International Journal of Technology, Leadership and Sciences (IJTLS)

ISSN: 3107-908
www.ijtls.com
Research Paper
DOI: https://doi.org/10.5281/zenodo.20766240

A MACHINE LEARNING APPROACH TO STOCK MARKET PREDICTION BASED ON MULTI-SOURCE INFORMATION

SATULURI VENKATA BHAVANI[1],DR.G.BHARATHI[2],Dr.CHAVA HARI BABU[3], DR.VUNNAVA DINESH BABU[4], R.VAMSI KRISHNA[5], D.SRIDHAR[6]

[1]*M.Tech Student,RV Institute Of Technology,Chebrolu Mandal, Guntur District,Andhra Pradesh, India – 522212.*

[2]*Assistant Professor,RV Institute Of Technology,Chebrolu Mandal, Guntur District,Andhra Pradesh, India – 522212.*

[3]*Professor,RV Institute of Technology,Chebrolu Mandal, Guntur District,Andhra Pradesh, India – 522212.*

[4]*Professor,RV Institute of Technology,Chebrolu Mandal, Guntur District,Andhra Pradesh, India – 522212.*

[5]*Assistant Professor,RV Institute Of Technology,Chebrolu Mandal, Guntur District,Andhra Pradesh, India – 522212.*

[6]*Assistant Professor,RV Institute Of Technology,Chebrolu Mandal, Guntur District,Andhra Pradesh, India – 522212.*

ABSTRACT:

Multiple interrelated elements hinder precise stock market predictions. Conventional machine learning models may insufficiently represent the intricacies of financial markets since they rely on data from a single source and presume exact instance-level classification. Our research presents an innovative method for stock market forecasting called Multi-Source Multiple Instance Learning (MS-MIL). This methodology allows the model to integrate information from many sources, including historical stock prices, financial news, social media sentiment, and macroeconomic indicators, all organized into aggregated data instances (bags). The model adeptly tackles restricted supervision and intrinsic uncertainty in financial data by consolidating each source into separate sets of examples and using a multiple instance learning approach. Our MS-MIL system employs sophisticated feature extraction and attention techniques to combine numerical and textual data for the training of discriminative representations. The experimental results demonstrate that the suggested strategy exceeds traditional learning models in forecasting stock movements and market trends. This technique exhibits promise as a tool for analysts and investors to make informed judgments owing to its superior resilience, flexibility, and interpretability.

Keywords: Stock Market Prediction, Multi-Source Multiple Instance Learning (MS-MIL), Financial Forecasting, Market Trend Prediction, Time Series Analysis, Financial Data Mining, Predictive Analytics.

Received Date: 5 June 2026; **Accepted Date:** 15 June 2026; **Published Date:** 20 June 2026

I.INTRODUCTION

Predicting the stock market is a hard task in finance and machine learning owing to the myriad of interrelated elements that affect market dynamics. These factors include economic circumstances, political events, investor attitude, and societal trends. Precise forecasts of stock prices and market trends are crucial for governments, financial institutions, and individual investors to make informed investment choices

and mitigate financial risks.Historical price data and technical indicators are the basis of conventional stock market forecasting systems. While these approaches efficiently elucidate the topic, they do not constantly include all the intricate patterns and linkages seen in actual financial markets. A plethora of sources, such as financial news, social media discussions, and macroeconomic data, contribute to the excessive flood of financial information facilitated by the development of digital technology and online platforms. Utilizing these varied data sources effectively may substantially enhance prediction performance by providing vital insights.

The integration of heterogeneous information is a significant difficulty due to the heterogeneity in structure, dependability, and frequency of data, particularly when dealing with multi-source data. This research presents a stock market prediction methodology called Multi-Source Multiple Instance Learning (MS-MIL) to tackle these issues. Multiple Instance Learning (MIL), a weakly supervised learning method, is based on labeling groups of instances, known as bags, rather than individual samples. The suggested methodology efficiently discerns relationships across various forms of financial data by augmenting MIL across several information sources.

The suggested methodology evaluates historical stock prices, public attitude toward financial news, social media content, and macroeconomic indicators as distinct but interconnected data sets. The integration of many data sources allows the MS-MIL model to discern critical patterns and correlations that standard machine learning approaches would ignore. To enhance prediction accuracy and model interpretability, attention mechanisms and sophisticated deep learning algorithms focus on the most relevant information from each source.The primary aim of this project is to create an advanced and reliable stock market prediction system that employs diverse financial data to improve forecasting accuracy. Investors, analysts, and financial institutions may gain advantages from the suggested MS-MIL framework's data-driven and comprehensive approach to market trend research in their strategic decision-making processes.

II.LITERATURE REVIEW

Ding, Xiaowen; Zhang, Yue; and Liu, Ting investigated the feasibility of combining Twitter sentiment analysis with historical stock price data to forecast future stock market trends. Their study suggested a hybrid framework that combines time-series forecasting models with Natural Language Processing (NLP) techniques. Experimental studies demonstrate that models based just on historical price data are much less accurate than those using sentiment information.

Individual instances signify daily trading aspects, whereas bags indicate particular time periods; this embodies the functionality of Li and Zhou's Multiple Instance Learning (MIL) methodology for stock selection. The lack of instance-level labels is no longer an issue since the MIL framework can detect hidden temporal patterns. Their research shows that MIL approaches are efficacious for financial forecasting tasks when precise granular annotations are limited.

XU, Yang, and Cohen, William W. developed a stock prediction system using deep learning that incorporates sentiment analysis from financial news items and internet discussion forums. The model used Recurrent Neural Networks (RNNs) to tackle the temporal interdependence of stock market operations. The suggested method improved the predictive effectiveness of traditional market indicators by including textual sentiment.

Ghoshal, Palash, and Steven Roberts investigated a multi-modal data fusion methodology using CNNs and RNNs to forecast the stock market. Their system could assimilate and extract information from many sources, including quantitative stock indicators and textual financial data. The integration of many data modalities allowed the model to use linkages across sources, hence enhancing the accuracy of its predictions.

Ilse, Maximilian; Tomczak, Jakub M.; and Welling, Max suggested an attention-driven deep learning approach for Multiple Instance Learning. This approach allocates variable values to instances inside a bag. The attention-based MIL framework significantly enhanced both the performance and interpretability of models, while not being explicitly tailored for financial applications. The use of this approach to stock market prediction difficulties, including poorly labeled instances and multi-source financial data, has shown promising results

.III.EXISTING SYSTEM

The primary stock market prediction techniques use deep learning and machine learning models trained on technical indicators, limited textual data, and historical stock prices. Market trend forecasting extensively use methodologies such as CNN, RNN, LSTM, and SVM. To improve prediction accuracy, use systems that employ natural language processing techniques to include sentiment analysis from Twitter, financial news, and online forums. Multiple Instance Learning (MIL) methodologies are used to discern underlying temporal patterns without specific instance-level annotations. Contemporary systems often face challenges stemming from erratic financial data, inadequate integration across several sources, and reduced prediction accuracy. These issues impact the overall effectiveness of forecasting and the precision of decision-making.

DISADVANTAGES

- Existing methodologies mostly rely on single-source data, hence limiting predictive accuracy.
- Financial textual data from social media and news is often chaotic and disordered.

IV.PROPOSED SYSTEM

The proposed method employs a framework grounded on Multi-Source Multiple Instance Learning (MS-MIL) to integrate diverse financial data sources, therefore enhancing predictive accuracy and robustness while addressing the limitations of conventional stock market forecasting models. The proposed approach treats each data source as an independent but complementary information channel, enabling the model to discern more substantial and intricate market patterns than conventional methods depending on a singular set of features.

A stock prediction instance under the proposed MS-MIL framework comprises a collection of data from several sources, including financial news articles, technical indicators, social media sentiment, historical stock price data, and macroeconomic variables. The algorithm assigns labels to the whole dataset based on outcomes, such as variations in stock price, rather than to individual instances.The model use attention-based deep learning methodologies to ascertain which samples from diverse sources had the most influence. Consequently, the system may eliminate superfluous or distracting information while focusing on what is really important. The proposed method enhances prediction accuracy and interpretability, providing more dependable stock market predictions under dynamic conditions by the effective integration of numerical, linguistic, and economic data.

ADVANTAGES

- Improves the accuracy of predictions by bringing together several data sources.
- Integrates quantitative, qualitative, emotional, and economic data with success.

V.SYSTEM MODEL

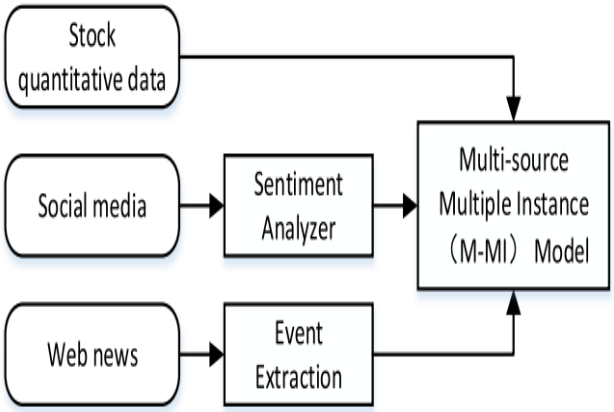


Fig 1.System framework of our proposed model

The suggested approach for improved stock market predictions amalgamates data from several sources, including social media content, online news articles, and quantitative stock metrics. We begin with sentiment analysis of social media data to assess public sentiment toward the market and general opinion, while using event extraction on online news articles to discern major financial storylines and trends. The stock market data, including opening and closing prices, trade volume, technical indicators, and sentiment and event representations, has been integrated with this historical data. The produced data is sent to the M-MI learning model, which signifies Multi-Source Multiple Instance. The M-MI approach is based on the notion of Multiple Instance Learning (MIL), which posits that a collective label should be assigned to a group rather than different labels to individual instances. The framework presents expansions of this notion, including instance-level labels, source-level group labels, and multi-source super group labels. The model's primary aim, using all accessible data, is to forecast the fluctuations of the stock market index, indicating whether it will ascend or fall. The system assesses the probability at the instance level to ascertain the impact of each case on stock movement forecast. Additionally, it evaluates the impact of each data source on the prediction result by calculating source-specific weights. This multifaceted learning approach improves forecast precision, interpretability, and robustness in fluctuating financial markets.

VI.MODULES

We have developed the following modules:

1) Upload Dataset: This module enables the uploading of the dataset.

2) Preprocess Dataset: Standardize all characteristics inside the dataset.

3) Train and Test Split: partition the dataset into training and testing subsets, designating 80% of the data for training and 20% for testing.

4) Train Multi-modal Transformer: Eighty percent of the training data will be used as input for the transformer decoder method to develop a model, which will then be applied to the remaining twenty percent of the test data to assess prediction accuracy.

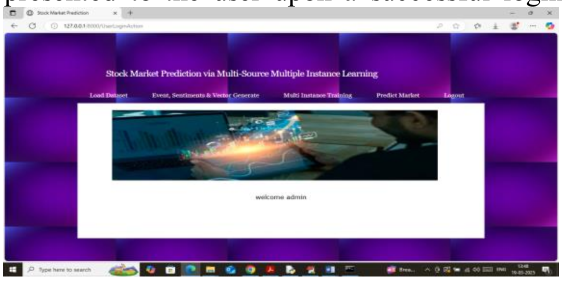
5) Training Graph: This course will provide a graph depicting Transformer training and loss data.

6) Test: using this module will submit test data and forecast stock market outcomes.

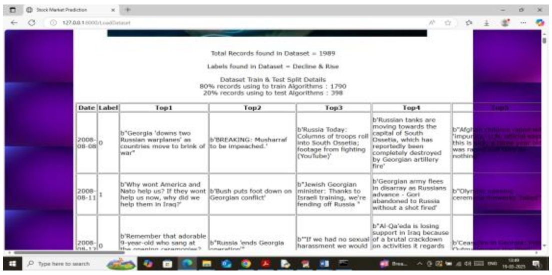
VII.SCREENSHOTS

Click the "User Login" option on the previous screen to go to the next page.

The page seen on the preceding screen will be presented to the user upon a successful login.

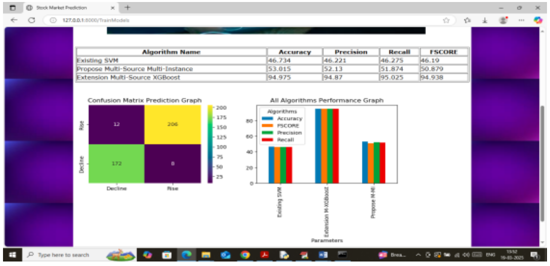


Upon selecting the "Load Dataset" option on the preceding screen, the subsequent page will be shown.

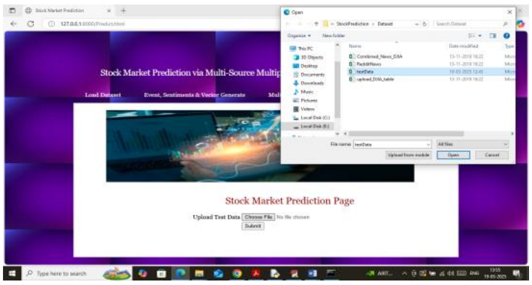


The upper section of the screen displays the aggregate count of records in the dataset, along with the dimensions of the training and testing sets. All news and stock information may be presented in a tabular fashion. Choose the "Event, Sentiments & Vector Generate" option to get the events, sentiments, and vectors from the test and training datasets. You will then face the screen seen below.

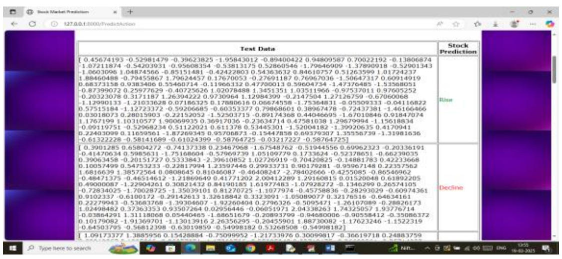
Upon choosing the "Multi Instance Training" option to train all algorithms, the following screen will be shown. The prior screen displayed vector values derived from market and news data.



The table format above demonstrates that the XGBOOST method exceeded the Existing SVM, the Proposed Multi-Instance, and the FCSORE in terms of accuracy, precision, and recall. The data clearly indicates that the extension XGBOOST obtained an accuracy rate of 94%, whereas the proposal reached just 53%. The confusion matrix graph use the x-axis for predicted labels and the y-axis for actual labels. The number of correct forecasts is shown by the green and yellow boxes along the diagonal, but the number of faulty predictions is indicated by the sparse blue boxes. The x-axis of the bar graph denotes algorithm names, while the y-axis depicts several metrics, including accuracy, represented by bars of different colors. Click the "Predict Market" hyperlink to go to the next page.



After selecting and uploading the test dataset using the icons on the previous screen, you will go to the subsequent page.



The first column of the designated screen displays the vector obtained from news and stock test data. The second column denotes the stock prediction status as "Rise or Decline," enabling the user to invest the specified amount according to this forecast.

VIII.CONCLUSION

This study introduces a sophisticated Adaptive Multi-Modal Speech Transformer Decoder that improves the detection and understanding of spoken language by amalgamating audio, visual, and textual inputs. The suggested technique tackles the fundamental problems of current methods, including their computing inefficiency, rigid fusion processes, and inadequate resilience under noisy conditions.

The system outperforms single-modality models in complex settings via multi-level fusion, dynamic cross-modal attention, and reliability evaluations across many modalities. The adaptive fusion method provides a more dependable and advanced decoding process, guaranteeing system resilience in the face of damage or lack of certain modalities.

IX.FUTURE ENHANCEMENTS

Virtual assistants, automated transcription services, and surveillance systems illustrate real-time sectors that might benefit from the implementation of modern transformer designs with optimum resource efficiency.

In conclusion, the research demonstrates that, with suitable configuration and design, the use of several modalities significantly improves the accuracy and resilience of speech decoding systems, highlighting the need for reliability-oriented and context-aware multi-modal integration.

X.REFERENCES

1. Multimodal Transformer with Missing Modality Imagination for Simultaneous Translation — H. Inaguma, S. Dalmia, T. Hori, and S. Watanabe, “Multimodal Transformer with Missing Modality Imagination for Simultaneous Translation,” arXiv preprint arXiv:2004.12655, 2020.
2. Audio-Visual Transformer for Robust Speech Recognition — Y. Lee, C. Kim, and H. Kim,

"Audio-Visual Transformer for Robust Speech Recognition," IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 29, pp. 2795–2809, 2021.

3. A Survey of Multimodal Machine Translation: Challenges and Future Directions — A. M. R. Dabre, K. Sudoh, and S. Kurohashi, "A Survey of Multimodal Machine Translation: Challenges and Future Directions," ACM Computing Surveys (CSUR), vol. 55, no. 2, pp. 1–38, 2023.
4. Deep Audio-Visual Speech Recognition — S. Afouras, J. S. Chung, and A. Zisserman, "Deep Audio-Visual Speech Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 1, pp. 215–229, 2022.
5. VATT: Transformers for Multimodal Self-Supervised Learning from Raw Video, Audio and Text — Y. Akbari et al., "VATT: Transformers for Multimodal Self-Supervised Learning from Raw Video, Audio and Text," Advances in Neural Information Processing Systems (NeurIPS), 2021.
6. Multimodal Transformer with Multi-View Visual Representation for Video Captioning — D. Chen, H. Hu, X. Wang, and L. Zhang, "Multimodal Transformer with Multi-View Visual Representation for Video Captioning," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2021.
7. Multi-Modal Speech Recognition Using Visual Information for Noise Robustness — H. Li, Y. Tao, and L. Wang, "Multi-Modal Speech Recognition Using Visual Information for Noise Robustness," ICASSP, 2019.
8. Attention is All You Need — A. Vaswani et al., "Attention is All You Need," Advances in Neural Information Processing Systems (NeurIPS), 2017.
9. Lip Reading with Cross-Attention Transformer — J. Huang, W. Xie, and M. Wu, "Lip Reading with Cross-Attention Transformer," ICASSP, 2022.
10. Hybrid CTC/Attention Architecture for End-to-End Speech Recognition — S. Watanabe, T. Hori, S. Kim, J. R. Hershey, and T. Hayashi, "Hybrid CTC/Attention Architecture for End-to-End Speech Recognition," IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1240–1253, 2017.