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Hybrid Information Mixing Module for Stock Movement Prediction

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ABSTRACT— With the continuing active research on deep learning, research on stock price prediction using deep learning has been actively conducted in the financial industry. This paper proposes a method for predicting stock price movement using stock and news data. The stock market is affected by many variables; thus, market volatility should be considered for predicting stock price movement. Because stock markets are efficient, all kinds of information are quickly reflected in stock prices. We create a new fusion mix by combining price and text data features and propose a hybrid information mixing module designed using two map blocks for effective interaction between the two features. We extract the multimodal interaction between the time-series features of the price data and the semantic features of the text data. In this paper, a multilayer perceptron-based model, the hybrid information mixing module, is applied to the stock price movement prediction to conduct a price fluctuation prediction experiment in a stock market with high volatility. In addition, the accuracy, Matthews correlation coefficient (MCC) and F1 score for the stock price movement prediction were used to verify the performance of the hybrid information mixing module.

INTRODUCTION

Stock market prediction is a challenging task due to the highly dynamic and volatile nature of financial markets, where prices are influenced by multiple factors such as historical trends, company performance, global events, and public sentiment. Traditional methods that rely only on past price data often fail to capture these complex relationships, resulting in lower accuracy. To overcome this limitation, this project proposes a hybrid deep learning approach that combines stock price data with textual data such as tweets. Time-series models like LSTM and GRU are used to analyze historical price patterns, while BERT is used to extract sentiment features from text data. These features are integrated using a Hybrid Information Mixing Module based on a Multilayer Perceptron (MLP), enabling better interaction between numerical and textual information. The system predicts whether stock prices will increase or decrease, aiming to improve accuracy and support better decision-making for investors and analysts.

I. PROBLEM DEFINITION

Predicting stock price movements is a challenging task due to the complex, volatile, and dynamic nature of financial markets, where prices are influenced by both historical numerical data and qualitative information such as news. Traditional models that rely solely on price data or textual information fail to capture the interaction between these heterogeneous sources, limiting their predictive accuracy. Rapid market reactions to new information further complicate forecasting, especially in highly volatile conditions. Therefore, there is a need for a robust framework that can effectively fuse time-series price features with semantic news features, model their multimodal interactions, and provide accurate and reliable stock price movement predictions, enhancing decision-making for investors.

1.2 PROJECT FEATURES

Several studies have explored the use of deep learning techniques for stock market prediction by integrating multiple data sources such as historical stock prices and social media data. Data preprocessing methods, including handling missing values and applying normalization techniques like Min-Max scaling, are commonly used to improve data quality and model performance. Advanced natural language processing models such as BERT are widely adopted for extracting meaningful semantic features from textual data like tweets, enabling better understanding of public sentiment and its impact on market trends. For analyzing time-series data, models such as LSTM and GRU are extensively used due to their ability to capture temporal dependencies and patterns in stock price movements. Hybrid approaches that combine numerical and textual features using models like Multilayer Perceptrons (MLP) have shown improved prediction accuracy compared to single-model techniques. These systems typically perform binary classification to predict stock movement (increase or decrease) and are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Visualization techniques, including graphs and confusion matrices, are often used to analyze and compare model performance. Additionally, many systems provide user-friendly interfaces for data input, model training, and result analysis, along with support for batch processing to handle large datasets efficiently. Despite these advancements, challenges such as data noise, model complexity, and generalization remain, highlighting the need for more robust and efficient hybrid models.

II. METHODOLOGY

The proposed system follows a structured methodology to predict stock price movements by integrating both numerical stock data and textual sentiment data. The overall workflow consists of data collection, preprocessing, feature extraction, model development, training, and evaluation.

2.1 Data Collection

The system utilizes two primary data sources:

- **Stock Price Data**: Historical stock prices (open, high, low, close values) collected from financial datasets.
- **Textual Data**: Social media data such as tweets related to stock market trends and companies.

These datasets are used to capture both quantitative market behavior and qualitative public sentiment.

2.2 Data Preprocessing

Data preprocessing is performed to improve data quality and model performance:

- Missing values are handled by replacing them with appropriate values (e.g., zeros).
- Stock data is normalized using Min-Max scaling to bring all features into a common range.
- Tweets are cleaned by removing noise such as special characters and irrelevant content.
- The dataset is shuffled and split into training (80%) and testing (20%) sets.

2.3 Feature Extraction

Feature extraction is carried out separately for both data types:

- **Text Features**: A pre-trained BERT (Bidirectional Encoder Representations from Transformers) model is used to convert tweets into numerical embeddings that represent semantic meaning.
- **Time-Series Features**: Stock price data is processed using deep learning models like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) to capture temporal dependencies and trends.

2.4 Feature Fusion

The extracted features from stock data and tweet embeddings are combined to form a unified feature set. This fusion enables the model to learn relationships between market trends and public sentiment.

2.5 Model Development

Three models are developed and compared:

1.**LSTM Model** – Uses combined features to predict stock movement.

2.**Hybrid Model (LSTM + GRU)** – Integrates both LSTM and GRU layers to enhance learning capability.

3.**Extended Hybrid Model (LSTM + GRU + Bidirectional)** – Incorporates bidirectional learning for better feature optimization.

All models are implemented using deep learning frameworks such as TensorFlow and Keras.

2.6 Training and Testing

•Models are trained using the training dataset with multiple epochs and batch processing.

•Dropout layers are used to reduce overfitting.

•Model weights are saved and reused to optimize training time.

2.7 Performance Evaluation

The performance of the models is evaluated using standard metrics:

•Accuracy

•Precision

•Recall

•F1-Score

•Confusion Matrix

These metrics help in assessing the effectiveness of the system in predicting whether stock prices will increase or decrease.

2.8 Prediction

The final trained model is used to predict stock price movement for new input data. The system outputs a binary result indicating whether the stock price will go **up** or **down**.

III. PROPOSED SYSTEM

The proposed system aims to improve stock market prediction by using a hybrid deep learning approach that overcomes the limitations of existing methods. It integrates multiple data sources, including historical stock price data and social media data such as tweets, to provide a more comprehensive understanding of market behavior. The system uses advanced techniques like BERT for sentiment analysis to extract meaningful information from textual data and understand public opinion. At the same time, LSTM and GRU models are applied to analyze time-series stock data and capture patterns and long-term dependencies effectively

4.IMPLEMENTATION DETAILS

The implementation phase focuses on developing the proposed system using appropriate tools, technologies, and deep learning models. This section describes the practical execution of the system, including environment setup, data handling, model building, and prediction process.

4.1 ALGORITHMS USED

4.1.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) designed to handle sequential data and long-term dependencies. It is widely used in time-series forecasting because it can effectively capture patterns over long periods. LSTM overcomes the vanishing gradient problem, which is common in traditional RNNs, making it suitable for learning complex temporal relationships. In this project, LSTM is used to analyze historical stock price data and identify trends over time, which helps in predicting future stock movements accurately.

4.1.2 Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is a simplified version of LSTM that uses fewer parameters while maintaining similar performance. It is computationally efficient and faster to train compared to LSTM, making it suitable for large datasets. GRU effectively captures short-term dependencies in sequential data and reduces model complexity. In this project, GRU is used alongside LSTM to improve efficiency and enhance the model's ability to learn temporal features from stock price data.

4.1. Bidirectional Recurrent Neural Network (Bi-GRU / Bi-LSTM)

Bidirectional Recurrent Neural Networks process data in both forward and backward directions, allowing the model to capture information from past as well as future contexts. This improves sequence understanding and enhances prediction accuracy. By analyzing the data in two directions, the model gains a deeper understanding of temporal relationships. In this project, a Bidirectional GRU is used in the extended model to improve feature learning and provide better prediction results.

4.1.4 BERT (Bidirectional Encoder Representations from Transformers)

BERT is a transformer-based model used for Natural Language Processing tasks. It is pre-trained on large text datasets and is capable of understanding the context of words in both forward and backward directions. BERT generates high-quality embeddings that capture the semantic meaning of text. In this project, BERT is used to extract meaningful features from tweets, enabling the system to understand public sentiment and its impact on stock market movements.

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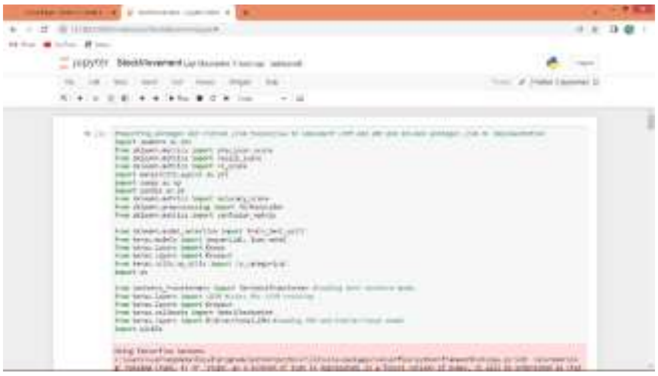
4.1.5 Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP) is a fully connected neural network used for classification tasks. It is capable of learning complex patterns and nonlinear relationships between input features. MLP combines multiple features and processes them through hidden layers to produce accurate predictions. In this project, MLP is used as part of the hybrid information mixing module to combine features from stock price data and tweet embeddings, resulting in improved prediction performance.

RESULTS AND DISCUSSION

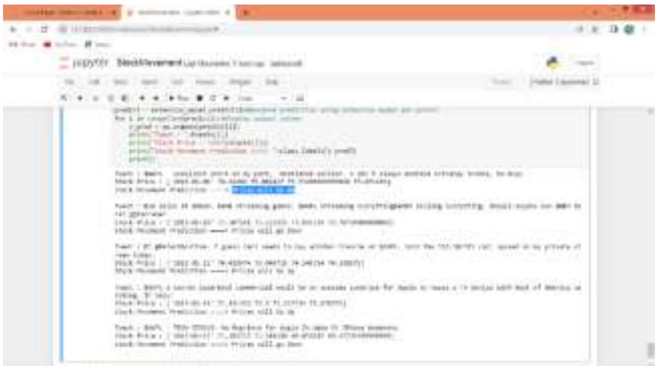
The results show that the hybrid deep learning approach improves stock price prediction accuracy. The LSTM model achieved about 79% accuracy, while the Hybrid (LSTM + GRU) model improved it to around 83%. The Extended Hybrid Model (LSTM + GRU + Bidirectional) performed best with approximately 85% accuracy. Evaluation metrics like precision, recall, and F1-score also improved across models. Overall, combining stock data with tweet sentiment using hybrid models provides more accurate and reliable predictions.

Jupiter NoteBook Main Execution:



Jupyter Notebook Main Execution Screen of the deep learning-based image augmentation approach in agricultural applications.

Fig. 1. Final Output Page



VI. CONCLUSION

In conclusion, the project has successfully achieved its objectives by developing an efficient and intelligent system for detecting and classifying inappropriate content in YouTube videos using advanced deep learning techniques. The use of models such as EfficientNet-B7, BiLSTM, and attention mechanisms has improved the accuracy and reliability of the system, providing effective results in content classification. The implementation was carefully planned and executed, leading to valuable insights and better performance compared to traditional methods. In the future, the system can be further enhanced by integrating more advanced models, expanding datasets, and improving real-time processing capabilities. These improvements will increase scalability, accuracy, and efficiency, ensuring that the system remains relevant and contributes to creating a safer online environment.

VII. FUTURE SCOPE

The future scope of this project includes enhancing the model by integrating more advanced deep learning techniques such as transformer-based architectures and attention mechanisms to further improve prediction accuracy. The system can be extended by incorporating additional data sources like financial news, economic indicators, and global market trends for better analysis. Real-time stock prediction can be implemented to provide instant insights for users. The model can also be deployed on cloud platforms to improve scalability and handle large datasets efficiently. Furthermore, improving the user interface and adding mobile or web-based applications can make the system more accessible and user-friendly. Continuous learning using updated data and user feedback can also help in making the system more robust and adaptive to changing market conditions.

IX. REFERENCES

[1] Y. Xu and S. B. Cohen, ''Stock movement prediction from tweets and historical prices,'' in Proc. 56th Annu. Meeting Assoc. Comput. Linguistics, Melbourne, VIC, Australia, 2018, pp. 1970–1979.

[2] T. Lin, T. Guo, and K. Aberer, ''Hybrid neural networks for learning the trend in time series,'' in Proc. 26th Int. Joint Conf. Artif. Intell., Melbourne, VIC, Australia, Aug. 2017, pp. 2273–2279.

[3] E. Jang, H. R. Choi, and H. C. Lee, ''Stock prediction using combination of BERT sentiment analysis and macro economy index,'' J. Korea Soc. Comput. Inf., vol. 25, no. 5, pp. 47–56, 2020.

[4] X. Li, Y. Li, H. Yang, L. Yang, and X.-Y. Liu, ''DP-LSTM: Differential privacy-inspired LSTM for stock prediction using financial news,'' 2019, arXiv:1912.10806.

[5] P. Sonkiya, V. Bajpai, and A. Bansal, ''Stock price prediction using BERT and GAN,'' 2021, arXiv:2107.09055.

[6] R. Sawhney, S. Agarwal, A. Wadhwa, and R. R. Shah, ''Deep attentive learning for stock movement prediction from social media text and company correlations,'' in Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP), 2020, pp. 8415–8426. [Online]. Available: https://aclanthology.org/2020.emnlp-main.676

[7] Y. Zhao, H. Du, Y. Liu, S. Wei, X. Chen, F. Zhuang, Q. Li, J. Liu, and G. Kou, ''Stock movement prediction based on bi-typed hybridrelational market knowledge graph via dual attention networks,'' 2022, arXiv:2201.04965.

[8] I. Tolstikhin, N. Houlsby, A. Kolesnikov, L. Beyer, X. Zhai, T. Unterthiner, J. Yung, D. Keysers, J. Uszkoreit, M. Lucic, and A. Dosovitskiy, ''MLPmixer: An all-MLP architecture for vision,'' in Proc. Adv. Neural Inf. Process. Sys., vol. 34, 2021, pp. 24261–24272. [Online]. Available: https://proceedings.neurips.cc/paper/2021/hash/cba0a4ee5ccd02fda0fe3f 9a3e7b89fe-Abstract.html

[9] H. Liu, Z. Dai, D. So, and Q. V. Le, ''Pay attention to MLPs,'' in Proc. Int. Conf. Neural Inf. Process. Syst., vol. 34, 2021, pp. 9204–9215. [Online]. Available: https://openreview.net/pdf?id=KBnXrODoBW 28788 VOLUME 11, 2023

[10] M. Li, X. Zhao, C. Lyu, M. Zhao, R. Wu, and R. Guo, ''MLP4Rec: A pure MLP architecture for sequential recommendations,'' in Proc. 31st Int. Joint Conf. Artif. Intell., Vienna, Austria, Jul. 2022, pp. 2138–2144.

[11] H. Touvron, P. Bojanowski, M. Caron, M. Cord, A. El-Nouby, E. Grave, G. Izacard, A. Joulin, G. Synnaeve, J. Verbeek, and H. Jégou, ''ResMLP: Feedforward networks for image classification with data-efficient training,'' 2021, arXiv:2105.03404.

[12] F. Mai, A. Pannatier, F. Fehr, H. Chen, F. Marelli, F. Fleuret, and J. Henderson, ''HyperMixer: An MLP-based green AI alternative to transformers,'' 2022, arXiv:2203.03691.

[13] R. Kim, C. H. So, M. Jeong, S. Lee, J. Kim, and J. Kang, ''HATS: A hierarchical graph attention network for stock movement prediction,'' 2019, arXiv:1908.07999.

[14] X. Ding, Y. Zhang, T. Liu, and J. Duan, ''Deep learning for event-driven stock prediction,'' in Proc. 24th Int. Joint Conf. Artif. Intell., Buenos Aires, Argentina, 2015, pp. 2327–2333.

[15] Z. Hu, W. Liu, J. Bian, X. Liu, and T.-Y. Liu, ''Listening to chaotic whispers: A deep learning framework for news-oriented stock trend prediction,'' in Proc. 11th ACM Int. Conf. Web Search Data Mining, New York, NY, USA, Feb. 2018, pp. 261–269.

[16] Q. Liu, X. Cheng, S. Su, and S. Zhu, ''Hierarchical complementary attention network for predicting stock price movements with news,'' in Proc. 27th ACM Int. Conf. Inf. Knowl. Manage., Italy, Oct. 2018, pp. 1603–1606.

17] X. Du and K. Tanaka-Ishii, ''Stock embeddings acquired from news articles and price history, and an application to portfolio optimization,'' in Proc. 58th Annu. Meeting Assoc. Comput. Linguistics, Seattle, WA, USA, 2020, pp. 3353–3363.

[18] L. Zhang, C. Aggarwal, and G.-J. Qi, ''Stock price prediction via discovering multi-frequency trading patterns,'' in Proc. 23rd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Halifax, NS, Canada, Aug. 2017, pp. 2141–2149.

[19] T. H. Nguyen and K. Shirai, ''Topic modeling based sentiment analysis on social media for stock market prediction,'' in Proc. 53rd Annu. Meeting Assoc. Comput. Linguistics 7th Int. Joint Conf. Natural Lang. Process., Beijing, China, vol. 1, 2015, pp. 1354–1364.

[20] X. Li, H. Xie, L. Chen, J. Wang, and X. Deng, ''News impact on stock price return via sentiment analysis,'' Knowl.-Based Syst., vol. 69, pp. 14–23, Oct. 2014.

[21] C. Rui and Q. Li, ''Modeling the momentum spillover effect for stock prediction via attribute-driven graph attention networks,'' in Proc. AAAI Conf. Artif. Intell., vol. 35 no. 1, 2021, pp. 55–62. [Online]. Available:

https://ojs.aaai.org/index.php/AAAI/article/view/16077

[22] K. Stankeviciute, A. M. Alaa, and M. van der Schaar, ‘‘Conformal timeseries forecasting,’’ in Proc. Adv. Neural Inf. Process. Sys., vol. 34, 2021, pp. 6216–6228. [Online]. Available: https://proceedings.neurips.cc/paper/2021/hash/312f1ba2a72318edaaa995a67835fad5-Abstract.html

[23] C. Li, D. Song, and D. Tao, ‘‘Multi-task recurrent neural networks and higher-order Markov random fields for stock price movement prediction: Multi-task RNN and higer-order MRFs for stock price classification,’’ in Proc. 25th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Anchorage, AK, USA, Jul. 2019, pp. 1141–1151.

[24] D. M. Q. Nelson, A. C. M. Pereira, and R. A. de Oliveira, ‘‘Stock market's price movement prediction with LSTM neural networks,’’ in Proc. Int. Joint Conf. Neural Netw. (IJCNN), Anchorage, AK, USA, May 2017, pp. 1419–1426.

[25] V. S. Pagolu, K. N. Reddy, G. Panda, and B. Majhi, ‘‘Sentiment analysis of Twitter data for predicting stock market movements,’’ in Proc. Int. Conf. Signal Process., Commun., Power Embedded Syst. (SCOPES), Paralakhemundi, Odisha, India, Oct. 2016, pp. 1345–1350.