**Natural Language Coding (NLC) for Autonomous Stock Trading: A New Dimension in No-Code/Low-Code (NCLC) AI**

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*Abstract*— In the evolving field of AI, the advent of Large Language Models (LLMs) and Natural Language Coding (NLC) represents a revolutionary step in programming and computational linguistics. This research, conducted by early-career scholars and their mentors, constructs a self-reliant stock trading bot using Transformer Neural Networks, Auto-GPT, and the Alpaca API, exploring the potentials of a No-Code/Code-Free AI framework rooted in NLC. This investigation assesses the effectiveness of this approach in stock trading influenced by social media dynamics and compares it with traditional trading mechanisms. Initially focused on the financial analysis of the platform “X”, formerly Twitter, the study has adapted to the continuous transformations in social media landscapes and advancements in AI. The results highlight the extensive capabilities of LLMs in tasks such as code generation, data analytics, and app development, suggesting NLC as an emerging frontier in AI.

Keywords- Natural Language Coding (NLC), ChatGPT, Social Media Stock Prediction, Autonomous Trading Bot.

# Introduction

In the realm of programming languages, ranging from machine and assembly to Python and SQL, many researchers agree that the era for interfacing with computers through everyday, natural language has arrived. This research outlines the creation of an autonomous stock trading bot, highlighting the pivotal role of the ChatGPT-4 Large Language Model (LLM) in its development. This model served as an invaluable guide, supplying comprehensive code, visual representations, and setup directives for both coding and trading platforms. Additionally, Google’s Bard bot contributed insights on data sourcing and delivered the most precise predictions. By synthesizing advice from both models, junior developers with no prior financial knowledge could construct an autonomous trading bot with a sophisticated deep-learning backend. Every interaction with the bots was thoroughly documented [1], validated, and is replicable. This research emphasizes the role of AI pair programming, where LLMs take the lead, and humans act as the navigators [2].

# Related Work

The rise of No-Code/Code-Free AI signifies a shift in AI approaches, emphasizing user-centric solutions and decreasing reliance on data scientists, as noted by Jamthe [3]. This evolution, evident even before current LLMs mirrored by the growth of user-friendly No-Code AI tools [4], focuses on chatbot-mediated learning over traditional coding. The study distinctively combines AI chatbots and APIs, leveraging ChatGPT-4 [5] capabilities, to facilitate code-free predictions in social media stock trading, showcasing a unique methodology in the sector.

# Initial Work

Our research commenced with a traditional coding approach, sourcing data from Kaggle with a focus on 'Twitter Stock Prediction' spanning November 2013 to October 2022. Notably, a year post this timeframe, Twitter transitioned to "X", ceasing its public trading. Our initial exploration involved predicting Close stock prices. Figure 1 demonstrates the data we have started with.

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Figure 1. X (former Twitter) Stock Close prices from November 2013 through October 2022 (USD vs frequency).

Figure 1 depicts the Close price's fluctuations, indicating a growing market confidence in “X”. The distribution of X's Close stock prices predominantly aligns with a normal distribution, with notable deviations.

For our analysis, we employed a Long Short-Term Memory (LSTM) network, a variant of Recurrent Neural Networks (RNN), leveraging the Keras library. Our data was reshaped for the LSTM layer, and the model was initialized with specific parameters. The Adam optimizer was utilized for iterative network weight updates.

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Figure 2. Close price of X prediction results (original price vs predicted).

The dataset, consisting of 2000 records, was divided into training and testing subsets. After the training phase, the model made predictions for the following year, and the results are depicted in Figure 3.

Chart, line chart

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Figure 3. Open price prediction using RNN.

Our validation process was exhaustive, involving multiple trials as detailed in Table 1.

Table 1. Validation Parameters

| *Trial #* | *Testing Parameters* | | |
| --- | --- | --- | --- |
| # of Epochs | Batch Size | Learning rate |
| 1 | 60 | 64 | 0.001 |
| 2 | 40 | 48 | 0.001 |
| 3 | 20 | 24 | 0.001 |
| 4 | 120 | 128 | 0.0001 |
| 5 | 60 | 64 | 0.0001 |
| 6 | 40 | 48 | 0.0001 |
| 7 | 20 | 24 | 0.0001 |
| 8 | 60 | 64 | 0.001 |

While RNNs have been fundamental in AI, after 2020, there's been a noticeable shift towards Transformer models, recognized for their superior accuracy. Our study compares the outcomes from the RNN model with more recent Transformer models, focusing on a No-Code approach.

# Time Series, Transformerts and NLC

The uniqueness of the proposed approach is that not only all code (100%) was generated by ChatGPT-4, but all software development life cycle (SDLC) was managed by the AI systems, mainly ChatGPT and Bard. They suggested what to do, researched how to do it, they did all the work [Fig. 4].

A screenshot of a computer

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Figure 4. ChatGPT assists with Alpaca API connection.

Preliminary results of trading can be seen in Figure 5. The overall amount invested in a portfolio, the sum of the values of all of the investments in the portfolio, increased from initial $100,000 to $101,000.92 USD.

A graph of a stock market

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Figure 4. Illustration of the Portfolio's expansion.

To further improve the results testing available LLMs from all possible angles and choosing the best is required [6].

# Conclusion

This study examines whether Code-Free AI can redefine social media stock trading and if AI-driven apps can match the predictive accuracy of traditional trading bots. The collaboration with ChatGPT-4 and Bard bots demonstrated the efficacy of low-code solutions in stock trading, showing that Large Language Models (LLMs) can democratize complex processes, making them accessible to non-experts. While AI chatbots with APIs provide a competitive advantage in stock predictions and streamline real-time data analysis, users must still bear responsibility for outcomes. Future research will further explore the topic and an extended version of the study will soon be ready to be published.

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