

# WALL STREET THROUGH A NEURAL LENS

Forecasting NASDAQ and NYSE Stock Prices with a Residual Network 2D CNN

Sarah Eve Tucker, London South Bank University



## Introduction

Stock markets are dynamic systems influenced by economic, geopolitical and investor sentiment. Traditional forecasting methods, such as ARIMA and LSTM, often fail to account for the non-linear and high-dimensional nature of financial data. This study investigates whether transforming numerical stock data into image-like representations improves predictive accuracy for NASDAQ and NYSE prices using a residual network 2D CNN by capturing spatial, temporal and inter-feature relationships.

## Methodology

A Grid-Based Temporal-Feature Structuring (GTFS) technique converted weekly stock prices and economic indicators into 2D grids, enabling the CNN to capture spatial and temporal patterns [1] & [2]. The dataset includes 3,280 weekly stock prices from June 2020 to March 2024, alongside macroeconomic indicators such as CPI, industrial production and money supply. Data preprocessing included Min-Max scaling to normalise features [3] and Pearson's Correlation to select relevant variables [4]. Models were evaluated using Mean Squared Error (MSE),  $R^2$  score and volatility analysis, with generalisability assessed through future horizon forecasting.

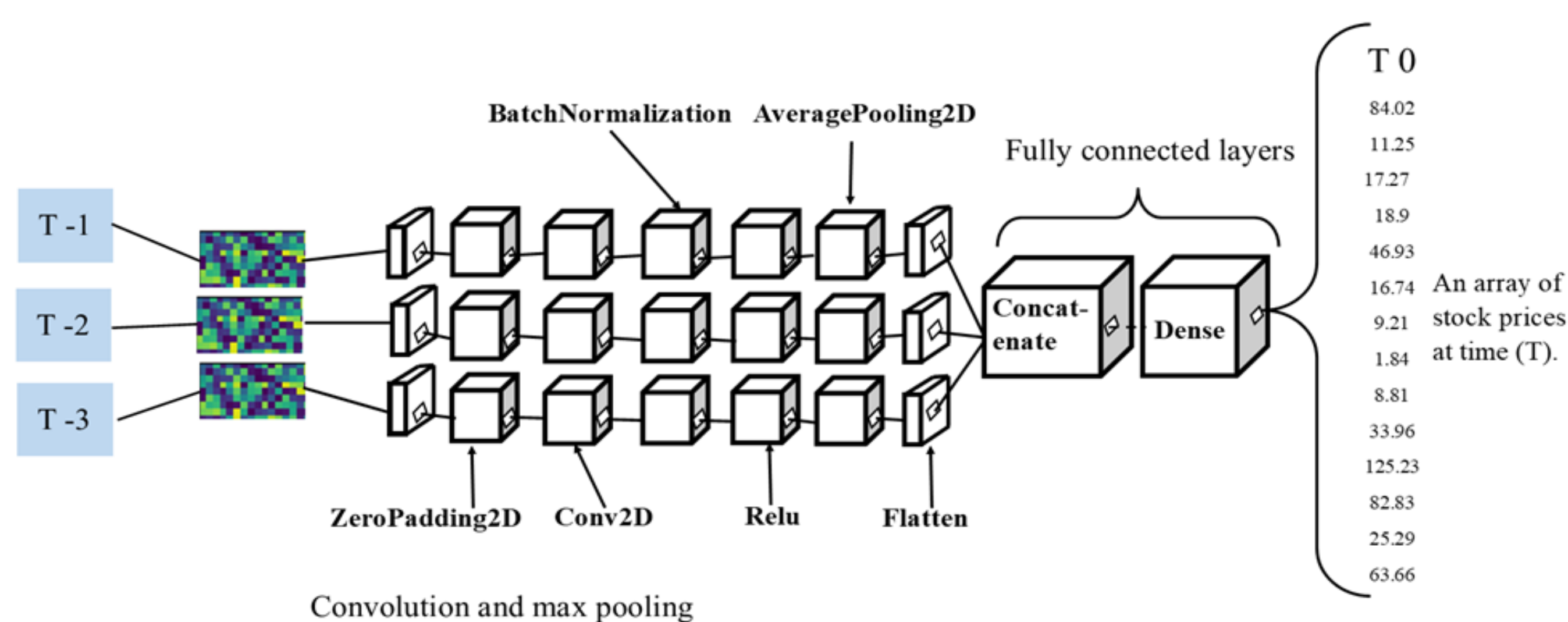


Figure 1: Residual network architecture

## Results

The experiments demonstrated progressively strong predictive accuracy, with E1 achieving an  $R^2$  of 0.97. While accuracy improved progressively, the marginal gain from E2 to E3 (0.009) suggests limited additional benefit from extra features. Forecasting performance declined when forecasting beyond the trained data horizon, exposing limitations under volatile market conditions.

Experiment	Description	$R^2$ score
E1	Historical prices only	0.970
E2	+ Positively correlated indices	0.981
E3	+ Macroeconomic indicators	0.990

Table 1:  $R^2$  scores for standard testing across three experiments.

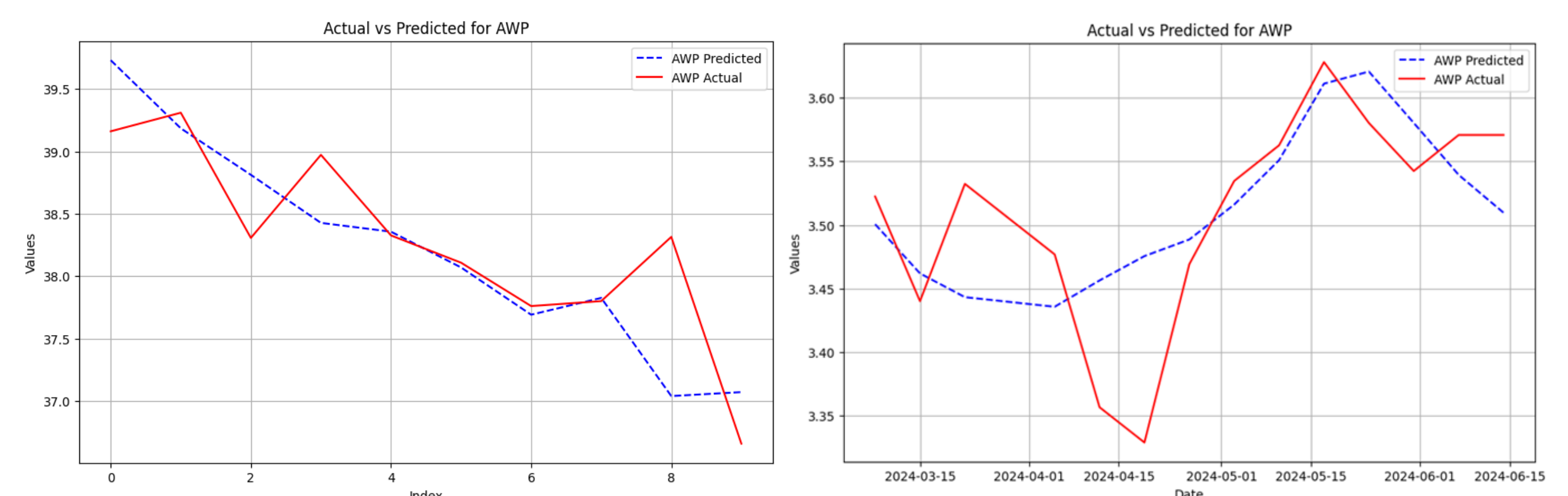


Figure 2: Model predictions vs actual stock prices for AWP under (a) standard test conditions and (b) future horizon forecasting.

## Discussion & Future Work

Image-based forecasting with residual networks outperformed conventional models under stable conditions. However, future horizon forecasts exposed weaknesses in handling market volatility.

Future work could explore incorporating daily data to capture intra-week fluctuations, alongside refining feature engineering to reduce noise and improve generalisability.

## References

1. G. Anand and R. Nayak, "DeLTa: Deep local pattern representation for time-series clustering and classification," Knowledge-Based Systems, vol. 212, 2020.
2. S. Barra, S. M. Carta, A. Corrigan, A. S. Podda and D. R. Recupero, "Deep Learning and Time Series-to-Image Encoding for Financial Forecasting," CAA Journal of Automatica Sinica, vol. 7, no. 3, pp. 683-692, 2020.
3. S. Jeong, I. Park, H. S. Kim, C. H. Song and H. K. Kim, "Temperature Prediction Based on Bidirectional Long Short-Term Memory and Convolutional Neural Network Combining Observed and Numerical Forecast Data," Sensors, vol. 21, no. 3, pp. 1-20, 2021.
4. G. Li, A. Zhang, Q. Zhang, D. Wu and C. Zhan, "Pearson Correlation Coefficient-Based Performance Enhancement of Broad Learning System for Stock Price Prediction," IEEE, vol. 69, no. 5, pp. 2413 - 2417, 2022.



12<sup>th</sup> ACM Celebration of Women in Computing: womENCourage™  
Braşov, Romania  
17-19 September, 2025  
Theme: Computer Science: a Catalyst for Educational Change

