

AI-Driven Multilingual Voice Assistant for Stock Market Forecasting Using LSTM

P. Sunitha Devi¹, Sama Riddhima Reddy², Mudide Om Sri³, Gopathi Rishitha⁴

¹Associate Professor, CSE, GNITS, Hyderabad, India

^{2,3,4}Student, CSE, GNITS, Hyderabad, India

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ABSTRACT

Stock market prediction systems often require financial knowledge and technically complex interfaces, which can create accessibility barriers for novice users and users from regional language backgrounds. This paper presents a multilingual voice-enabled stock forecasting system that integrates Long Short-Term Memory (LSTM) networks with speech recognition, language translation, and text-to-speech technologies. Historical stock price data are stored locally in CSV format, and the closing-price series is processed using Min-Max normalization and a 60-step sliding-window approach. A two-layer LSTM architecture is trained to forecast future closing prices. The system accepts text or voice queries in multiple Indian languages and presents predicted prices, percentage changes, graphical trends, and rule-based investment suggestions. Experimental testing was performed on six Indian stocks: HDFC Bank, TCS, Reliance, Infosys, Hindustan, and ITC. The system demonstrates how deep-learning-based forecasting can be combined with multilingual voice interaction to provide an accessible interface for stock-market analysis.

Keywords—Stock Price Prediction, LSTM, Time-Series Forecasting, Multilingual Speech Processing, Speech Recognition, Text-to-Speech

INTRODUCTION

The rapid advancement of artificial intelligence has significantly influenced financial analytics and stock market forecasting. However, most predictive systems are designed for experienced investors and depend on technical indicators, statistical charts, and English-based user interfaces. These factors create accessibility barriers for users with limited financial knowledge or non-English language backgrounds.

In multilingual countries, financial literacy is often constrained by language limitations and complex technical interfaces. Conventional stock market tools present data visually through graphs and dashboards, requiring interpretation skills that many retail investors lack. Additionally, most systems do not support hands-free interaction, further restricting accessibility.

To address these challenges, this paper presents a multilingual AI-based stock forecasting system that combines LSTM-based time-series forecasting with multilingual voice interaction. The system allows users to enter a company name or a natural-language query, processes voice input through speech recognition and translation when required, performs stock prediction using locally stored historical data, and presents the result as text, graphical output, and optional speech.

The primary contributions of this work include:

1. Development of a voice-enabled multilingual stock prediction system.
2. Integration of speech recognition, translation, and deep learning forecasting.
3. Design of a local-data-based architecture that reduces dependence on live stock-market data APIs.

4. Evaluation of the forecasting interface and rule-based recommendation mechanism on six selected Indian stocks.

LITERATURE SURVEY

Stock market prediction has attracted significant research interest due to the highly volatile and nonlinear nature of financial markets. Over the years, researchers have explored statistical, machine learning, and deep learning approaches to improve forecasting accuracy. This section reviews prominent methodologies and identifies research gaps addressed by the proposed framework.

A. Statistical and Econometric Models

Early stock forecasting techniques were primarily based on statistical time-series models such as Autoregressive (AR), Moving Average (MA), and Autoregressive Integrated Moving Average (ARIMA). [3] These models assume linear relationships and stationarity in financial data [10].

Several studies reported that ARIMA performs reasonably well for short-term forecasting under stable market conditions. However, financial markets are inherently nonlinear and influenced by unpredictable macroeconomic and behavioral factors. As a result, purely statistical models fail to capture sudden fluctuations, long-term dependencies, and hidden temporal correlations present in stock data.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models were also introduced to model volatility clustering in stock returns. Although volatility estimation improved, prediction accuracy for price direction remained limited.

B. Machine Learning Approaches

With advancements in computational intelligence, machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, and Random Forests were applied to stock market prediction problems [14].

Support Vector Regression (SVR) demonstrated improved nonlinear mapping capability compared to linear regression models. Random Forest models showed robustness against overfitting by aggregating multiple decision trees. Ensemble learning techniques further enhanced classification performance in predicting stock movement direction (upward or downward).

Despite these improvements, traditional machine learning methods treat input samples independently and do not inherently model sequential dependencies. Financial time-series data possess strong temporal correlations, making memory-based architectures more suitable.

C. Deep Learning-Based Forecasting

Deep learning models have significantly advanced financial time-series analysis[3]. Among them, Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have shown promising performance in stock forecasting [2].

LSTM networks use gated memory cells to retain information across time steps, making them suitable for sequential financial data. Previous studies have investigated LSTM-based forecasting for stock prices and market indices [11].

Hybrid models combining Convolutional Neural Networks (CNN) with LSTM have also been proposed to extract complementary temporal and feature representations [5].

Recent studies have integrated sentiment analysis from financial news and social media platforms to provide additional contextual information for stock forecasting[15].

D. Voice-Based and Multilingual Systems in Financial Applications

Parallel developments in Automatic Speech Recognition (ASR) and Natural Language Processing (NLP) have enabled conversational AI systems in banking and e-commerce sectors. Voice assistants are widely used for account inquiries, transaction support, and customer service.

However, the integration of voice-enabled systems with stock market forecasting remains limited. Existing trading platforms primarily rely on graphical dashboards and English-based interfaces. These systems require users to interpret complex charts and financial indicators, restricting accessibility for non-technical and regional-language users.

Furthermore, most research efforts focus on improving prediction accuracy rather than enhancing usability, inclusivity, and human–AI interaction. Multilingual voice-driven stock forecasting systems have not been extensively explored in academic literature.

E. Research Gap Analysis

From the reviewed literature, the following research gaps are identified:

1. Majority of studies emphasize prediction accuracy without addressing accessibility challenges.
2. Limited integration of multilingual voice interfaces with deep learning-based forecasting.
3. Heavy reliance on real-time APIs and internet connectivity.
4. Lack of local-data-based, user-friendly systems designed for non-expert investors.
5. Minimal focus on financial literacy enhancement through AI-driven interaction.

To address these limitations, the proposed system integrates LSTM-based stock prediction with multilingual speech recognition and translation mechanisms. The implementation emphasizes accessible interaction and clear presentation of prediction outputs rather than claiming comparative superiority over other forecasting models.

METHODOLOGY

The proposed framework integrates multilingual voice interaction with deep-learning-based stock market forecasting. The methodology consists of data loading, preprocessing, LSTM model construction and training, multilingual speech processing, rule-based recommendation generation, and result presentation.

A. System Overview

The architecture of the proposed system follows a modular design consisting of the following components:

1. Voice Input and Speech Recognition Module
2. Language Translation Module
3. Stock Data Processing Unit
4. LSTM-Based Prediction Engine
5. Investment Recommendation Module
6. Multilingual Text-to-Speech Output Module

The user can provide a company name or natural-language query through text or voice. Voice input is converted to text, and non-English input is translated into English for processing. The system loads the corresponding local

CSV datasets, generates an LSTM prediction, calculates the percentage change from the latest closing price, and presents the prediction and rule-based recommendation in text and optional audio form.

B. Data Collection and Dataset Description

Historical stock-price data for six selected Indian companies are stored locally in CSV format. The companies considered by the implementation are HDFC Bank, TCS, Reliance, Infosys, Hindustan, and ITC. The forecasting model uses the Date and Close Price fields; other fields, if present in the CSV files, are not used as model inputs. Table 1 summarizes the fields relevant to the forecasting pipeline.

Table 1. Dataset attributes used by the forecasting pipeline.

Attribute	Description	Used
Date	Trading date used for chronological ordering	Yes
Close	Daily closing price	Yes
Open	Opening price, if present	No
High	Highest price, if present	No
Low	Lowest price, if present	No
Adjusted Close	Adjusted closing price, if present	No
Volume	Trading volume, if present	No

The datasets are stored locally in CSV format, which allows the forecasting pipeline to operate on a fixed historical dataset without requiring a live market-data API.

C. Data Preprocessing

Data preprocessing prepares the historical closing-price series for sequential modeling. The implementation converts the date field to datetime format, removes formatting characters from the closing-price values, converts them to numeric form, sorts records chronologically, applies Min-Max scaling, and constructs sequences using a 60-observation sliding window.

1. Data preparation: Date values are converted to datetime values and closing-price strings are converted to floating-point values.
2. Chronological sorting: Records are sorted by date before sequence construction.
3. Feature selection: The Close price is the only numerical feature passed to the forecasting model.
4. Normalization: Min-Max scaling is applied to the closing-price series.
5. Sequence generation: A sliding window of 60 previous observations is used to construct each input sequence.

Min-Max normalization:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

(1)

The closing-price data are normalized using Min-Max normalization as shown in **Eq. (1)**.

60-step sequence:

$$\begin{aligned} X_t &= [x_{t-60}, x_{t-59}, \dots, x_{t-1}] \\ y_t &= x_t \end{aligned} \quad (2)$$

The normalized data are organized into 60-step input sequences, as represented in **Eq. (2)**.

D. LSTM Model Architecture

LSTM networks model sequential dependencies. The model uses 60 normalized closing-price observations, two stacked LSTM layers, and a single-neuron Dense output layer.

The model is compiled using the Adam optimizer and Mean Squared Error (MSE) loss. The MSE loss function used during training is defined in **Eq. (3)**. Training is performed for 20 epochs with a batch size of 32.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3)$$

Table 2. LSTM model configuration used in the implementation.

Parameter	Value
Input sequence length	60
Input features	1 (Close price)
LSTM layer 1	50 units; return_sequences=True
LSTM layer 2	50 units
Dense output	1 neuron
Optimizer	Adam
Loss	Mean Squared Error (MSE)
Epochs	20
Batch size	32
Dropout	Not used

- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam

E. Voice Recognition and Language Processing

To enhance accessibility, the system integrates speech recognition, translation, and text-to-speech components. The implementation supports English, Hindi, Telugu, Tamil, Kannada, and Bengali.

1. Speech-to-Text Conversion: Voice input is captured through a microphone and converted into text using the SpeechRecognition library and Google speech recognition service.
2. Language Translation: For non-English input, the recognized text is translated into English for company matching and prediction processing.
3. Company matching: The query is checked for supported company names. A query containing “which company” evaluates all six supported companies.

This enables users to interact with the system using natural conversational speech rather than complex commands.

F. Investment Recommendation Strategy

After generating the predicted closing price, the system calculates the percentage change relative to the latest closing price using **Eq. (4)** and applies fixed thresholds to generate a rule-based recommendation.

Percentage change:

$$\Delta P(\%) = \frac{P_{\text{pred}} - P_{\text{last}}}{P_{\text{last}}} \times 100 \quad (4)$$

Table 3. Rule-based recommendation thresholds.

Percentage change	Recommendation	Suggested action
> 2%	Strong Buy	₹10,000
> 0.5% and ≤ 2%	Moderate Buy	₹5,000
≥ −0.5% and ≤ 0.5%	Hold	Wait
< −0.5%	Avoid	Do not invest

When multiple companies are evaluated, the implementation compares predicted growth percentages and identifies the company with the highest predicted percentage increase. This is a rule-based comparative output, not a validated financial recommendation.

G. Multilingual Output and User Interaction

The final prediction results and investment suggestions are presented graphically using price-trend visualization, translated into the selected language, and optionally converted into audio using gTTS.

- Displayed graphically using price trend visualization
- Converted into text in the user’s preferred language
- Delivered as audio output using text-to-speech technology

This provides a simple interaction layer for users who prefer voice or multilingual input.

H. System Deployment

The system is implemented in Python and presented through a Streamlit interface. The stock datasets are stored locally, while speech recognition, translation, and text-to-speech components may use external services. The architecture can be extended in future work with live market-data APIs and alternative forecasting models.

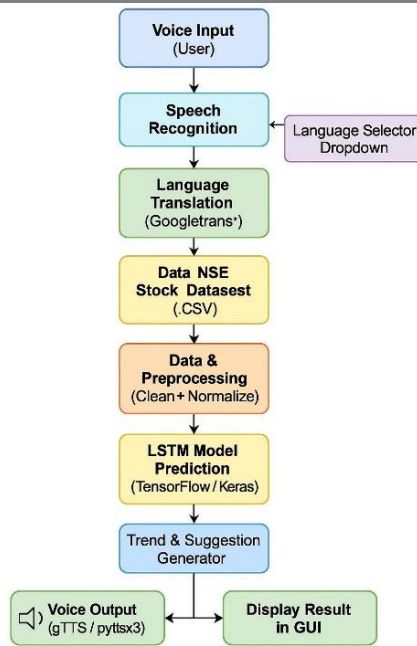


Fig. 1. Architecture of the proposed system.

RESULTS

The proposed system was implemented using the LSTM architecture described in Table 2 and evaluated using historical closing-price data for HDFC Bank, TCS, Reliance, Infosys, Hindustan, and ITC. The model was trained for 20 epochs using Adam optimization and MSE loss. The application displays the latest closing price, predicted price, percentage change, recommendation, suggested investment amount where applicable, estimated profit, and risk label generated by the rule-based module.

Company	Close (₹)	Pred. (₹)	Horizon	Rec.	Invest (₹)	P/L (₹)	Risk
HDFC Bank	1,769.15	1,771.69	7–10d	Hold	5,000	+7.18	Low
TCS	3,292.95	3,500.29	3–5d	Strong Buy	10,000	+629.65	Low
Reliance	1,182.20	1,238.43	3–5d	Strong Buy	10,000	+475.63	Low
Infosys	1,428.80	1,528.98	3–5d	Strong Buy	10,000	+701.18	Low
Hindustan	2,289.25	2,262.91	7–10d	Avoid	5,000	-57.53	High
ITC	412.55	414.01	7–10d	Hold	5,000	+17.70	Low

Table 4. Prediction outputs obtained from the demonstrated run.

- Latest closing price
- Forecasted price range (next 7–10 days)
- Expected rise/fall percentage
- Suggested investment amount
- Estimated profit
- Risk level assessment

A. Prediction Results from the Demonstrated Run

To evaluate multilingual performance, prediction tests were conducted across different companies using voice-based queries.

1) HDFC Bank Prediction Dashboard

For HDFC Bank, the demonstrated run produced a latest closing price of ₹1769.15 and a predicted price of ₹1771.69, corresponding to a 0.14% change and a Hold recommendation. The output is shown in Fig. 2.

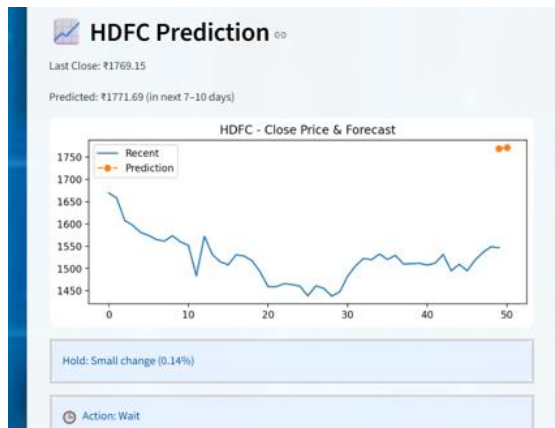


Fig. 2. HDFC Bank prediction dashboard output.

TCS Prediction Dashboard

For TCS, the predicted price was ₹3500.29 compared with a latest close of ₹3292.95, corresponding to a 6.30% increase and a Strong Buy label under the implemented threshold rules. The output is shown in Fig. 3.

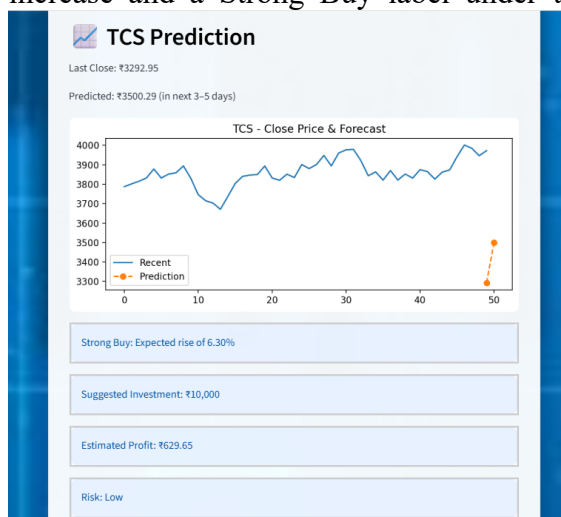


Fig. 3. TCS prediction dashboard output.

The plots visualize the recent 50 closing-price observations and the model prediction point. The numerical summary is reported in Table 4.

2) Reliance Prediction Dashboard

For Reliance, the demonstrated run produced a predicted price of ₹1238.43 from a latest close of ₹1182.20, corresponding to a 4.76% increase. The rule-based module labeled the result Strong Buy. The output is shown in Fig. 4.

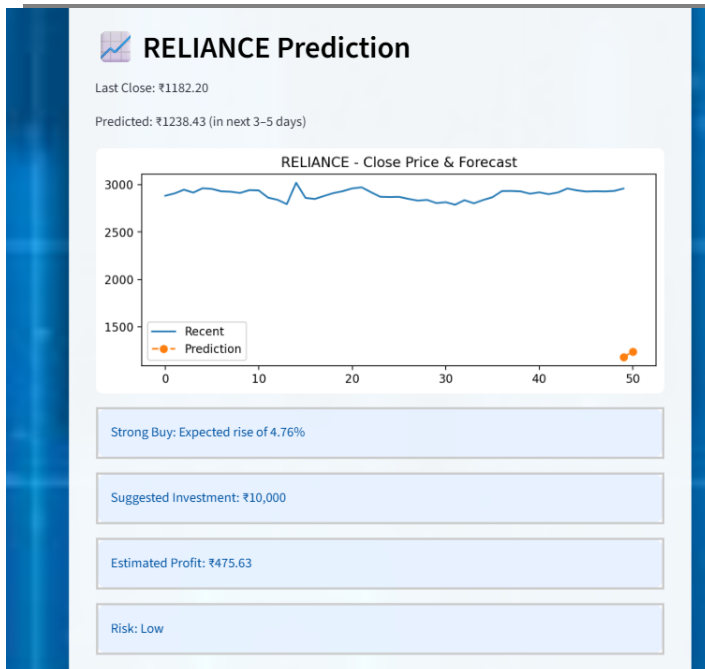


Fig. 4. Reliance prediction dashboard output.

3) Infosys Prediction Dashboard

For Infosys, the predicted price was ₹1528.98 from a latest close of ₹1428.80, corresponding to a 7.01% increase. The rule-based module labeled the result Strong Buy, with a suggested investment of ₹10,000 and an estimated profit of ₹701.18. The output is shown in Fig. 5.

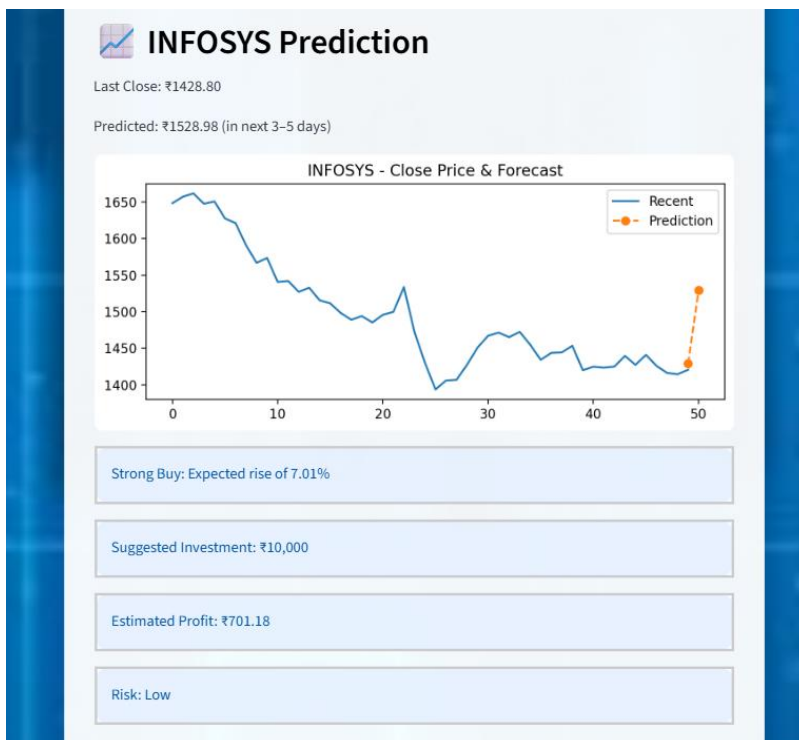


Fig. 5. Infosys prediction dashboard output.

4) Hindustan Prediction Dashboard

For Hindustan, the demonstrated prediction was ₹2262.91 from a latest close of ₹2289.25, a -1.15% change and an Avoid label. The output is shown in Fig. 6.



Fig. 6. Hindustan prediction dashboard output.

5) ITC Prediction Dashboard

For ITC, the predicted price was ₹414.01 from a latest close of ₹412.55, corresponding to a 0.35% change and a Hold label. The output is shown in Fig. 7.

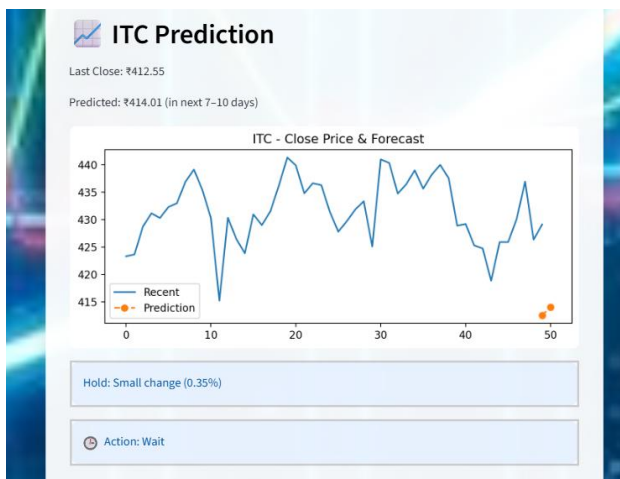


Fig. 7. ITC prediction dashboard output.

6) B. Comparative Prediction Output

The system evaluates all six supported companies when the query asks which company to invest in. In the demonstrated run, Infosys had the highest predicted percentage increase at 7.01%. The displayed output identified Infosys as the top result for that run, with a suggested investment of ₹10,000 and an estimated profit of ₹701.18 under the application's rule-based calculation. The comparative output is shown in Fig. 8 and summarized in Table 4.

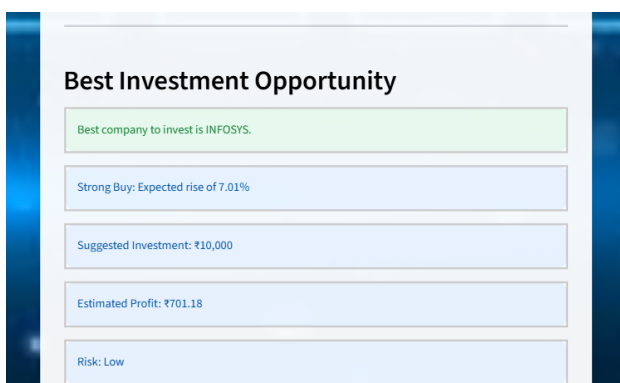


Fig. 8. Comparative recommendation output for the demonstrated run.

CONCLUSION

This paper presented a multilingual voice-enabled stock forecasting system that integrates LSTM-based time-series prediction with speech recognition, language translation, and text-to-speech technologies. The system processes historical closing-price data stored in CSV files and uses a 60-step sequence to generate predicted prices. A rule-based decision module converts predicted price changes into Strong Buy, Moderate Buy, Hold, or Avoid labels. Experimental testing across six selected Indian stocks demonstrated the operation of the forecasting and multilingual interaction pipeline.

The implemented dashboard presents recent price trends, predicted prices, percentage changes, and rule-based investment information. The current implementation should be interpreted as a forecasting and interaction prototype; it does not calculate a held-out prediction accuracy metric in the demonstrated workflow.

The graphical dashboard provides visualization of historical trends, forecasted values, and structured outputs including suggested investment amounts, estimated profit, and rule-based risk labels.

Although the system currently operates on historical CSV datasets, future work can include live market-data API integration, formal train/test evaluation, MAE/RMSE and directional-accuracy reporting, transformer-based time-series forecasting, improved noise-resistant speech recognition, and sentiment analysis from financial news.

- Real-time stock market API integration
- Transformer-based time-series forecasting
- Improved noise-resistant speech recognition
- Sentiment analysis from financial news

REFERENCES

1. Aadhitya, R. Rajapriya, R. S. Vineetha, and M. A. Bagde, "Predicting Stock Market Time-Series Data Using CNN-LSTM Neural Network Model," arXiv preprint arXiv:2305.14378, May 2023.
2. Ijaz, Z. Li, A. S. Gill, and M. K. Rana, "Stock Price Prediction Using Long Short-Term Memory (LSTM) Network," *Innovations in Applied Engineering and Technology*, vol. 2, no. 1, pp. 97–106, Jan. 2023.
3. Moghar and M. Hamiche, "Stock Market Prediction Using LSTM Recurrent Neural Network," *Procedia Computer Science*, vol. 170, pp. 1168–1173, 2020.
4. C.-R. Ko and H.-T. Chang, "Stock Price Forecasting Based on LSTM Neural Network with Sentiment Analysis," *PeerJ Computer Science*, vol. 7, e679, 2021.
5. Zhang, N. N. A. Sjarif, and R. Ibrahim, "1D-CapsNet-LSTM: A Deep Learning-Based Model for Multi-Step Stock Index Forecasting," arXiv preprint arXiv:2310.02090, Oct. 2023.
6. J. Xiao, T. Deng, and S. Bi, "Comparative Analysis of LSTM, GRU, and Transformer Models for Stock Price Prediction," arXiv preprint arXiv:2411.05790, Oct. 2024.
7. K. Pardeshi, S. S. Gill, and A. M. Abdelmoniem, "Stock Market Price Prediction: A Hybrid LSTM and Sequential Self-Attention Based Approach," arXiv preprint arXiv:2308.04419, Aug. 2023.
8. M. Ali, F. Ahmad, M. Khan, and M. U. G. Khan, "Stock Market Prediction Using Hybrid EMD and LSTM Model," *Applied Sciences*, vol. 13, no. 1, pp. 1–17, 2023.
9. M. Sharaf, T. Taha, S. A. A. Badr, and F. M. Bayoumi, "Hybrid LSTM Model for Stock Trend Prediction with Sentiment Analysis during COVID-19," *Multimedia Tools and Applications*, vol. 82, pp. 16253–16273, 2023.
10. N. S. Nareshsathya and A. Enllawar, "Stock Market Predictions Using Moving Average and LSTM Techniques," *Proceedings of the International Conference on Intelligent Systems and Machine Learning (ICISML)*, EAI, Jan. 2024.

11. Q. Li, N. Kamaruddin, S. S. Yuhaniz, and H. A. A. Al-Jaifi, "Forecasting Stock Prices Changes Using Long-Short Term Memory Neural Network with Symbolic Genetic Programming," *Scientific Reports*, vol. 14, no. 1, Article 422, Jan. 2024.
12. S. Joshi, R. Gupta, and A. Pradhan, "A Hybrid CNN-LSTM Model for Stock Market Forecasting," *Journal of Artificial Intelligence and Technology*, vol. 5, no. 2, pp. 88–97, 2025.
13. S. Mahato and B. Ghosh, "Application of Recurrent Neural Networks for Forecasting Indian Stock Market Indices," *Procedia Computer Science*, vol. 132, pp. 1043–1050, 2018.
14. S. Mehtab and J. Sen, "A Robust Predictive Model for Stock Price Prediction Using Deep Learning and Technical Indicators," *arXiv preprint, arXiv:2012.14544*, 2020.
15. S. Raut and N. Kazi, "Sentiment-Enhanced Stock Market Forecasting Using LSTM," *International Journal of Computer Sciences and Engineering*, vol. 8, no. 10, pp. 331–336, Oct. 2020.