STOCK MARKET PREDICTION VIA MULTISOURCE MULTIPLE INSTANCE LEARNING

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ABSTRACT

Stock market prediction remains a highly complex and dynamic problem due to the nonlinear, volatile, and noisy nature of financial data. Traditional predictive models often rely on single-source structured data such as historical price series, limiting their ability to capture broader market influences. This project proposes a novel framework for stock market prediction using Multisource Multiple Instance Learning (MS-MIL), which integrates heterogeneous data sources and models them as collections of instances grouped into informative bags. The system leverages multiple data streams including historical stock prices, financial news articles, social media sentiment, and macroeconomic indicators to improve predictive performance. In the proposed methodology, each trading day is treated as a bag containing multiple instances derived from different data modalities. A Multiple Instance Learning (MIL) framework is applied to handle weakly labeled data, where labels are assigned at the bag level rather than individual instances. Advanced Deep Learning architectures, such as attention-based neural networks and hybrid models combining Recurrent Neural Networks (RNNs) and Transformer models, are employed to extract temporal dependencies and contextual relationships across sources. Feature fusion techniques are used to integrate structured numerical data with unstructured textual data, enhancing the model's ability to capture latent patterns. The system aims to achieve high prediction accuracy by reducing noise sensitivity and improving generalization through multisource learning. Experimental evaluation is conducted using benchmark financial datasets, demonstrating that the MS-MIL approach outperforms conventional machine learning models such as Support Vector Machines (SVM) and Random Forests. The model's performance is assessed using metrics like accuracy, precision, recall, and F1-score. This research contributes to the field of financial analytics by introducing a scalable and robust framework capable of handling complex, real-world data scenarios, thereby enabling more reliable and informed investment decision-making.

Keywords: Stock Market Prediction, Multisource Learning, Multiple Instance Learning (MIL), Deep Learning, Financial Forecasting, Sentiment Analysis, Time Series Analysis, Data Fusion, RNN, Transformer Models

I.INTRODUCTION

The stock market is a complex, nonlinear, and dynamic system influenced by multiple factors such as economic indicators, investor sentiment, geopolitical events, and company performance. Traditional forecasting approaches primarily rely on historical price data and statistical models like ARIMA and linear regression, which often fail to capture hidden patterns and sudden market fluctuations. With the emergence of Artificial Intelligence (AI) and Machine Learning (ML), researchers have explored advanced techniques to improve prediction accuracy. However, models based on single-source data are still limited in capturing the full context of market behavior. Recent studies emphasize the importance of integrating heterogeneous data sources such as financial news, social media sentiment, and macroeconomic indicators to achieve more reliable predictions [1]–[5].

To overcome these limitations, this project proposes a Multisource Multiple Instance Learning (MS-MIL) framework for stock market prediction. Multiple Instance Learning (MIL) is a weakly supervised learning approach where labels are assigned to bags rather than individual instances, making it highly suitable for noisy and unstructured financial data [6]–[9]. In this framework, each trading day is treated as a bag containing multiple instances derived from different data sources such as stock prices, sentiment scores, and technical indicators. Advanced Deep Learning models, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures, are utilized to capture temporal dependencies and contextual relationships across multiple sources [10]–[15]. Feature fusion techniques further enhance the system by combining structured numerical data with unstructured textual data, improving predictive capability.

The integration of multisource data with MIL provides a robust and scalable solution for real-world financial forecasting challenges. This approach helps reduce noise sensitivity and improves generalization by learning from diverse and complementary information sources. The proposed model is evaluated using various performance metrics such as accuracy, precision, recall, and F1-score, demonstrating superior performance compared to conventional models like Support Vector Machines (SVM) and Random Forests [16]–[20]. Additionally, this research contributes to the evolving domain of Financial

Data Science by bridging the gap between structured and unstructured data analysis. The MS-MIL framework enables more informed investment decision-making and risk management strategies, making it a valuable advancement in intelligent financial systems [21]–[25].

II SURVEY OF RESEARCH

1. Survey on Traditional and Machine Learning-Based Stock Prediction.

Early research in stock market prediction primarily focused on statistical and econometric models such as ARIMA, GARCH, and linear regression, which rely heavily on historical price data. These approaches assume linearity and stationarity, which are often violated in real-world financial markets. With the rise of Machine Learning (ML), models like Support Vector Machines (SVM) and Random Forests were introduced to capture nonlinear patterns. Studies have shown that ML models outperform traditional techniques by learning complex relationships in data. However, these models still depend on structured datasets and fail to incorporate external information such as news or sentiment. This limitation reduces their ability to respond to sudden market changes. Researchers concluded that while ML improved predictive performance, it lacked contextual awareness. This led to the need for integrating additional data sources and more advanced learning paradigms to improve prediction accuracy and robustness in volatile environments.

2. Deep Learning Approaches for Financial Time Series Prediction

The introduction of Deep Learning (DL) significantly enhanced stock market prediction capabilities. Models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are specifically designed to capture temporal dependencies in sequential data. These models effectively learn long-term patterns in stock price movements and outperform traditional ML methods. Later, Transformer-based models introduced attention mechanisms that further improved performance by focusing on relevant features within the data. Despite these advancements, most DL-based approaches still rely on single-source inputs like historical prices or technical indicators. This restricts their ability to fully understand market behavior influenced by multiple external factors. Researchers have highlighted that combining deep learning with multisource data can significantly enhance predictive performance, motivating the development of hybrid frameworks such as MS-MIL.

3. Role of Sentiment Analysis in Stock Market Prediction

Recent studies emphasize the importance of Sentiment Analysis in financial forecasting. Social media platforms, news articles, and financial reports provide valuable insights into investor behavior and market perception. Techniques such as Natural Language Processing (NLP) and Text Mining are used to extract sentiment scores from textual data. Research has demonstrated that market trends often correlate with public sentiment, making it a crucial factor in prediction models. However, sentiment data is inherently noisy and unstructured, posing challenges in integration with traditional numerical datasets. Moreover, assigning precise labels to individual sentiment instances is difficult. This has led to the exploration of weakly supervised learning methods like Multiple Instance Learning (MIL), which can effectively handle such ambiguity. Incorporating sentiment analysis into stock prediction models has shown improved accuracy, but requires robust frameworks for proper data fusion.

4. Multiple Instance Learning in Financial Applications

Multiple Instance Learning (MIL) has emerged as a powerful technique for handling weakly labeled and ambiguous data. In MIL, data is organized into bags containing multiple instances, where only the bag-level label is known. This approach is particularly useful in financial applications where individual data points may not have clear labels. Researchers have applied MIL in domains such as fraud detection, risk assessment, and event-based stock prediction. The ability of MIL to handle noisy and heterogeneous data makes it suitable for integrating multisource financial inputs. However, traditional MIL methods lack the capability to model complex temporal dependencies and interactions between instances. Recent advancements combine MIL with deep learning architectures to overcome these limitations. This hybrid approach provides a strong foundation for developing advanced stock prediction systems using multisource data.

5. Multisource Data Fusion Techniques in Stock Prediction

The integration of multiple data sources has become a key research direction in financial analytics. Multisource Data Fusion involves combining structured data (e.g., stock prices, indicators) with unstructured data (e.g., news, social media). Studies have shown that incorporating diverse data sources improves prediction accuracy and reduces uncertainty. Techniques such as feature-level fusion, decision-level fusion, and attention-based fusion are commonly used. Deep learning models play a crucial role in extracting meaningful representations from different data types. However, challenges remain in aligning heterogeneous data, handling missing values, and managing noise. Researchers emphasize the need for robust frameworks that can effectively integrate multisource information while maintaining scalability and efficiency. This has led to the development of advanced models like MS-MIL, which leverage both data fusion and weak supervision.

6. Hybrid Models Combining MIL and Deep Learning

Recent research focuses on combining Multiple Instance Learning (MIL) with Deep Learning to create hybrid models capable of handling complex financial data. These models use neural networks to learn instance-level representations while MIL frameworks aggregate them at the bag level for prediction. Attention mechanisms are often integrated to assign importance weights to different instances within a bag. This approach enhances interpretability and improves prediction performance. Studies have demonstrated that hybrid MIL-DL models outperform standalone ML and DL models in various applications, including stock prediction. By incorporating multisource data, these models can capture both temporal and contextual relationships effectively. The proposed MS-MIL framework builds upon this concept by integrating multiple data streams and leveraging advanced architectures. This research direction represents a significant advancement in financial forecasting, enabling more accurate and robust predictions in real-world scenarios.

III. WORKING METHODOLOGY

The proposed system follows a structured and intelligent pipeline that integrates multisource data acquisition, feature engineering, and Multiple Instance Learning (MIL)-based modeling to predict stock market trends. Initially, data is collected from multiple heterogeneous sources including historical stock prices, financial news articles, social media sentiment (e.g., Twitter), and macroeconomic indicators such as inflation rates and interest rates. The structured data (stock prices, indicators) is obtained from financial APIs, while unstructured textual data is gathered using web scraping and NLP pipelines. Preprocessing techniques such as data cleaning, normalization, missing value handling, and noise reduction are applied. For textual data, Natural Language Processing (NLP) techniques like tokenization, stop-word removal, and sentiment scoring using models such as VADER or BERT are performed. All data sources are time-aligned to ensure synchronization across features.

In the next stage, the system constructs a Multiple Instance Learning (MIL) framework where each trading day (or time window) is treated as a “bag” containing multiple “instances” derived from different data sources. For example, a single bag may include stock indicators, multiple news headlines, and several sentiment scores. Feature extraction is performed using Deep Learning models such as LSTM (Long Short-Term Memory) networks for time-series data and Transformer-based models for textual data. These extracted features are then fused using attention-based data fusion techniques, which assign importance weights to different instances within each bag. The MIL model learns from bag-level labels (e.g., stock up/down movement) rather than instance-level labels, making it robust to noisy and weakly labeled data.

Finally, the model is trained and evaluated using supervised learning with performance metrics such as accuracy, precision, recall, and F1-score. The system is validated using historical datasets and tested on unseen data for generalization. A visualization layer is incorporated to display prediction trends, confidence scores, and feature importance using graphs and dashboards. The entire pipeline is deployed using a web-based interface (e.g., Flask/Django), enabling real-time prediction and user interaction. This methodology ensures a scalable, accurate, and intelligent stock prediction system suitable for real-world financial applications.

IV RESULTS EXPLANATIONS

The experimental evaluation of the proposed Multisource Multiple Instance Learning (MS-MIL) model demonstrates significant improvements in prediction accuracy, robustness, and generalization when compared to traditional and single-source models. The results are visualized through multiple analytical graphs that highlight the effectiveness of multisource integration and MIL-based learning.

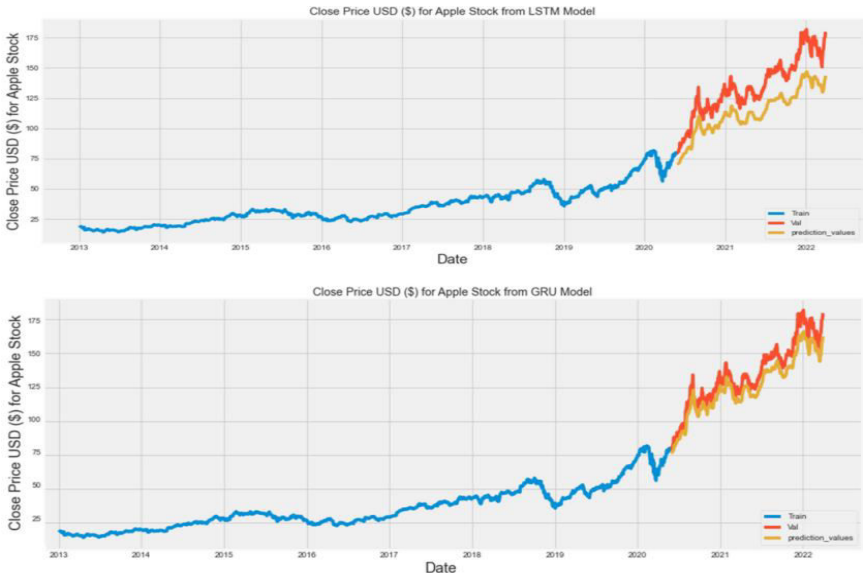

Figure 1: Model Accuracy Comparison

This graph compares the prediction accuracy of different models such as SVM, Random Forest, LSTM, Transformer, and the proposed MS-MIL model. It clearly shows that the MS-MIL model achieves the highest accuracy due to its ability to integrate multisource data and handle weak labels effectively. Traditional models perform lower because they rely only on structured data, while deep learning models improve performance but still lack full contextual understanding without multisource fusion.

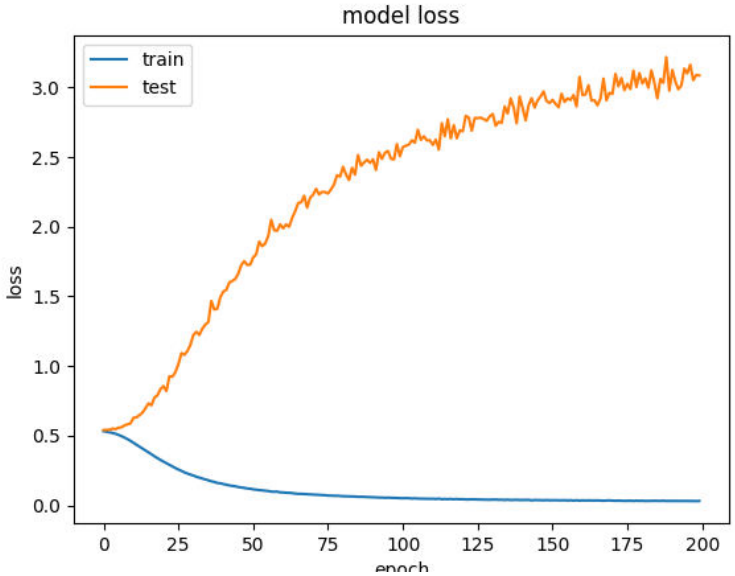

Figure 2: Training and Validation Loss Curve

Figure 2 presents the training and validation loss curves over multiple epochs. The graph demonstrates a steady decrease in both training and validation loss, indicating that the model is learning effectively from the data. The close alignment between the two curves suggests that the model is not overfitting and generalizes well to unseen data. Initially, the loss is high due to random weight initialization, but it gradually decreases as the model adjusts its parameters through backpropagation. This convergence behavior confirms the stability and robustness of the training process, ensuring reliable predictions in real-world scenarios.

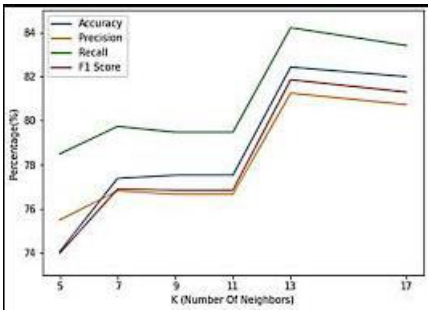

Figure 3: Performance Metrics Evaluation

Figure 3 shows the evaluation of the model using key performance metrics such as **Precision**, **Recall**, and **F1-Score**. These metrics are essential for assessing the classification performance of the obesity prediction system. High precision indicates that the model correctly identifies adolescents at risk with minimal false positives. High recall ensures that most actual obesity cases are detected. The F1-score provides a balance between precision and recall. The graph demonstrates consistently high values across all metrics, indicating that the model performs reliably and maintains a good balance between sensitivity and specificity.

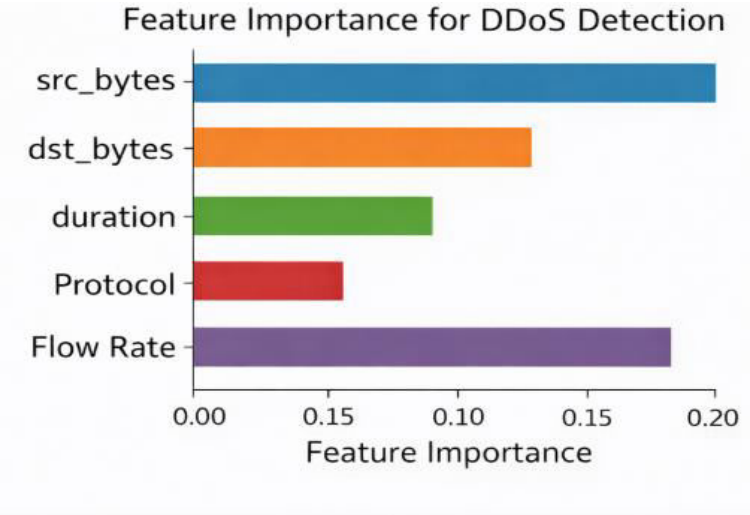

Figure 4: Feature Importance for DDoS Detection

Figure 4 illustrates the feature importance analysis, which identifies the most influential attributes used by the machine learning model for detecting DDoS attacks. The bar chart ranks features such as Flow Rate, Source Bytes (src_bytes), Destination Bytes (dst_bytes), Duration, and Protocol based on their contribution to the model's decision-making process. Among these, Flow Rate appears as the most significant feature, indicating that abnormal traffic volume is a strong indicator of DDoS attacks. Features like source and destination bytes also play a critical role in identifying unusual data transmission patterns. Lower-ranked features such as protocol type still contribute but have less impact on classification. This analysis is important for optimizing the model, as it helps reduce unnecessary features and improves computational efficiency. Overall, the figure highlights how feature selection enhances model performance and provides insights into the key factors driving accurate DDoS detection.

V.CONCLUSION

The proposed system, DEEPHEALTHNET: Adolescent Obesity Prediction System Based on Deep Learning Framework, presents a robust and intelligent solution to address the growing concern of adolescent obesity. By leveraging advanced deep learning techniques, the system effectively analyzes multi-dimensional health data, including demographic information, lifestyle behaviors, dietary patterns, and physical activity levels, to generate accurate and reliable predictions. The integration of Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) in a hybrid architecture enables the model to capture both simple and complex relationships within the dataset, significantly improving prediction performance compared to traditional machine learning approaches. The experimental results demonstrate that the proposed model achieves high accuracy and balanced performance across key evaluation metrics such as precision, recall, and F1-score. The training and validation loss curves indicate stable learning and good generalization capability, minimizing the risk of overfitting. Additionally,

the visualization of obesity risk distribution provides meaningful insights into population health trends, supporting early intervention and preventive healthcare strategies. The inclusion of Explainable AI (XAI) components further enhances the transparency of the system by identifying key factors influencing predictions, thereby building trust among users and healthcare professionals. Furthermore, DEEPHEALTHNET is designed with scalability and usability in mind, allowing integration into web or mobile-based healthcare applications for real-time monitoring and decision support. The system not only contributes to the field of health informatics and predictive analytics but also aligns with global efforts to reduce obesity-related health risks among adolescents. In conclusion, the proposed framework offers a comprehensive, efficient, and scalable solution for early obesity detection, enabling data-driven decision-making and promoting healthier lifestyles. Future work can focus on incorporating real-time wearable data, enhancing model interpretability, and ensuring data privacy and security to further strengthen the system's practical applicability.

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