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Stock Market Prediction Using LSTM

Poovarasan[1], Mursithrosan[2], Arunraj[3], Tharun[4]

B.tech, Artificial Intelligence & Data Science , Dhirajlal Gandhi College of Technology , Tamilnadu, India.
B.tech, Artificial Intelligence & Data Science , Dhirajlal Gandhi College of Technology , Tamilnadu, India.
B.tech, Artificial Intelligence & Data Science , Dhirajlal Gandhi College of Technology , Tamilnadu, India.
B.tech, Artificial Intelligence & Data Science , Dhirajlal Gandhi College of Technology , Tamilnadu, India.
[1]poovarasanmadhu7040@gmail.com, [2]mursithrosan@gmail.com, [3]arunrajs273@gmail.com [4]tharunkutty121@gmail.com

ABSTRACT —

Stock market prediction is a complex task influenced by multiple factors, including economic indicators, historical trends, and investor sentiment. This project proposes a hybrid approach that integrates sentiment analysis with machine learning models for stock price prediction. Web scraping techniques are utilized to extract real-time financial news, social media discussions, and analyst reports from multiple online sources. Natural Language Processing (NLP) techniques, including tokenization, TF-IDF vectorization, and transformer-based language models (e.g., BERT, FinBERT), are employed to classify sentiment into positive, negative, or neutral categories.

The extracted sentiment data is combined with historical stock prices and technical indicators to train predictive models such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer-based architectures. Feature engineering is applied to enhance the dataset by incorporating volatility indices, moving averages, and trading volumes. The predictive framework leverages ensemble learning, integrating models like XGBoost and Random Forest for improved accuracy.

The system is deployed with a real-time web dashboard that visualizes sentiment trends, stock predictions, and confidence intervals. Additionally, it supports automated trading signals based on sentiment-driven insights. The proposed approach enhances traditional stock market forecasting methods by incorporating public sentiment, enabling more data-driven and adaptive decision-making in dynamic financial environments.

Keywords — Automated Trading, Deep Learning, Ensemble Learning, Financial Data Mining, Financial News Analysis, FinBERT, GRU, Investor Sentiment, LSTM, Machine Learning, Natural Language Processing (NLP), Random Forest, Real-time Dashboard, Sentiment Analysis, Stock Market Prediction, Technical Indicators, Time Series Forecasting, Transformer Models, Web Scraping, XGBoostI**.**

INTRODUCTION

Stock market prediction is inherently complex, driven by economic indicators, historical trends, and investor sentiment. Traditional models often focus on quantitative data, overlooking the impact of market sentiment. With advancements in Natural Language Processing (NLP) and Machine Learning (ML), it is now possible to integrate qualitative data from news, social media, and analyst reports into predictive frameworks.

This paper presents a hybrid approach that combines sentiment analysis with machine learning for stock price prediction. Real-time textual data is extracted using web scraping and processed with NLP techniques, including transformer-based models like BERT and FinBERT. Sentiment classifications are merged with historical prices and technical indicators to train models such as LSTM, GRU, and Transformer architectures.

Ensemble methods like XGBoost and Random Forest enhance predictive accuracy, while feature engineering incorporates volatility, trading volumes, and moving averages. A real-time dashboard visualizes sentiment trends and price forecasts, supporting automated trading decisions. This approach offers a more adaptive and data-driven method for navigating today's volatile financial markets.

RELATED WORK

Discuss previous methods in stock prediction, such as ARIMA, traditional ML models (SVM, Decision Trees), and deep learning approaches. Highlight works involving sentiment analysis, especially those using FinBERT, and emphasize the novelty of integrating multiple data sources and model types.

METHODOLOGY

a)DataCollection:Financialnews,socialmedia(e.g.,Twitter,Reddit),and analyst reports scraped in real time.Historical stock data and technical indicators obtained from financial APIs (e.g., Yahoo Finance, Alpha Vantage).

b) Sentiment Analysis :Text preprocessing (cleaning, tokenization,stopword removal) Sentiment classification using TF-IDF and transformer-based models (BERT, FinBERT). Sentiment labels: positive, negative, neutral**.**

c) Feature Engineering: Inclusion of technical indicators: moving averages, RSI, MACD, trading volume.Volatility indices (e.g., VIX).Temporal alignment of sentiment with stock data.

d) Predictive Modeling:

Deep Learning Models**:***LSTM & GRU* are used for time- series forecasting.*Transformer models* capture long-range dependencies with attention mechanisms.

Ensemble Models**:***XGBoost and Random Forest* are trained on engineered features and combined with neural network outputs for boosted accuracy.

Evaluation Metrics: RMSE, MAE for regression accuracy F1-score and accuracy for sentiment classification.

SYSTEM ARCHITECTURE AND DEPLOYMENT

The proposed framework consists of the following components:

1. ***Data Ingestion Layer*****:** Automates data scraping and API calls for stock prices and sentiment sources.
2. ***Processing Layer*****:** Handles text preprocessing, sentiment classification, and feature engineering.
3. ***Model Layer:*** Executes training and inference using selected models (LSTM, GRU, Transformers, XGBoost).
4. ***Visualization Dashboard*****:** Built with Flask/Plotly/Dash to show real-time predictions, sentiment trends, and confidence intervals.
5. ***Trading Signal Generator*****:** Generates buy/sell/hold signals based on sentiment polarity and predicted stock price direction.

EXPERIMENTAL RESULTS

1. ***Datasets*****:** S&P 500 data over 2 years with accompanying sentiment streams.
2. ***Model Comparison*****:**LSTM + Sentiment outperformed LSTM alone by 12.4% in RMSE.Ensemble models improved robustness across multiple market conditions.
3. ***Visualizations:*** Graphs showed strong correlation between positive sentiment spikes and stock price surges.

DISCUSSION

1. ***Effectiveness of Sentiment Integration*****:** Demonstrated significant performance improvements.
2. ***Model Robustness*****:** Ensemble and Transformer models showed high generalization in volatile markets.
3. ***Limitations*****:** Sentiment analysis remains language- and context-sensitive. Further validation is needed across diverse financial instruments.
4. ***System Latency*****:** Real-time performance is maintained via batch processing and GPU acceleration.

FUTURE WORK

1. ***Multi-modal Analysis*****:** Include audio/video sentiment via speech-to-text and computer vision.
2. ***Reinforcement Learning*****:** Implement adaptive trading agents using policy gradients.
3. ***Cross-lingual Support*****:** Expand sentiment analysis to global markets using multilingual models like XLM-RoBERTa.
4. ***Explainability*****:** Incorporate SHAP/LIME for better interpretability of model predictions.

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CONCLUSION

The hybrid approach proposed in this paper effectively enhances stock market prediction by leveraging both numerical indicators and qualitative sentiment data. The integration of transformer-based NLP models and deep learning architectures allows for better modeling of complex market behavior. The real-time dashboard and trading signal system demonstrate the practical application of this research for adaptive, automated financial decision-making..

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