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Daily Investment Advice: LSTM Neural Network for Stock Forecasting

Integrating Technical, Financial, and Contextual Data for Smarter Stock Predictions

Paper review from **Ricchiuti & Sperlí (2025)**

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Inside the Framework & Key Outcomes

Challenges

On average, AI-based stock forecasting **focus on one side**: either sentiment, fundamentals, or technical rules without contextual information crucial to stock forecasting. Meanwhile, AI models have several challenges such as **feature selection, evaluation measure, large content / news, unforeseeable events, & external factors** (i.e., people's feelings, expert's opinion, and security breaches).

Proposed Approach

An Advisor Neural Network framework using Long-Short-Term Memory (LSTM)-based is proposed to **integrating technical indicators, contextual information, and financial data** for Daily Investment Advice. The output prediction from the LSTM is **then ranked by an advice unit** by heuristic stock selection, which recommends the best K stocks.

Related Works

- Many Studies proved that **LSTM outperforms** other machine learning model when it comes to stock price foracasting (Zhong et al., 2023).
- Feature selection (Htun et al., 2023), evaluation metrics (Dessain 2022), unforeseen events (Ahelegbey et al. 2022) are **the challenges.**
- **News** is useful for 1-day forecasts, while **social media** provides signals for up to 5 days (Dong et al. 2022).

Key Outcomes

- Integration of data source framework
- Heuristic stock selection algorithm
- Enhanced LSTM-based forecasting
- Robust evaluation (MAE, MSE, RMSE, & Daily Return (DR))
- Handling unforeseen events (contextual news)

Models/Tools

Task/Objective

The task of stock forecasting is to **predict future stock prices** as continuous numerical values using regression methods. The objective is to **minimize forecasting errors** in order to reduce financial risks and provide more reliable guidance for investment decisions.

Data → **LSTM Forecasting** → **Tuning, Feature Selection, Evaluation** → **Advice Unit** → **Reliable Guidance**

Data Dictionary

- Historical data (daily stock prices, returns, and technical indicators)
- Contextual information (news volume and sentiment scores)
- Seasonal data (time-based patterns)
- Considering a subset 417 stocks & 67 cryptocurrencies 3+ years, respectively

System Components

Data collection module, feature processing module, forecasting unit (LSTM-based), Advice unit (Heuristic Stock Selection), Evaluation Module.

Performance Metrics & Recalibration Recommendations

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

The Mean Absolute Error (MAE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

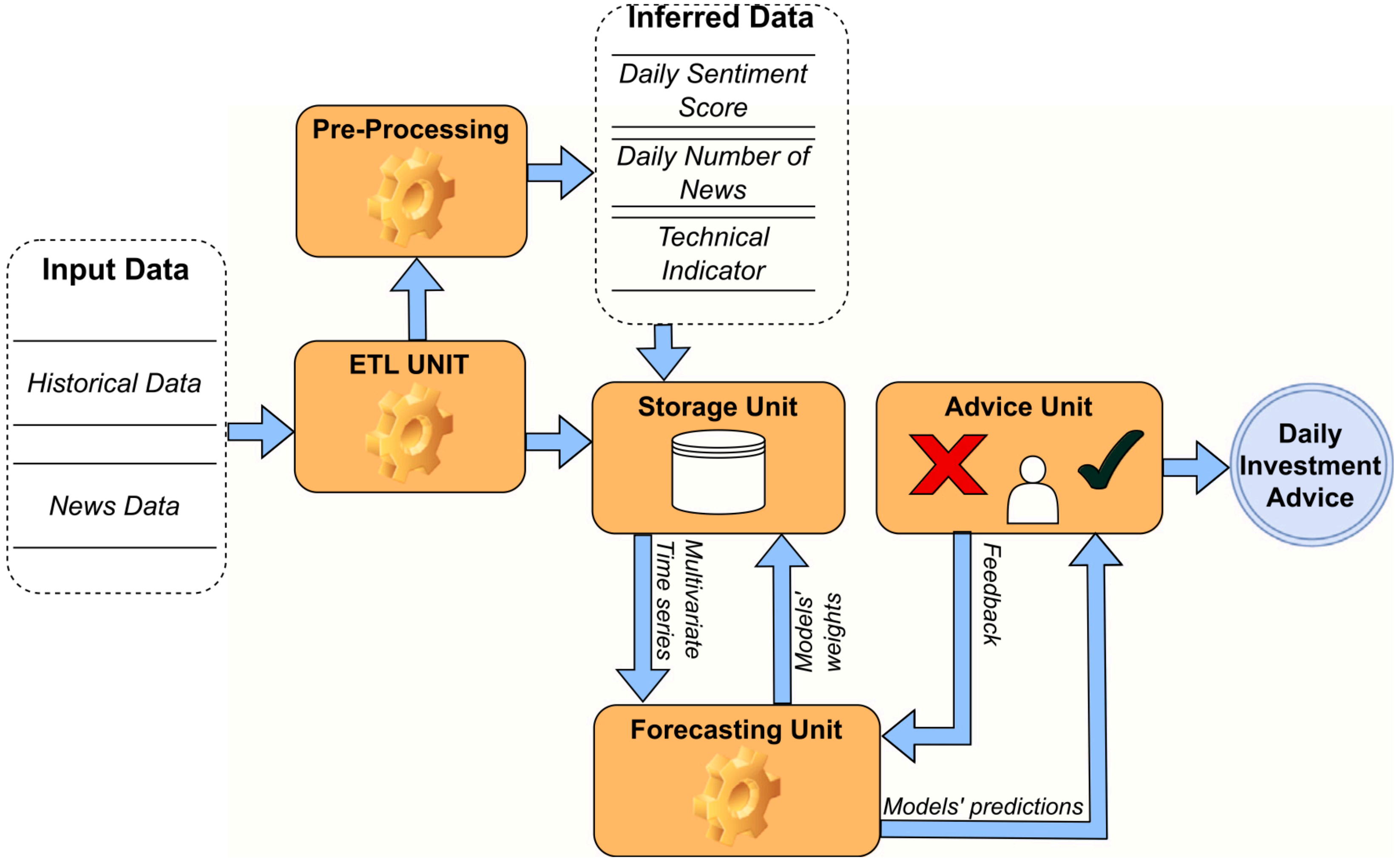
The Mean Squared Error (MSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

The Root Mean Squared Error (RMSE)

General Framework Proposes

Architecture / Framework



Proposed framework aims to provide daily stock market advice. It is mainly composed of three modules: Data Ingestion, Stock Forecasting, & Advice Suggestion

Three Modules:

Data Ingestion

Extracted from **several heterogeneous sources** through Application Programming Interface (API).

Stock Forecasting

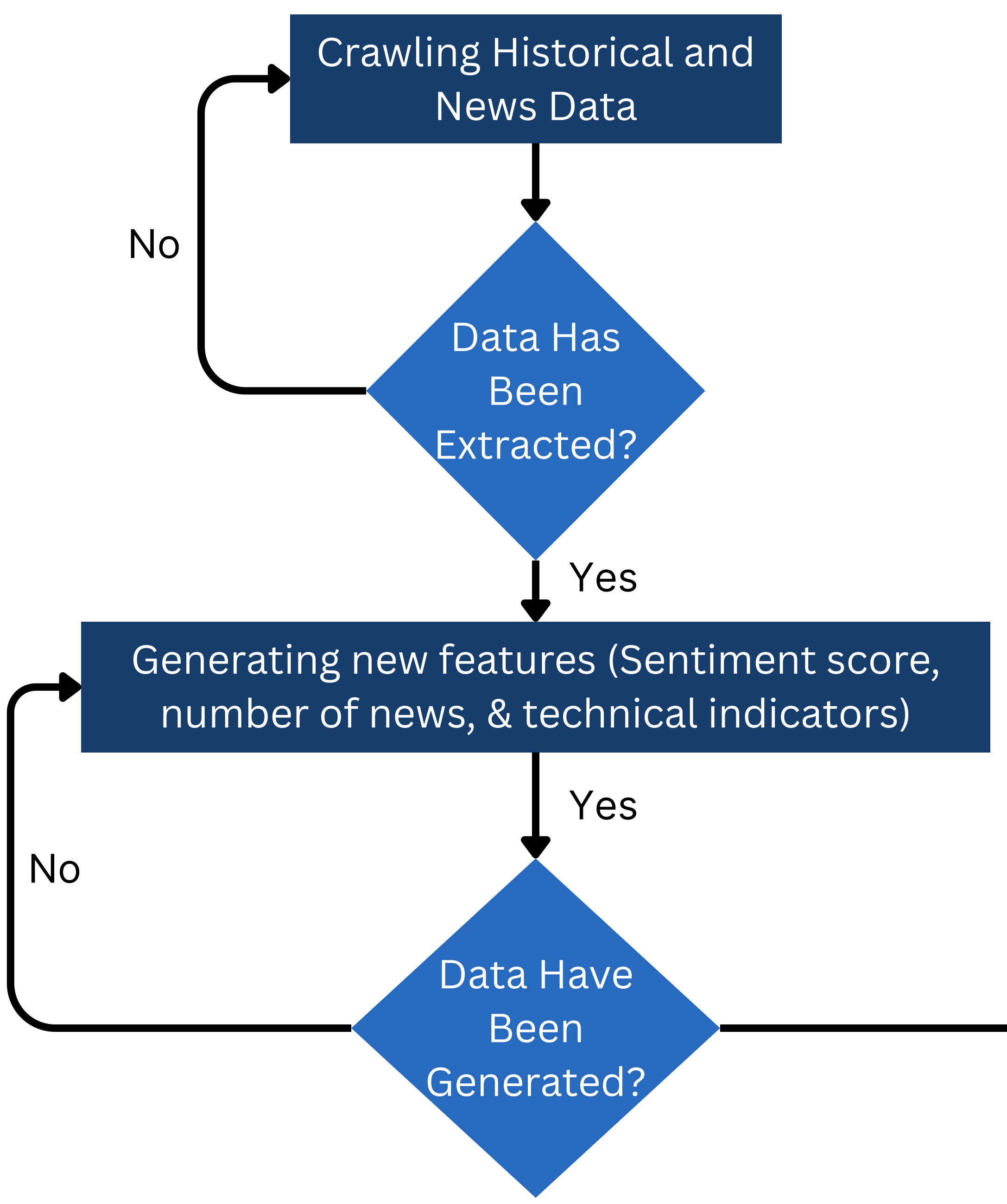
Relies on **LSTM models.** The crawled data modeled as a time series to be fed as input to the LSTM-based model stock forecasting.

Advice Suggestion

Relies on the output of forecasting layer to provide daily investment advice by **ranking the stocks** according to a novel index

Data Ingestion

Flow Diagram



Altough financial information has been classified into financial data and technical indicators.

The paper improving by extensive set of contextual information, such as:

- Historical Finance Data
- Seasonal Data
- News Data
- Technical Indicator

After Technical Indicator Computed, Historical Data will be removed.

Historical Data

Crawling from specific portals (Yahoo Finance & Google Finance). Main features are **Date, Open Price, High Price, Low Price, Close Price, Volume**.

Seasonal Data

From the date field of the crawled historical data, such as: **day of the week, day of the month, month, quarter**.

News Data

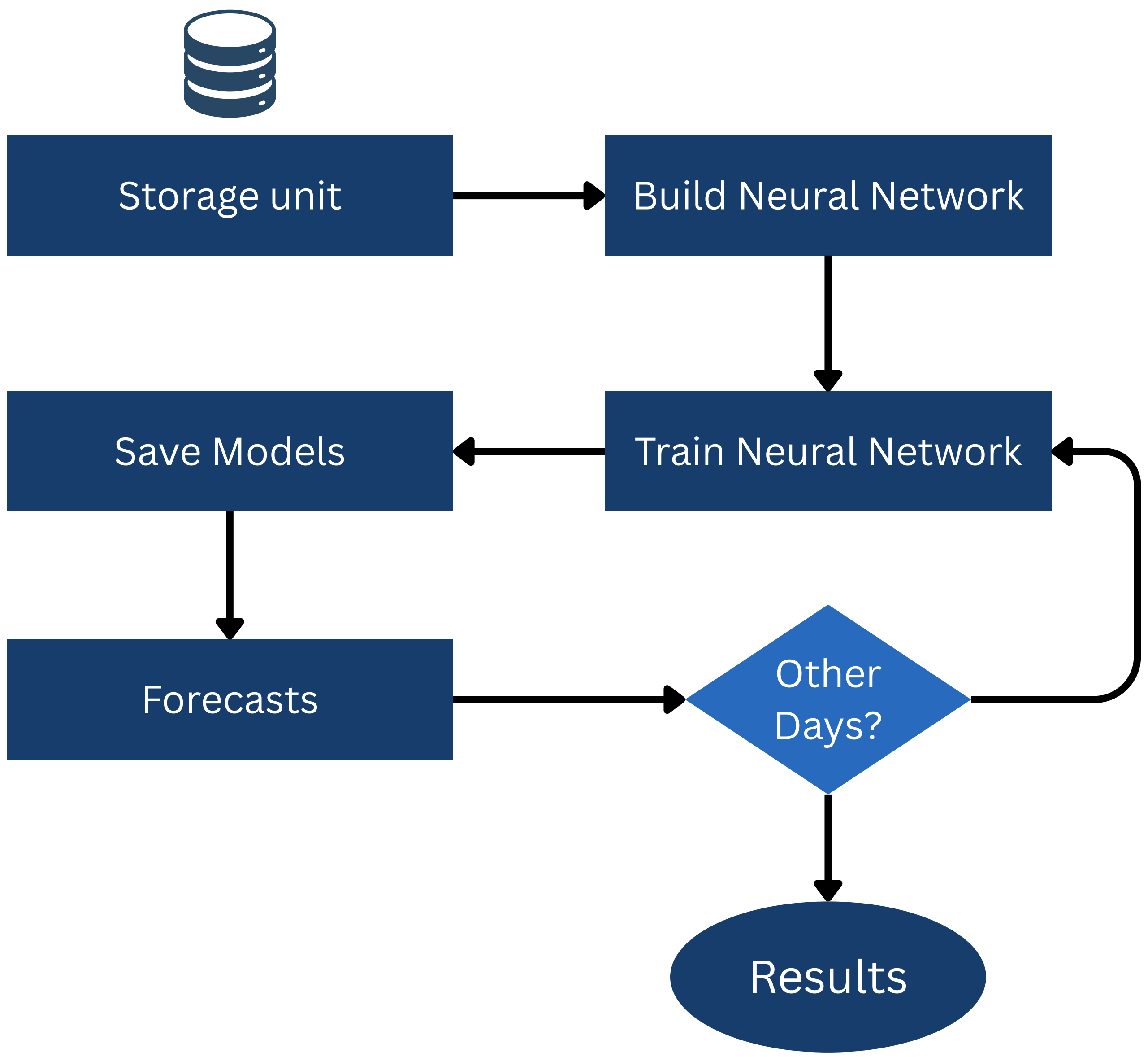
News data from EOD platform → daily article count + average sentiment score (**–1 to +1**).

Technical Indicator

6 Indicators: Awesome Oscilator **(AO)**, Relative Strength Index **(RSI)**, Average True Range **(ATR)**, Average Directional Movement Index **(ADX)**. Aaron Indicator **(AI)**, Daily Return **(DR).**

Stock Forecasting

Flow Diagram



A neural network is a computer system that **learns patterns like the human brain.**

It builds a neural network for **each stocks.**

Forecasting unit is responsible for designing and updating the Neural Networks.

This unit consist of three sub-unit: (1) Builder, (2) Update, (3) Prediction.

Three Sub-unit

Builder The aim is predicting the trend of each stocks

Update Neural network that has been build is evaluated through a novel metric.

Prediction Performs stock value forecast based on multivariate time series fed as input.

Neural Network for LSTM Architecture (Main Model)

(1) Input Layer

(2) LSTM Layer

(3) Dropout Layer

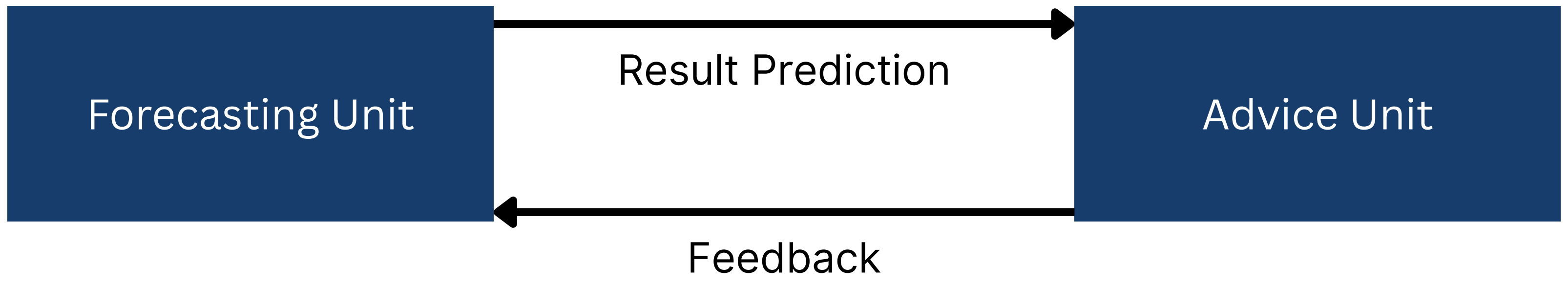
(4) Dense Layer

The training phase aims to minimize loss funtion called **Mean Squared Error** (chosen) and use Optimizer called **Adam Optimizer.**

Once training complete, **model can be saved** into storage unit

Advice Unit

Mechanism



The Advice unit relies on the prediction score of the Forecasting Unit to suggest profitable stocks in which to invest in

This unit suggest ***K* stocks** whose Daily Return (DR) is expected to be higher on the following day. Two main components of this unit: (1) *Stocks Selection* and (2) *Advice Production*

Two Components

Stocks Selection

Let ***N*** models are trained in each stocks. Then there is chosen the first ***K*** stocks that are sorted descending.

Advice Production

Let ***M*** is the selected models. then ***M*** model are used to predict the next day's Daily Return. Return predictions are sorted from the highest to the lowest.

Experimental Results

Feature Selection

The writer compare the forecasting performance of each feature by experimenting on MAE, MAPE, and RMSE metrics. The results are:

- ***Daily Return (DR)*** performs better than *Closing Price* as the forecasting target.
- Using ***Seasonal Data*** improves performance compared to not using it.
- ***Technical Indicators*** perform better than only Financial Features.
- Including ***News Data*** improves performance compared to excluding it

Results:

Table 7
Comparison of expected Close price and Daily return on 70 days in the test set for each stock on the basis of average scores of MAE, MAPE, and RMSE metrics.

Stock	Close	DR	(Close-DR)
MAE	4.076	3.100	**0.976**
MAPE	0.028	0.021	**0.007**
RMSE	5.165	3.895	**1.270**

Table 9
Comparative analysis of forecasting module with financial features and with technical indicator on the basis of average scores of MAE, MAPE, and RMSE metrics.

Stock	Financial	Indicators	Difference
MAE	2.873	2.484	**0.390**
MAPE	0.020	0.017	**0.003**
RMSE	3.574	3.257	**0.316**

Table 8
Comparative analysis of forecasting module with and without seasonal data on the basis of average scores of MAE, MAPE, and RMSE metrics.

Stock	No Seasonal	Seasonal	Difference
MAE	3.100	2.874	**0.226**
MAPE	0.021	0.020	**0.001**
RMSE	3.895	3.574	**0.321**

Table 10
Comparative analysis of forecasting module with and without news data on the basis of average scores of MAE, MAPE, and RMSE metrics.

Stock	No News	News	Difference
MAE	2.484	2.469	**0.015**
MAPE	0.017	0.017	**4.943e−05**
RMSE	3.258	3.223	**0.035**

Hyperparameter tuning

To optimize the model, there is 2 main things, such as:

- *Time Window* (2 - 8 days)
- Choosing Neural Network Models

Table 11
Effectiveness performance of Forecasting module varying the window size on the basis of MAE, MAPE and RMSE metrics.

Window	MAE	MAPE	RMSE
2 Days	2.477	0.0174	3.238
3 Days	**2.464**	**0.0173**	**3.209**
4 Days	2.478	0.0173	3.247
5 Days	2.472	0.0173	3.227
6 Days	2.473	0.0174	3.228
7 Days	2.502	0.0174	3.249
8 Days	2.490	0.0174	3.257

Table 13
Comparison of the proposed LSTM-based model w.r.t. seven baselines.

Model	MAE	MAPE	RMSE
LSTM	**2.458**	**0.0173**	**3.213**
BI-LSTM	2.476	0.0175	3.239
GRU	2.504	0.0178	3.254
BI-GRU	2.541	0.0177	3.315
STKD LSTM	2.459	0.0174	3.217
STKD BI-LSTM	2.507	0.0174	3.276
STKD GRU	2.515	0.0174	3.274
STKD BI-GRU	2.510	0.0176	3.275

The results is **3-day time window give the best results & LSTM is outperform** 7 baseline Neural Network Models (Bi-LSTM, GRU, etc).

Also, **RMSE is the most important metric** because it gives bigger penalties for large mistakes, and lower RMSE means more accurate predictions.

Experimental Results

Effectiveness Analysis

After the best model is achieved, which is LSTM-based are used. There is **market tested** with NASDAQ (65 trading days, Aug–Oct 2022) & Cryptocurrencies (92 days).

Selection procedure:

- Each day, framework selects 50 stocks with the most predictable behavior.
- Then pick top 5 with the highest expected return

Trading Strategy:

- Capital equally divided across the 5 selected stocks.
- Buy at Opening Price, sell at Closing Price (no transaction fees).
- All capital reinvested daily (compound interest).

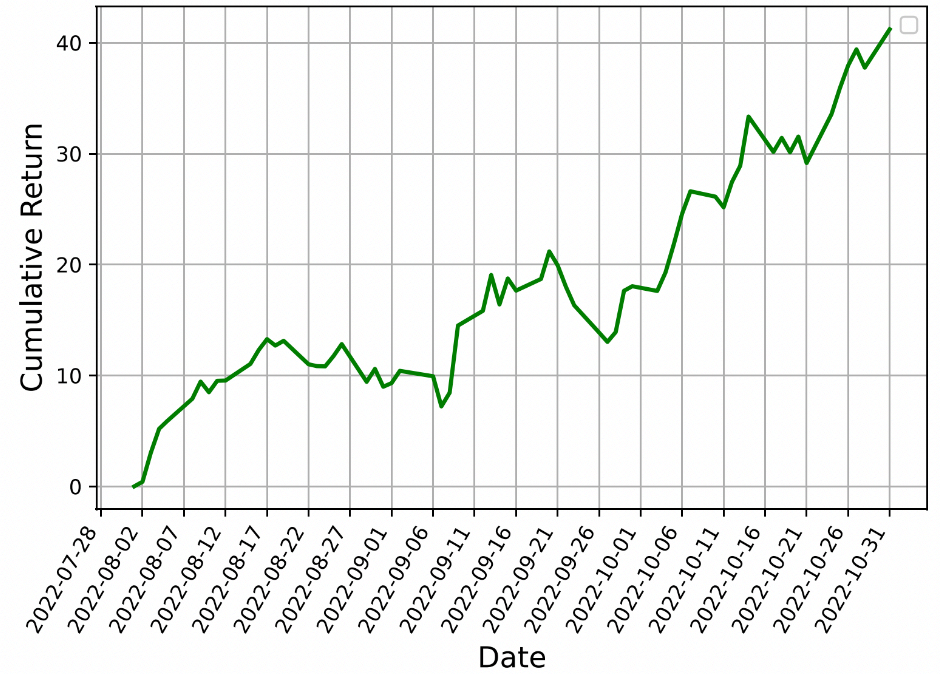
Results: NASDAQ Stocks

- Accuracy: 64.62% (42 profitable days, 23 loss days).
- Economic gain: +41.21% of initial capital (cumulative).

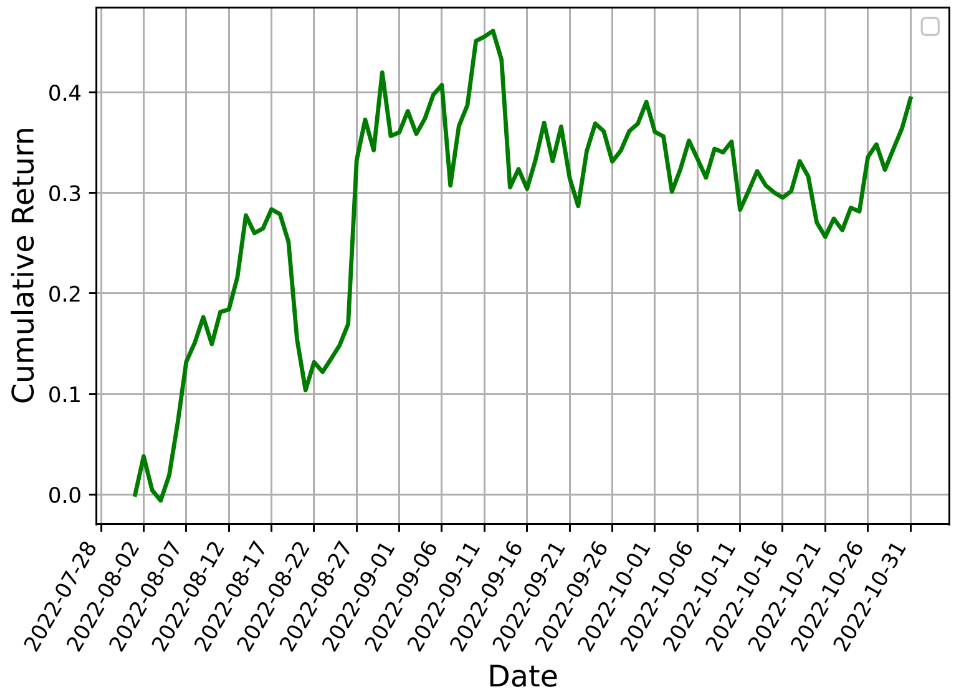
Results: Cryptocurrencies

- Accuracy: 59.78% (55 profitable days, 37 loss days).
- Economic gain: +39.38% of initial capital (cumulative).

NASDAQ:



Cryptocurrencies:



Experimental Results

Comparison to other state-of-the-art methods

The writer evalaute the propose approach (LSTM-based) with others state-of-the-art in the same test dataset. Metrics used is MAE, MAPE, and RMSE.

The proposed approach **outperforms baselines** by combining contextual information (news and sentiment) with historical stock data, improving future performance prediction.

The proposed advice strategy outperforms Ghosh et al. (2022) and buy & hold strategy, achieving **higher cumulative returns.**

Table 15
Effectiveness comparison of the proposed framework w.r.t. several state-of-the-art approaches.

	Stock Market			Cryptocurrencies		
Approaches	MAE	MAPE	RMSE	MAE	MAPE	RMSE
Banik et al. (2022)	3.294	0.023	4.305	4.112	0.029	5.375
Hafiz et al. (2023)	3.228	0.023	4.219	4.030	0.028	5.268
Anbaee Farimani et al. (2022)	3.146	0.022	4.113	3.991	0.028	5.217
Chen et al. (2019)	2.950	0.021	3.856	3.870	0.027	5.059
Wang et al. (2022a)	3.490	0.025	4.562	4.172	0.029	5.454
Proposed	**2.728**	**0.019**	**3.566**	**3.749**	**0.026**	**4.900**

Table 16
Effectiveness comparison of the proposed advice strategy w.r.t. the buy & hold and the one designed by Ghosh et al. (2022).

	Cumulative Return	
	Stock	Crypto
Buy & hold strategy	28.31%	26.42%
Ghosh et al. (2022)	35.46%	33.81%
Proposal	**41.21%**	**39.38%**

Conclusions

Contributions of This Paper

- **Developed an LSTM-based framework** for daily stock advice.
- **Integrates heterogeneous data**: financial info, sentiment (news), and seasonality.
- Introduced a **Heuristic Stock Selection algorithm** to pick most predictable stocks.

Evaluation Results

- NASDAQ stocks (3 months, 400+ stocks) → **economic gain +41.21%**, even during a downward trend.
- Cryptocurrency market → **economic gain +39.38%.**
- **Outperforms** several state-of-the-art approaches in both markets.
- Efficient in terms of memory and training time due to **optimal 3-day time** window.

Thank You

See You Next Time..