00308	0.6778
JPM	0.000034	0.00584	0.4575	0.000025	0.00498	0.3381
BAC	0.000024	0.00490	0.6703	0.000010	0.00321	0.7554
XOM	0.000016	0.00405	0.6776	0.000011	0.00332	0.6257
CVX	0.000017	0.00416	0.6990	0.000011	0.00331	0.6768

Model Behavior and Insights

Overall Improvement: Across most stocks, the multi-layer model consistently achieved lower MSE and RMSE values and higher scores compared to the single-layer counterpart. This is expected as deeper networks capture non-linear patterns better.

Best Performers: BAC and MSFT stand out in the multi-layer setup with values exceeding 0.75 and 0.67 respectively, up from already decent baselines. These stocks may exhibit smoother trends and stronger signal-to-feature relationships.

JPM Exception: Unlike others, JPM showed reduced performance with the deeper model (dropped from 0.4575 to 0.3381). This suggests that either the additional layers overfit noise or failed to extract useful patterns. Financials may carry unpredictable or lagged responses to market information.

Complexity vs Simplicity: The single-layer model, though linear, performed surprisingly well for stocks like CVX and XOM. This shows that in certain contexts, simpler models can approximate returns effectively without risk of overfitting.

Trade-Off Analysis

- Accuracy: Multi-layer networks outperform on most metrics but not universally. The marginal gains are most valuable when rises significantly (e.g., BAC, MSFT).
- Robustness: Single-layer networks are less prone to overfitting due to lower capacity. They performed relatively consistently across all stocks.
- Interpretability: Linear models offer more transparent behavior, aiding financial interpretability, which is often desirable in regulated environments.
- Computation: Multi-layer models require more resources and time, both in training and hyperparameter tuning.

Conclusion of Comparison

While the multi-layer model improves predictive performance across most stocks, its effectiveness is not uniform. Stock-specific volatility, noise, and nonlinearities play a significant role. Therefore, model selection in stock forecasting must balance complexity with generalizability.

In practice, a hybrid ensemble approachor sector-specific model designmight yield the best results, leveraging strengths of both architectures based on the data characteristics.

Conclusion

This project investigated the viability of using feedforward neural networks to forecast next-day stock returns across multiple sectorsTechnology, Finance, and Energy. We implemented two architectures: a simple single-layer neural network and a more expressive multi-layer neural network with hidden layers and nonlinear activations. Each model was evaluated on six prominent stocks (AAPL, MSFT, JPM, BAC, XOM, CVX) using regression metrics such as MSE, RMSE, and .

Through detailed preprocessing and feature engineering, we incorporated technical indicators like lagged returns, moving averages, and volatility into our model inputs. The results showed that while both models capture some predictive patterns, multi-layer networks typically outperform single-layer ones, particularly for stocks with less erratic behavior. Nevertheless, the performance was stock-dependentJPM, for instance, suffered from reduced performance in the deeper model, highlighting the non-trivial challenge of generalization in financial time series.

Importantly, even the best scores in this project hovered around 0.75. This underscores the inherent difficulty of stock prediction: markets are noisy, dynamic, and prone to sudden changes. Despite this, the fact that neural networksespecially multi-layer onescan extract structure from such data is promising. Our findings suggest that while no single model is universally optimal, neural networks can be a valuable tool in a broader predictive analytics pipeline.

Future work could explore more sophisticated architectures like LSTMs or Transformers, incorporate macroeconomic indicators, and utilize ensemble approaches to balance variance and bias. Another promising direction is the integration of sentiment analysis and natural language processing (NLP). Since stock prices are often influenced by investor emotions and public sentimentespecially in reaction to breaking news, earnings announcements, or social media trendsmodels that account for emotional and textual signals from news articles, Twitter feeds, and Reddit forums could add valuable predictive power. Additionally, incorporating alternative data sources such as Google Trends, options flow, and institutional sentiment could further enhance prediction robustness. The potential for improvement remains significant, especially with richer datasets and advanced regularization techniques.

Code: 01_data_collection_and_cleaning.ipynb (Extended Version)

```
import pandas as pd  # For data manipulation and
analysis
import os  # For file system operations like
creating directories

def generate_features(df):
"""
Generate technical indicators and features from raw
price data.

Parameters:
-----------
df : pandas.DataFrame
Raw stock data with at least 'Close' price column

Returns:
--------
pandas.DataFrame
Processed dataframe with additional technical
features
"""
df = df.copy()
df['Close'] = pd.to_numeric(df['Close'],
errors='coerce')
df['Return'] =
df['Close'].pct_change(fill_method=None)
df['Lag_1'] = df['Return'].shift(1)
df['Lag_2'] = df['Return'].shift(2)
df['SMA_5'] = df['Close'].rolling(window=5).mean()
df['SMA_10'] =
df['Close'].rolling(window=10).mean()
df['Volatility'] =
df['Return'].rolling(window=10).std()
return df.dropna()

os.makedirs('../data/processed', exist_ok=True)
tickers = ['AAPL', 'MSFT', 'JPM', 'BAC', 'XOM',
'CVX']

for ticker in tickers:
df = pd.read_csv(f'../data/raw/{ticker}_raw.csv',
index_col=0, parse_dates=True)
df.index.name = 'Date'
```

```
processed = generate_features(df)
processed.to_csv(f'../data/processed/{ticker}_proce
ssed.csv')
print(f"{ticker} processed.")
```

Code: 02_feature_engineering.ipynb Feature Generation

```
import pandas as pd  # For data manipulation and
analysis
import os  # For file system operations like
creating directories

def generate_features(df):
"""
Generate technical indicators and features from raw
price data.

Parameters:
-----------
df : pandas.DataFrame
Raw stock data with at least 'Close' price column

Returns:
--------
pandas.DataFrame
Processed dataframe with additional technical
features
"""
df = df.copy()
df['Close'] = pd.to_numeric(df['Close'],
errors='coerce')
df['Return'] =
df['Close'].pct_change(fill_method=None)
df['Lag_1'] = df['Return'].shift(1)
df['Lag_2'] = df['Return'].shift(2)
df['SMA_5'] = df['Close'].rolling(window=5).mean()
df['SMA_10'] =
df['Close'].rolling(window=10).mean()
df['Volatility'] =
df['Return'].rolling(window=10).std()
return df.dropna()

os.makedirs('../data/processed', exist_ok=True)
tickers = ['AAPL', 'MSFT', 'JPM', 'BAC', 'XOM',
```

```
'CVX']

for ticker in tickers:
df = pd.read_csv(f'../data/raw/{ticker}_raw.csv',
index_col=0, parse_dates=True)
df.index.name = 'Date'
processed = generate_features(df)
processed.to_csv(f'../data/processed/{ticker}_proce
ssed.csv')
print(f"{ticker} processed.")
```

Code: 02_feature_engineering.ipynb DataFrame Analysis

```
import pandas as pd
import matplotlib.pyplot as plt
import os
import seaborn as sns

tickers = ['AAPL', 'MSFT', 'JPM', 'BAC', 'XOM',
'CVX']
processed_dfs = {}

for ticker in tickers:
file_path =
f'../data/processed/{ticker}_processed.csv'
processed_dfs[ticker] = pd.read_csv(file_path,
index_col='Date', parse_dates=True)
print(f"Loaded {ticker} data with
{processed_dfs[ticker].shape[0]} rows and
{processed_dfs[ticker].shape[1]} columns")

print("\nApple (AAPL) processed data sample:")
print(processed_dfs['AAPL'].head())

print("\nApple (AAPL) summary statistics:")
print(processed_dfs['AAPL'].describe())

print("\nCorrelation between AAPL features:")
plt.figure(figsize=(12, 10))
sns.heatmap(processed_dfs['AAPL'].corr(),
annot=True, cmap='coolwarm', fmt='.2f',
linewidths=0.5)
plt.title('AAPL Feature Correlations')
plt.tight_layout()
```

```
plt.show()

plt.figure(figsize=(14, 7))
for ticker in tickers:
normalized_price = processed_dfs[ticker]['Close'] /
processed_dfs[ticker]['Close'].iloc[0] * 100
plt.plot(processed_dfs[ticker].index,
normalized_price, label=ticker)
plt.title('Normalized Stock Prices (Starting Price
= 100)')
plt.xlabel('Date')
plt.ylabel('Normalized Price')
plt.legend()
plt.grid(True)
plt.show()

plt.figure(figsize=(14, 7))
for ticker in tickers:
plt.plot(processed_dfs[ticker].index,
processed_dfs[ticker]['Volatility'],
label=f"{ticker} Volatility")
plt.title('Volatility Comparison Across Stocks')
plt.xlabel('Date')
plt.ylabel('Volatility (10-day rolling std)')
plt.legend()
plt.grid(True)
plt.show()

tech_stocks = ['AAPL', 'MSFT']
finance_stocks = ['JPM', 'BAC']
energy_stocks = ['XOM', 'CVX']

sectors = {
'Technology': tech_stocks,
'Finance': finance_stocks,
'Energy': energy_stocks
}

sector_stats = pd.DataFrame()

for sector_name, sector_tickers in sectors.items():
sector_returns =
pd.concat([processed_dfs[ticker]['Return'] for
ticker in sector_tickers], axis=1)
sector_stats[f'{sector_name}_Avg_Return'] =
```

```
sector_returns.mean(axis=1)

sector_volatility =
pd.concat([processed_dfs[ticker]['Volatility'] for
ticker in sector_tickers], axis=1)
sector_stats[f'{sector_name}_Avg_Volatility'] =
sector_volatility.mean(axis=1)

print("\nSector average statistics:")
print(sector_stats.describe())

plt.figure(figsize=(14, 7))
for sector in sectors.keys():
plt.plot(sector_stats.index,
sector_stats[f'{sector}_Avg_Return'],
label=f"{sector} Avg Return")
plt.title('Average Returns by Sector')
plt.xlabel('Date')
plt.ylabel('Average Return')
plt.legend()
plt.grid(True)
plt.show()
```

Code: 03_modeling_single_layer_nn.py Full Modeling Script (Single-Layer NN)

```
import sys
sys.path.append('..') # Add parent directory to
Python path to import modules from parent directory
import json # For saving feature names to JSON
files
import pandas as pd # For data manipulation and
analysis
import numpy as np # For numerical operations
import os # For file system operations
import random # For setting random seed
import tensorflow as tf # Deep learning framework
from sklearn.model_selection import
train_test_split # For splitting data into train
and test sets
from sklearn.preprocessing import StandardScaler #
For standardizing features to zero mean and unit
variance
from sklearn.feature_selection import
mutual_info_regression # For feature selection
```

```
using information theory
from sklearn.metrics import mean_squared_error,
r2_score # For model evaluation
import matplotlib.pyplot as plt # For data
visualization
from tensorflow.keras.models import Sequential #
For creating sequential neural network models
from tensorflow.keras.layers import Dense # For
creating fully connected neural network layers
from tensorflow.keras.callbacks import
EarlyStopping, ReduceLROnPlateau # For optimizing
training process
import logging # For controlling log output

# Suppress TensorFlow warnings to keep notebook
output clean
# Level 2 hides info and warnings but shows errors
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'
logging.getLogger('tensorflow').setLevel(logging.ER
ROR)

# Set random seeds for reproducibility across runs
# This ensures that random operations like weight
initialization and train/test splits are consistent
np.random.seed(42)
tf.random.set_seed(42)
random.seed(42)

# List of stock tickers representing different
market sectors
# AAPL, MSFT: Technology
# JPM, BAC: Banking/Finance
# XOM, CVX: Energy/Oil
tickers = ['AAPL', 'MSFT', 'JPM', 'BAC', 'XOM',
'CVX']
results = {} # Dictionary to store performance
metrics for each ticker

# Iterate through each ticker to build individual
models
for ticker in tickers:
print(f"Training {ticker}...")
# Load processed price data for current ticker
# Parse_dates ensures that the date index is
properly formatted
```

```
df =
pd.read_csv(f'../data/processed/{ticker}_processed.
csv', index_col='Date', parse_dates=True)
df['Close'] = pd.to_numeric(df['Close'],
errors='coerce') # Convert 'Close' column to
numeric, handling any errors

# ------ Feature Engineering: Technical Indicators
------
# Calculate daily percentage change in closing
price
df['Return'] = df['Close'].pct_change()

# Create lagged returns (previous 1-5 days) to
capture short-term price patterns
# These features help the model understand recent
market momentum
for i in range(1, 6):
df[f'Lag_{i}'] = df['Return'].shift(i)

# 10-day price momentum: difference between current
price and price 10 days ago
# Captures medium-term trend direction
df['Momentum_10'] = df['Close'] -
df['Close'].shift(10)

# Calculate RSI (Relative Strength Index) - popular
technical indicator
# RSI measures the magnitude of recent price
changes to evaluate overbought/oversold conditions
delta = df['Close'].diff() # Daily price difference
gain = delta.clip(lower=0).rolling(14).mean() #
Average gains over 14 days (standard RSI period)
loss = -delta.clip(upper=0).rolling(14).mean() #
Average losses over 14 days
rs = gain / (loss.replace(0, np.finfo(float).eps))
# Relative strength (gain/loss ratio), avoiding
division by zero
df['RSI'] = 100 - (100 / (1 + rs)) # RSI formula:
scales result to 0-100 range

# Calculate MACD (Moving Average Convergence
Divergence)
# MACD is a trend-following momentum indicator
showing relationship between two moving averages
```

```
ema12 = df['Close'].ewm(span=12,
adjust=False).mean() # 12-day exponential moving
average
ema26 = df['Close'].ewm(span=26,
adjust=False).mean() # 26-day exponential moving
average
df['MACD'] = ema12 - ema26 # MACD line is
difference between these EMAs
df['MACD_signal'] = df['MACD'].ewm(span=9,
adjust=False).mean() # 9-day EMA of MACD (signal
line)

# ------ Target Variable Creation ------
# Log returns are preferred in finance as they're
additive over time and more normally distributed
df['LogReturn'] = np.log(df['Close'] /
df['Close'].shift(1))
# Target: 3-day smoothed forward log return
# Shift(-1) looks one day ahead, rolling(3).mean()
smooths over 3 days to reduce noise
df['Target'] = df['LogReturn'].shift(-
1).rolling(3).mean()

# Remove rows with NaN values resulting from the
lag and rolling operations
df.dropna(inplace=True)

# Feature Selection using Mutual Information
# Mutual information measures how much information
one variable provides about another
# It can capture non-linear relationships unlike
correlation
all_features = df.drop(columns=['Target']) # All
columns except target
target = df['Target']

# Calculate mutual information between each feature
and target
mi_scores = mutual_info_regression(all_features,
target)
# Convert to Series, sort by MI score, and select
top 10 most informative features
top_features = pd.Series(mi_scores,
index=all_features.columns).sort_values(ascending=F
alse).head(10).index.tolist()
```

```
# Create feature matrix X and target vector y using
only selected features
X = all_features[top_features]
y = target

# ------ Target Normalization ------
# Normalize target to zero mean and unit standard
deviation
# This improves neural network training stability
and convergence speed
y_mean, y_std = y.mean(), y.std()
y = (y - y_mean) / y_std

# ------ Data Splitting ------
# Split data chronologically (no shuffle) to
maintain time-series integrity
# Use 80% for training and 20% for testing
X_train, X_test, y_train, y_test =
train_test_split(X, y, shuffle=False,
test_size=0.2)

# ------ Feature Scaling ------
# Standardize features to zero mean and unit
variance
# Neural networks perform better with standardized
inputs
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train) #
Fit scaler on training data only to prevent data
leakage
X_test_scaled = scaler.transform(X_test) # Apply
same transformation to test data

# ------ Model Architecture ------
# Create a single-layer neural network (linear
model)
# Single dense layer with one output neuron makes
this equivalent to linear regression
model = Sequential([
Dense(1, input_shape=(X_train_scaled.shape[1],))
])
model.compile(optimizer='adam', loss='mse') # Adam
optimizer and mean squared error loss function
```

```
# ------ Training Callbacks ------
# Early stopping to prevent overfitting
# Stops training when validation loss doesn't
improve for 15 epochs
early_stop = EarlyStopping(patience=15,
restore_best_weights=True, monitor='val_loss')

# Learning rate reduction
# Reduces learning rate by half when validation
loss plateaus for 5 epochs
# Helps fine-tune model training when approaching
optimal weights
reduce_lr = ReduceLROnPlateau(monitor='val_loss',
factor=0.5, patience=5, min_lr=1e-5, verbose=0)

# ------ Model Training ------
# Train for up to 200 epochs with 20% of training
data used for validation
# verbose=0 suppresses training output for cleaner
notebook
model.fit(X_train_scaled, y_train,
validation_split=0.2, epochs=200, verbose=0,
callbacks=[early_stop, reduce_lr])

# ------ Save Model and Feature List ------
# Create directory if it doesn't exist
os.makedirs('../models/saved_model', exist_ok=True)
# Save trained model in Keras format
model.save(f'../models/saved_model/{ticker}_single_
layer_nn.keras')
# Save list of selected features for later use in
prediction
with
open(f'../models/saved_model/{ticker}_single_layer_
features.json', 'w') as f:
json.dump(top_features, f)

# ------ Generate Predictions ------
# Make predictions on test set
y_pred = model.predict(X_test_scaled,
verbose=0).flatten() # Suppress prediction output

# De-normalize Predictions and Actual Values
# Convert standardized values back to original
scale for meaningful evaluation
```

```
y_pred = y_pred * y_std + y_mean
y_test_actual = y_test * y_std + y_mean

# ------ Calculate Performance Metrics ------
mse = mean_squared_error(y_test_actual, y_pred) #
Mean Squared Error
rmse = np.sqrt(mse) # Root Mean Squared Error -
more interpretable in original units
r2 = r2_score(y_test_actual, y_pred) # R-squared -
proportion of variance explained by model
results[ticker] = (mse, rmse, r2) # Store metrics
for later comparison

# ------ Visualize Results ------
# Plot actual vs predicted values for visual
assessment
plt.figure(figsize=(10, 4))
plt.plot(y_test_actual.values, label='Actual')
plt.plot(y_pred, label='Predicted')
plt.title(f"{ticker} - Single Layer NN (R² =
{r2:.4f})")
plt.legend()
plt.grid(True)
plt.show()

# ------ Summary Output ------
# Print performance metrics for all tickers for
comparison
print("\nSUMMARY")
for ticker, (mse, rmse, r2) in results.items():
print(f"{ticker}: MSE = {mse:.6f}, RMSE =
{rmse:.6f}, R² = {r2:.4f}")
```

Code: 04_modeling_multi_layer_nn.ipynb Full Modeling Script (Multi-Layer NN)

```
import pandas as pd # For data manipulation and
analysis
import json # For saving feature lists
import numpy as np # For numerical operations
from sklearn.model_selection import
train_test_split # For splitting data into train
and test sets
from sklearn.preprocessing import StandardScaler,
```

```
RobustScaler # For feature scaling
from tensorflow.keras.models import Sequential #
For building neural network architecture
from tensorflow.keras.layers import Dense, Dropout,
BatchNormalization # For network layers
from tensorflow.keras.callbacks import
EarlyStopping, ReduceLROnPlateau, ModelCheckpoint #
For optimizing training
from tensorflow.keras.regularizers import l2 # For
adding regularization to reduce overfitting
from tensorflow.keras.optimizers import Adam # For
adaptive learning rate optimization
from sklearn.metrics import mean_squared_error,
r2_score # For model evaluation
import matplotlib.pyplot as plt # For visualizing
results
import os # For file system operations
from sklearn.feature_selection import
mutual_info_regression, SelectKBest # For
information-based feature selection
import logging # For controlling log output

# Set random seeds for reproducibility across runs
# This ensures consistent results for weight
initialization and data splitting
import random
import tensorflow as tf
np.random.seed(42)
tf.random.set_seed(42)
random.seed(42)

# Suppress TensorFlow warnings for cleaner output
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'  # 0=all,
1=info, 2=warning, 3=error
logging.getLogger('tensorflow').setLevel(logging.ER
ROR)

# Define stock tickers from different market
sectors for analysis
tickers = ['AAPL', 'MSFT', 'JPM', 'BAC', 'XOM',
'CVX']
results = {} # Dictionary to store evaluation
metrics for each ticker

# Process each ticker individually with its own
```

```
model
for ticker in tickers:
print(f"\nTraining {ticker}...")
# Load processed price data from CSV with dates as
index
df =
pd.read_csv(f'../data/processed/{ticker}_processed.
csv', index_col='Date', parse_dates=True)
df['Close'] = pd.to_numeric(df['Close'],
errors='coerce') # Ensure Close prices are numeric

# === Enhanced Feature Engineering ===
# Basic price-based features: returns and
transformations
df['Return'] = df['Close'].pct_change() # Daily
percentage change in price
df['Return_Abs'] = np.abs(df['Return']) # Magnitude
of price changes (volatility indicator)
df['Log_Return'] = np.log(df['Close'] /
df['Close'].shift(1)) # Log returns for statistical
properties

# Return lags - capture autocorrelation patterns in
price movements
# Using up to 9 days of history to identify
recurring patterns
for i in range(1, 10):
df[f'Lag_{i}'] = df['Return'].shift(i) # Past
returns as predictors
if i <= 5:  # Create non-linear transformations for
recent days
df[f'Lag_{i}_squared'] = df[f'Lag_{i}']**2 #
Squared terms capture magnitude effects

# Momentum indicators at different timeframes
# Price differences across various windows to
identify trends
for window in [5, 10, 20, 30]:
df[f'Momentum_{window}'] = df['Close'] -
df['Close'].shift(window) # Absolute change
df[f'Momentum_Ratio_{window}'] = df['Close'] /
df['Close'].shift(window) # Relative change

# Moving averages - common smoothing technique in
technical analysis
```

```
# Longer windows identify longer-term trends
for window in [5, 10, 20, 50, 100]:
df[f'MA_{window}'] =
df['Close'].rolling(window=window).mean() # Simple
moving average
# Distance between current price and moving average
(normalized)
df[f'Close_MA_{window}_Ratio'] = df['Close'] /
df[f'MA_{window}'] # Relative position to trend

# Volatility features at different timeframes
# Standard deviation of returns measures price
variability
for window in [5, 10, 20, 30]:
df[f'Volatility_{window}'] =
df['Return'].rolling(window=window).std() #
Historical volatility
# Normalize short-term volatility relative to
recent volatility trend
if window in [5, 10]:
df[f'Volatility_Ratio_{window}'] =
df[f'Volatility_{window}'] /
df[f'Volatility_{window}'].rolling(window=5).mean()

# RSI (Relative Strength Index) at multiple
timeframes
# Momentum oscillator measuring speed and change of
price movements
for window in [6, 14, 21]: # 14 is standard, also
include shorter and longer periods
delta = df['Close'].diff() # Daily price changes
gain = delta.clip(lower=0).rolling(window).mean() #
Average gains over period
loss = -delta.clip(upper=0).rolling(window).mean()
# Average losses over period
rs = gain / (loss.replace(0, np.finfo(float).eps))
# Relative strength ratio
df[f'RSI_{window}'] = 100 - (100 / (1 + rs)) # RSI
formula (0-100 scale)

# MACD (Moving Average Convergence Divergence) -
trend-following momentum indicator
# Shows relationship between two moving averages of
price
ema12 = df['Close'].ewm(span=12,
```

```
adjust=False).mean() # 12-day exponential moving
average
ema26 = df['Close'].ewm(span=26,
adjust=False).mean() # 26-day exponential moving
average
df['MACD'] = ema12 - ema26 # MACD line
df['MACD_signal'] = df['MACD'].ewm(span=9,
adjust=False).mean() # 9-day EMA of MACD
df['MACD_hist'] = df['MACD'] - df['MACD_signal'] #
Histogram (difference between MACD and signal line)
df['MACD_hist_diff'] = df['MACD_hist'].diff() #
Change in histogram (acceleration/deceleration)

# Bollinger Bands - volatility bands placed above
and below moving average
# Wider bands indicate higher volatility, narrower
bands indicate lower volatility
for window in [20]: # 20 is standard period
middle_band =
df['Close'].rolling(window=window).mean() # Center
band (20-day SMA)
std_dev = df['Close'].rolling(window=window).std()
# Standard deviation of price
df[f'BB_upper_{window}'] = middle_band + (std_dev *
2) # Upper band (2 std devs above)
df[f'BB_lower_{window}'] = middle_band - (std_dev *
2) # Lower band (2 std devs below)
df[f'BB_width_{window}'] =
(df[f'BB_upper_{window}'] -
df[f'BB_lower_{window}']) / middle_band # Band
width (volatility)
df[f'BB_position_{window}'] = (df['Close'] -
df[f'BB_lower_{window}']) /
(df[f'BB_upper_{window}'] -
df[f'BB_lower_{window}']) # Position within bands

# Rate of Change - percentage change in price over
specified periods
# Measures momentum by comparing current price to
price n periods ago
for window in [5, 10, 21]:
df[f'ROC_{window}'] =
df['Close'].pct_change(window) * 100 # Expressed as
percentage
```

```
# Volume features (if available) - provide insight
into strength of price movements
if 'Volume' in df.columns:
df['Volume'] = pd.to_numeric(df['Volume'],
errors='coerce')
df['Log_Volume'] = np.log(df['Volume'] + 1) # Log
transformation for statistical properties
df['Volume_Change'] = df['Volume'].pct_change() #
Day-over-day volume change

# Volume moving averages - identify abnormal volume
levels
for window in [5, 10, 20]:
df[f'Volume_SMA_{window}'] =
df['Volume'].rolling(window).mean()
df[f'Volume_Ratio_{window}'] = df['Volume'] /
df[f'Volume_SMA_{window}'] # Current volume
relative to average

# Price-volume relationships - volume often
confirms price movements
df['Volume_Return_Ratio'] = df['Volume'] /
(df['Return_Abs'] + 0.001) # Avoid division by zero
df['Volume_Close_Ratio'] = df['Volume'] /
df['Close'] # Volume relative to price level

# Define target variable: 5-day smoothed forward
log return
# Using 5-day smoothing reduces noise in the
prediction target
df['LogReturn'] = np.log(df['Close'] /
df['Close'].shift(1))
df['Target'] = df['LogReturn'].shift(-
1).rolling(5).mean() # Looking ahead 1 day,
smoothing over 5 days

# Remove rows with NaN values from lag operations
and rolling windows
df = df.dropna()

# Handle outliers by clipping extreme values
# This prevents rare events from dominating model
training
for col in df.columns:
if col != 'Close' and col != 'Target':  # Preserve
```

```
original price and target
lower_bound = df[col].quantile(0.005) # 0.5%
percentile
upper_bound = df[col].quantile(0.995) # 99.5%
percentile
df[col] = df[col].clip(lower=lower_bound,
upper=upper_bound) # Trim outliers
# Feature selection using mutual information
# This measures the non-linear relationship between
each feature and target
if df.shape[1] > 30:  # Only perform selection if
we have many features
X_temp = df.drop(columns=['Close', 'Target',
'LogReturn', 'Return']) # Candidate features
y_temp = df['Target'] # Target variable

# Calculate mutual information between each feature
and target
mi_scores = mutual_info_regression(X_temp, y_temp)
mi_df = pd.DataFrame({'Feature': X_temp.columns,
'MI_Score': mi_scores})
mi_df = mi_df.sort_values('MI_Score',
ascending=False) # Rank features by information
content

# Select top 25 features plus essential technical
indicators
top_features = mi_df.head(25)['Feature'].tolist() #
Top 25 by mutual information
essential_features = [col for col in X_temp.columns
if 'RSI' in col or 'MACD' in col
or 'Momentum' in col or 'Volatility' in col] # Key
technical indicators
selected_features = list(set(top_features +
essential_features)) # Combine lists, remove
duplicates

# Create feature matrix with only selected features
X = df[selected_features]
else:
# If few features, just drop redundant ones
X = df.drop(columns=['Return', 'Close', 'Target',
'LogReturn', 'Log_Return'])

# Define target vector
```

```
y = df['Target']

# Normalize target variable to improve model
convergence
y_mean, y_std = y.mean(), y.std() # Calculate
statistics
# Split chronologically without shuffling to
preserve time-series nature
y_train, y_test = train_test_split(y,
shuffle=False, test_size=0.2)
y_train_norm = (y_train - y_mean) / y_std #
Standardize training targets
y_test_norm = (y_test - y_mean) / y_std #
Standardize test targets using same parameters

# Split features chronologically (train-test split)
X_train, X_test = train_test_split(X,
shuffle=False, test_size=0.2)

# Scale features with RobustScaler which is less
influenced by outliers than StandardScaler
scaler = RobustScaler()  # Uses median and
interquartile range instead of mean and variance
X_train_scaled = scaler.fit_transform(X_train) #
Fit on training data only
X_test_scaled = scaler.transform(X_test) # Apply
same transformation to test data

# === Build a deep neural network with
regularization ===
# Architecture designed to balance complexity,
overfitting prevention, and learning capacity

model = Sequential([
# First layer - largest to capture complex patterns
Dense(192, activation='relu',
input_shape=(X_train_scaled.shape[1],),
kernel_regularizer=l2(0.0001)), # L2 regularization
prevents large weights
BatchNormalization(), # Normalizes layer inputs for
more stable training
Dropout(0.3), # Randomly drops 30% of neurons
during training to prevent overfitting

# Second layer - halve the neurons
```

```
Dense(96, activation='relu',
kernel_regularizer=l2(0.0001)),
BatchNormalization(),
Dropout(0.2), # Gradually decrease dropout rate in
deeper layers

# Third layer - further reduction in complexity
Dense(48, activation='relu',
kernel_regularizer=l2(0.0001)),
BatchNormalization(),
Dropout(0.2),

# Fourth layer - final hidden layer for fine-tuning
Dense(24, activation='relu',
kernel_regularizer=l2(0.0001)),
BatchNormalization(),
Dropout(0.1),

# Output layer - single neuron for regression
prediction
Dense(1) # No activation function for unbounded
regression output
])

# Compile with Adam optimizer - adaptive learning
rate method
optimizer = Adam(learning_rate=0.001) # Initial
learning rate
model.compile(optimizer=optimizer, loss='mse') #
Mean squared error loss for regression

# === Training Strategy with Advanced Callbacks ===

# Create a weight folder for this ticker to save
checkpoints
model_folder =
f'../models/saved_model/{ticker}_weights'
os.makedirs(model_folder, exist_ok=True)

# Model checkpoint to save the best model during
training
checkpoint = ModelCheckpoint(
filepath=f'{model_folder}/best_checkpoint_v4.keras'
, # Use .keras format instead of .h5
monitor='val_loss', # Track validation loss
```

```
save_best_only=True, # Only save when model
improves
mode='min', # Lower validation loss is better
verbose=0  # Suppress output messages
)

# Early stopping to prevent overfitting
# Stops training when validation loss stops
improving
early_stop = EarlyStopping(
monitor='val_loss',
patience=25, # Wait 25 epochs before stopping
restore_best_weights=True, # Restore weights from
epoch with best validation loss
mode='min',
verbose=0  # Suppress output messages
)

# Learning rate reduction when training plateaus
# Reduces learning rate when validation loss stops
improving
reduce_lr = ReduceLROnPlateau(
monitor='val_loss',
factor=0.5,  # Multiply learning rate by 0.5 when
triggered
patience=8,  # Wait 8 epochs before reducing
min_lr=1e-6, # Minimum learning rate
mode='min',
verbose=0  # Suppress output messages
)

# Train model with validation split for monitoring
print(f"Training {ticker} model...")
history = model.fit(
X_train_scaled, y_train_norm, # Training data
validation_split=0.2, # Use 20% of training data
for validation
epochs=100, # Maximum number of epochs
batch_size=64, # Process 64 samples per gradient
update
verbose=0, # Suppress epoch-by-epoch output
callbacks=[early_stop, reduce_lr, checkpoint] # Use
all three callbacks
)
```

```
# Save final model and selected features
os.makedirs('../models/saved_model', exist_ok=True)
model.save(f'../models/saved_model/{ticker}_multi_l
ayer_nn.keras') # Use .keras format
with
open(f'../models/saved_model/{ticker}_multi_layer_f
eatures.json', 'w') as f:
json.dump(selected_features, f)  # Save feature
names for later use

# === Generate predictions and evaluate model
performance ===
y_pred_norm = model.predict(X_test_scaled,
verbose=0).flatten()  # Suppress prediction output
# Convert standardized predictions back to original
scale
y_pred = y_pred_norm * y_std + y_mean # De-
normalize predictions
y_test_actual = y_test.values # Actual values for
comparison

# Calculate performance metrics
mse = mean_squared_error(y_test_actual, y_pred) #
Mean Squared Error
rmse = np.sqrt(mse)  # Root Mean Squared Error (in
original units)
r2 = r2_score(y_test_actual, y_pred) # R-squared
(proportion of variance explained)
results[ticker] = (mse, rmse, r2)  # Store metrics
for comparison

# Visualize predictions vs actual values
plt.figure(figsize=(10, 4))
plt.plot(y_test_actual, label='Actual')
plt.plot(y_pred, label='Predicted')
plt.title(f"{ticker} - Multi-layer NN (R² =
{r2:.4f})")
plt.legend()
plt.grid(True)
plt.show()

# Print summary of results for all tickers
print("\nSUMMARY OF MULTI-LAYER NN MODEL")
for ticker, (mse, rmse, r2) in results.items():
```

```
print(f"{ticker}: MSE = {mse:.6f}, RMSE =
{rmse:.6f}, R² = {r2:.4f}")
```