

# Stock-Crypto-App – Recommendation System for Stock and Cryptocurrency Market Using Cutting Edge Machine Learning Technology

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**Abstract** - In the dynamic world of financial markets, the prediction of stock performance and bitcoin trading is undergoing a significant transformation due to the integration of advanced technologies and novel methodologies. The incorporation of Transformer models alongside Time Embeddings significantly improves the precision of stock market predictions by effectively capturing intricate temporal relationships and mitigating the presence of overly simplistic assumptions. The integration of real-time social media data with sentiment analysis based on BERT provides significant value in understanding investor sentiment. Additionally, the application of language model pre-training, as exemplified by BERT, brings about a transformative impact on text classification for predicting stock prices. Within the domain of cryptocurrency, sophisticated algorithms such as Transformers, Long Short-Term Memory (LSTM), Deep Convolutional LSTM (DC-LSTM), and Neural Networks (NN) have demonstrated enhanced capabilities in predicting price movements. These algorithms are further bolstered by the implementation of a comprehensive trading strategy. Automated systems for bitcoin trading introduce elements of personalization and adaptability to the trading process, thereby facilitating broader access to a diverse group of traders. The progress highlights the significant importance of the integration of technology and methodologies in the field of financial analysis. This integration enables investors and traders to possess the necessary resources for making well-informed choices within the ever-changing landscape of financial markets.

**Keywords:** financial markets, prediction, stock performance, bitcoin trading, advanced technologies, novel methodologies, Transformer models, Time Embeddings, precision, temporal relationships, simplistic assumptions, real-time social media data, sentiment analysis, BERT, language model pre-training, text classification, cryptocurrency, algorithms, Long Short-Term Memory (LSTM), Deep Convolutional LSTM (DC-LSTM), Neural Networks (NN), price movements, trading

strategy, automated systems, personalization, adaptability, technology integration, financial analysis, investors, traders.

## I. INTRODUCTION

The contemporary financial landscape is marked by ever-evolving complexities, characterized by the integration of digital assets, real-time information flows, and the constant quest for precise investment strategies. In response to these challenges, this research paper embarks on a comprehensive exploration of advanced machine learning techniques applied to both stock and cryptocurrency markets. Our objective is twofold: first, to assess the efficacy of these cutting-edge machine learning technologies in comparison to conventional methods, using rigorous quantitative metrics such as accuracy, precision, and recall; and second, to delve into the realm of system interpretability and the underlying factors driving these recommendations. By harnessing deep learning and ensemble methods and drawing insights from historical market data, news sentiment analysis, social media trends, and expert opinions, we aim to equip investors and traders with the tools and insights necessary to navigate the intricate and dynamic landscapes of stock and cryptocurrency markets with confidence.

This paper unfolds across four distinct yet interrelated components, each contributing to our overarching mission: Predicting the stock market using transformer and time embeddings, Predicting the trend of the stock market using real-time social media data, Predicting the future price of cryptocurrencies using transformers and time-series analysis, and developing an automated cryptocurrency trading system based on user preferences. Through these interconnected segments, this research seeks to expand the horizons of financial technology and provide a holistic guide for individuals navigating the multifaceted world of modern financial markets.

## II. LITERATURE SURVEY

Transformer models and time embeddings have become popular for stock market predictions in recent years. This section discusses relevant research papers and studies.

"Stock Price Prediction with Transformer Neural Networks" by Lee et al. (2020) examined transformer models for stock price prediction. A transformer-based architecture was trained on historical stock price data and evaluated using different metrics. Transformers accurately predicted stock prices and captured temporal dependencies.[1]

"Stock Price Prediction with Time Embedding Transformers" by Xu et al. (2021) introduced time embeddings in transformer models for stock price prediction. The model's input data included time information to better capture stock market data's temporal dynamics. The model's predictive performance improved with time embeddings.[2]

Wang et al. (2022) proposed "Stock Price Prediction using Transformer-based Attention Mechanism" using transformer models. The transformer architecture's attention mechanism improved the model's ability to capture stock market data's key features and relationships. The transformer-based attention mechanism improved the model's predictive accuracy and robustness in their experiments.[3]

Zhang et al. (2023) wrote "Deep Time Series Forecasting with Transformer Networks." Transformers were used to predict time series, including stock prices. The authors captured long-range dependencies and made accurate financial time series predictions using the transformer's attention mechanism.[4]

Liang et al. (2022) examined transformers and time embeddings in their paper "Transformer with Time Encoding for Stock Market Prediction." The researchers introduced a new time encoding mechanism to help the transformer understand stock market data temporal patterns. The proposed method improved stock market prediction in their experiments.[5]

The reviewed literature shows a growing interest in transformer models and time embeddings for stock market predictions. These studies show that transformer architectures, attention mechanisms, and time embeddings can capture temporal dynamics, long-range dependencies, and accurate stock price predictions. This paper expands on these findings by applying state-of-the-art transformer models with time embeddings to stock prediction.

In recent years, there has been a significant interest among researchers in forecasting stock market trends. The

advancements in NLP have motivated researchers to leverage textual data for extracting valuable information. Several studies [11, 12] have utilized news sentiment analysis to predict future stock market movements, while others [13, 14] have focused on using the Twitter micro-blogging platform for this purpose. [15] These have explored the use of StockTwits data by processing it through a pipeline API and applying NLP and sentiment analysis techniques.[16]

This attempted to combine BERT and LSTM models to predict the performance of three stocks listed on the Hong Kong Stock Exchange, namely Tencent, CCB, and Ping An. The results demonstrated that BERT outperformed other models such as FastText and Transformer with attention.[17]

Aimed to predict the direction of stocks in the Turkish stock market. The researchers compared the performance of BERT, LSTM, RNN, and CNN models. Their findings indicated that BERT achieved the highest accuracy, with an average accuracy value of 96.26% across the models considered.

Recent years have seen a rise in the use of transformer models and time series prediction for cryptocurrency forecasts. Relevant academic articles and studies are included in this area.

Recurrent deep learning approaches, in particular LSTM, outperform other models in predicting the daily prices of cryptocurrencies, according to Kate Murray and Andrea Rossi (2023), but taking into account covariates and the interdependencies between cryptocurrencies can further improve prediction accuracy.[6]

Huali Zhao, Martin Crane and Marija Bezbradica (2022) demonstrated that the Transformer model, which has a dual attention layer, performs better than LSTM in predicting sentiment for P2P enterprises, demonstrating the approach's ability to capture long-term relationships.[7]

Dr. Laayouni Lahcen, Dr. Azzouz Mohamed, Dr. Assaidi Abdelouahid (2023) performed the Transformer model is better at forecasting bitcoin values than the LSTM model. provide higher accuracy and a better dataset to obtain reduced RMSE with increased effectiveness.[8]

In recent years, a growing body of research has focused on automated cryptocurrency trading systems that incorporate user preferences and risk-based approaches. This section presents a brief overview of the related work in this field.

Lim et al. (2018) proposed a deep reinforcement learning framework for portfolio management, emphasizing the importance of incorporating user risk preferences [21]. Their

system utilized risk tolerance levels to optimize portfolio allocations and achieved improved risk-adjusted returns. This research highlighted the significance of personalized risk management in financial systems.

Regarding the two reinforcement learning models evaluated in this research, Proximal Policy Optimization (PPO) and Q-learning, they have been extensively studied in various domains. Schulman et al. (2017) introduced the PPO algorithm, emphasizing its stability and sample efficiency [22]. The authors demonstrated its effectiveness in complex control tasks. On the other hand, Q-learning, a classic reinforcement learning algorithm, was foundational work introduced by Watkins and Dayan (1992), showcasing its ability to learn optimal policies through trial-and-error interactions.[23]

Building upon the existing literature, this research combines user preferences, particularly risk tolerance, with reinforcement learning techniques in the context of cryptocurrency trading systems. The focus on risk-based approaches and the selection of PPO as the model of choice contributes to advancing intelligent trading systems that align with user preferences. Table I, below.

### III. METHODOLOGY

The methodology for developing a recommendation system for the stock market and cryptocurrency market involves collecting relevant data on historical market behavior, sentiment analysis, and expert opinions. Advanced machine learning techniques, such as deep learning and ensemble methods, are utilized to capture complex patterns and dynamics. The system integrates diverse data sources to generate comprehensive recommendations and evaluates its performance using accuracy and precision metrics.

Data collection and implementation methodologies will be discussed in these areas.

#### A) Stock predictions with state-of-the-art transformer and time embeddings

Firstly, a comprehensive dataset of historical stock market data is collected, including price data, trading volumes, and other financial indicators.

Next, the collected data is preprocessed to ensure its quality and consistency. This involves handling missing values, normalizing numerical data, and encoding categorical variables. The dataset is then split into training, validation, and testing sets, considering the temporal order of the data.

Feature engineering is performed to extract relevant features that can capture the underlying patterns and dynamics

of the stock market. Technical indicators such as moving averages, along with time-related features. Time embeddings are incorporated to represent the temporal information effectively.

A state-of-the-art transformer-based model architecture is designed, integrating the time embeddings. The model consists of multiple encoder layers with self-attention mechanisms to capture temporal dependencies and long-range relationships. The time embeddings are appropriately integrated into the model to enable it to understand and utilize the temporal dynamics of the stock market data.

The model is trained using the prepared training dataset. Regularization techniques like dropout or weight decay are employed to prevent overfitting.

The trained model is evaluated using the validation dataset, calculating metrics such as MAE, RMSE, and directional accuracy to assess its predictive performance. Comparison with baseline models or traditional approaches helps gauge the improvement achieved through the incorporation of transformer and time embedding techniques.

Fine-tuning and hyperparameter optimization are conducted by adjusting parameters such as learning rate, batch size, and the number of transformer layers. Identify optimal hyperparameter values.

The final model is validated using the testing dataset to assess its generalization ability and real-world performance. Evaluation metrics are calculated and analyzed to determine the model's effectiveness in making stock market predictions.

To ensure experiment reproducibility, details of the model architecture, hyperparameters, and data preprocessing steps are documented. Code and necessary instructions or dependencies are shared to enable others to reproduce the results and validate the findings.

#### B) Sentiment classification for long text inputs using BERT with a PyTorch interface from the hugging face transformers library

Firstly, a diverse dataset of real-time social media data will be collected from the Yahoo finance platform to contain discussions, opinions, and sentiments related to the stock market. The selection of data sources will be based on relevance, user engagement, and availability. This dataset will provide the foundation for sentiment analysis and trend prediction.

In the text preprocessing stage, the tokenization technique is applied to split the text into smaller units called tokens. The tokenization process is performed using the "bert-base-

uncased" version of the Bert Tokenizer from the Hugging Face Transformers library.

To ensure compatibility with the BERT model, the dataset is formatted following specific requirements. An attention mask is created to differentiate real tokens from padding tokens, guiding the BERT model's self-attention mechanism.

To handle long text inputs, the methodology follows the approach described in[18]. The input is segmented into smaller chunks of 200 tokens each, with a 50-token overlap. These segmented chunks are then fed into the BERT base model.

After the preprocessing steps, the BERT model is fine-tuned for sentiment classification using the "BertForSequenceClassification" class. This class modifies the pre-trained BERT model by adding an untrained classification layer on top, which is then trained specifically for the sentiment classification task.

During the fine-tuning process, the training hyperparameters are determined. The AdamW optimizer from the Hugging Face library is used, along with a linear scheduler for updating the learning rate. The performance is assessed using the Matthews correlation coefficient, a measure that evaluates the quality of binary classifications.

This methodology provides a systematic approach for sentiment classification of long text inputs using BERT with a PyTorch interface. The methodology includes text preprocessing, tokenization, formatting for BERT inputs, fine-tuning of the BERT model, and evaluation of the model's performance on the test set. Finally, the model's performance was evaluated on a separate test set using the Matthews correlation coefficient (MCC), which considers both true positives and true negatives. Which provided a reliable measure of prediction quality.

### **C) Cryptocurrency price prediction with LSTM, DC-LSTM, ARIMA and transformer**

First, an extensive dataset of previous cryptocurrency transactions is gathered, along with timestamps, volumes, and other crucial information. Following that, handle the outlier using preprocessing techniques to guarantee the dataset's quality and consistency.

Used different algorithms to model training find optimal algorithm for model training.

Both the LSTM and DC-LSTM models are designed with suitable input and output layers, introducing non-linearity via the ReLU activation function. Initialization is done for

hyperparameters such dropout rates, hidden units, and LSTM layer counts. The models are trained using the Adam optimizer, and the data is separated into testing, validation, and training sets. While the DC-LSTM model uses dilated convolutions to capture a broader context, the LSTM model uses recurrent layers for sequential data processing. Metrics like MSE, RMSE, and accuracy are used for performance evaluation. These models are made to handle various parts of the data and enhance feature extraction for forecasting cryptocurrency values.

The ARIMA model serves as a benchmark for comparison and is trained and assessed. The autoregressive and moving average components of the time series data are captured by the statistical model known as the ARIMA model. The autocorrelation function (ACF) and other methods for identifying the best-fitting model are used to select the ARIMA model's parameters (p, d, and q). The model is tested using metrics like MSE, RMSE, and accuracy after being trained using the preprocessed data.

Transformers are used to forecast future cryptocurrency values by making use of their capacity to identify intricate connections and patterns in sequential data. Transformers develop their understanding of underlying trends and swings by training on previous pricing data. Additionally, methods like attention mechanisms improve the model's accuracy by sharpening its focus on pertinent data with metrics like RMSE, MSE and MAE.

### **D) Automated cryptocurrency trading system based on user preferences**

The first step in developing the automated cryptocurrency trading system is to collect relevant data. Historical cryptocurrency market data, including price and volume information, is obtained from reliable sources such as cryptocurrency exchanges or financial data providers [24]. Additionally, user preference data related to risk tolerance is gathered through surveys or questionnaires administered to potential users of the system [25]. The collected data serves as the basis for training and evaluating the reinforcement learning models.

The collected data undergoes preprocessing to ensure its quality and suitability for model training. This involves cleaning the data by removing outliers, handling missing values, and normalizing the numerical features to a common scale [26]. By preprocessing the data, we ensure that the models receive consistent and accurate input, improving their performance during training and evaluation.

Two reinforcement learning models, Proximal Policy Optimization (PPO) and Q-learning, are trained using the

preprocessed data. PPO is a policy optimization algorithm that has shown promising results in various domains [27], while Q-learning is a widely used value-based reinforcement learning algorithm [28]. The models are trained to learn the optimal trading policies based on historical market data and user preferences.

The trained PPO and Q-learning models are evaluated using appropriate performance metrics to assess their effectiveness in capturing market trends and generating profitable trading strategies. Common evaluation metrics include profitability, risk-adjusted returns, and portfolio volatility [29]. By comparing the performance of the models, we can identify the model that best aligns with the objectives of the automated trading system.

Based on the evaluation results, the PPO model is selected as the preferred model for the automated cryptocurrency trading system. The selected model is then used to design and implement a personalized trading strategy that takes into account user preferences, particularly related to risk tolerance. The system integrates the PPO model's predictions and recommendations to automatically execute trades, aiming to maximize returns while managing risks based on the user's risk profile. This ensures that the trading system aligns with the individual user's preferences and objectives.

#### IV. RESULTS AND DISCUSSION

##### A) Stock predictions with state-of-the-art transformer and time embeddings

The results of predicting the stock market using LSTM and Transformer models with time embeddings reveal significant performance differences. The Transformer model outperforms LSTM across various metrics, with notably lower MAE and MSE on both validation and test sets, demonstrating its superior predictive capabilities. Additionally, the Transformer model exhibits substantially lower loss values and MAPE, indicating its effectiveness in capturing complex temporal patterns in stock market data.

Table 1: LSTM vs Transformer Matrices in Stock

Metric	LSTM	Transformer
Train MAE	4.0014	0.0228
Validation MAE	10.1052	0.0170
Test MAE	11.1125	0.0237
Train MSE	25.5171	N/A
Validation MSE	144.3482	N/A
Test MSE	157.3507	N/A
Train Loss	N/A	0.0010
Validation Loss	N/A	0.0005
Test Loss	N/A	0.0012
Train MAPE	N/A	4.4575
Validation MAPE	N/A	3.1420
Test MAPE	N/A	4.8182

##### B) Predicting the trend of stock market using real time social media data

###### 1) Performance Comparison with Existing Algorithms

This research investigates the integration of sentiment analysis and BERT-based long text classification into the stock market trend prediction framework. The primary goal is to assess whether this innovative approach can outperform existing algorithms and enhance the accuracy of stock market trend predictions.

Table 2 presents the performance metrics of various existing algorithms, including Naive Bayes, Support Vector Machine (SVM), Decision Tree, Random Tree, and Artificial Neural Network (ANN). These algorithms serve as benchmarks for comparing the newly trained model's performance.

Table 2: Comparison with Existing Algorithms

Method	Accuracy
Naive Bayes	33%
SVM	52%
Decision Tree	55%
Random Tree	53%
Artificial Neural Network	68%

###### 2) Proposed Trained Model with Sentiment and BERT

The research introduces a newly trained predictive model that combines sentiment analysis and BERT-based long text classification. Table 2 provides the performance metrics for this model across three training epochs.

Table 3: Proposed Trained Model Table

Epoch	Train Loss	Validate Loss	Accuracy	Train Time	Validate Time
1	0.71	0.69	0.64	0:00:32	0:00:02
2	0.70	0.69	0.67	0:00:32	0:00:02
3	0.70	0.67	0.69	0:00:32	0:00:02

The research findings offer valuable insights into the performance of the newly trained model with sentiment and BERT-based long text classification, as well as its comparison to existing algorithms.

Comparing the performance of the proposed trained model to existing algorithms, it is evident that the model surpasses all of them in terms of accuracy. This suggests that the incorporation of sentiment analysis and BERT-based text classification has a significant positive impact on the model's predictive capabilities.

Across the three training epochs, the model consistently exhibits high validation accuracy, reaching an impressive 0.69 in the final epoch. This indicates that the model has learned to

make accurate predictions on unseen data, which is a crucial attribute for stock market trend prediction.

The training and validation times remain consistent and efficient, which is essential for practical real-time applications in the financial domain.

### C) Predicting the future price of the cryptocurrency using transformers and time-series analysis

A comparison was done between Transformer model and LSTM to choose the ideal framework for forecasting price of the cryptocurrencies. The various evaluation criteria used for the time series analysis. Mean Squared Error (MSE) and Mean Absolute Error (MAE) used for the testing and validation with Nadam optimizer and learning rate of 0.001 used as hyperparameters in model training. Results are as follows.

Table 4: Metrics Comparison Metrics Comparison

Metrics	LSTM	Transformer
MSE	2769.44	0.0120
MAE	2663.91	0.0130
Validation loss	N/A	0.0301
Validation MSE	N/A	0.0301
Train Accuracy	60.13%	92.42%
Test Accuracy	42.54%	69.82%

### D) Automated cryptocurrency trading system based on user preferences

In light of the comparative analysis between Q-learning and Proximal Policy Optimization (PPO) within the context of automated cryptocurrency trading systems, the selection of PPO as the foundation for the automated trading bot is substantiated. PPO's suitability in handling continuous action spaces, its demonstrated sample efficiency with swift early-stage progress, and its inherent stability, along with its balanced approach to entropy loss, were pivotal factors influencing this decision. Furthermore, its effective handling of complex and high-dimensional state spaces is deemed fitting for the intricate and dynamic nature of cryptocurrency markets. By opting for PPO, the aim is to harness its adaptability to user preferences and its potential to yield optimized trading strategies, ensuring that the automated cryptocurrency trading bot offers a tailored and robust trading experience for users in the cryptocurrency ecosystem.

Table 5: Algorithm Comparison

Criteria	Q-learning	PPO (Proximal Policy Optimization)
Handling of Continuous Action Spaces	Less suited for continuous actions	Well-suited for continuous actions
Sample Efficiency	Requires more samples to converge	Shows better early-stage progress
Stability and	Can exhibit	Tends to run more

Robustness	instability	smoothly
Entropy Loss	Exploration-exploitation trade-off	Maintains a fair balance
Learning Rate	Value-based approach	Policy optimization may be more efficient
Policy vs. Value-based Approach	May lead to drastic policy changes	Keeps policy revisions in check
Approximate KL Divergence	May lead to drastic policy changes	Keeps policy revisions in check
Handling of High-Dimensional State Spaces	May struggle with high dimensionality	Effective in managing complex state spaces

The decision to opt for the Proximal Policy Optimization (PPO) algorithm over Q-learning in our automated Bitcoin trading system was motivated by several compelling factors. PPO's suitability for handling continuous action spaces, its demonstrated superior sample efficiency with rapid early-stage progress, and its inherent stability marked by reduced variability in key indicators such as policy gradient loss and value loss were all key considerations. Additionally, the balanced entropy loss maintained by PPO, its ability to adapt to changing market conditions, and its effective utilization of an appropriate learning rate underscored its selection for our trading system. Furthermore, the policy gradient approach employed by PPO was found to be advantageous in optimizing the policy function, while the low estimated KL divergence ensured smooth policy revisions and minimized unnecessary risks. Importantly, PPO's capability to effectively manage high-dimensional and continuous state spaces, which aligns with the intricate and data-rich nature of cryptocurrency markets, solidified its position as the algorithm of choice for our automated Bitcoin trading system.

## V. CONCLUSION

In this comprehensive research endeavor, we have navigated the intricate terrain of financial markets and cutting-edge machine learning techniques. From the promising advancements seen in stock predictions using Transformer models and time embeddings, the precision achieved through sentiment analysis and BERT-based classification for stock market trend prediction, to the robust cryptocurrency price forecasting capabilities of Transformers (nnlm-en-dim50), and the selection of Proximal Policy Optimization (PPO) for an automated cryptocurrency trading system, our exploration unveils a wealth of opportunities for enhancing decision-making and trading strategies. These findings collectively signify the transformative potential of machine learning in the financial realm, promising more accurate predictions and personalized trading experiences. As we conclude this journey, we recognize the profound impact these insights may have on investors and traders, empowering them to navigate the complexities of modern financial markets with greater confidence and effectiveness.

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