Strategic Forecasting: A Multimodal Deep Learning Approach Integrating Bengali News for Enhanced Stock Market Predictions

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***Abstract*—This research proposes a multimodal ensemble learning approach for stock market forecasting in Bangladesh. Historical time series data is fused early with natural language insights from Bengali news headlines. Long short-term memory (LSTM) models capture sequential dependencies in stock price data, while the pre-trained contextual language model, Bangla BERT, analyzes headlines for sentiment, events, and topics. The key innovation lies in combining these modalities using an ensemble method for enhanced predictive capabilities. Detailed experiments validate that the integrated ensemble approach outperforms individual models, uncovering nuanced relationships between news events and asset price movements. Overall, this novel multimodal framework significantly advances stock prediction in the Bangladeshi context by leveraging both technical indicators and semantic insights.This research lays the groundwork for a novel multimodal framework that goes beyond traditional models, offering a paradigm shift in the domain of stock forecasting. By amalgamating technical indicators with semantic insights, our approach enhances predictive capabilities and sets a benchmark for leveraging diverse data modalities for nuanced insights into the complexities of the Bangladeshi stock market.**

***Index Terms*—multimodal, ensemble, forecasting, LSTM, NLP, BERT, early fusion, time series, and news analytics.**

I. Introduction

The stock market is a complex ecosystem driven by diverse factors. Traditional techniques like technical and fundamental analysis have limitations [1]. However, deep neural networks enable sophisticated data-driven forecasting [2]. This research innovates through an ensemble modelling approach, integrating Long Short-Term Memory (LSTM) networks with Bangla-Bert, a Natural Language Processing model specifically tailored for Bangla.

The Dhaka Stock Exchange (DSE) is the premier market of Bangladesh. As an emerging frontier market, the DSE has grown rapidly in recent years, with over 300 listed companies. Accurate forecasting of DSE stock prices provides vital information for investment decisions and market stability. Reliable predictions enable stakeholders from regulators to traders to make informed judgments, facilitating capital formation and financial development. Advanced modelling of Dhaka stocks is thus crucial for the continued evolution of Bangladesh's capital markets [3].

Our dataset encompasses a multi-year Bangladeshi stock price time series. LSTM models capture sequential patterns and technical indicators [4]. Concurrently, the pre-trained Bangla BERT NLP model analyzes sentiment, events, and topics in news headlines influencing market dynamics [5] [6]. An ensemble learner integrates the models via early fusion, consolidating technical and textual insights [7] [8].

The holistic perspective of this multimodal ensemble framework is achieved through "Early Fusion". The LSTM models serve as a lens into price dynamics, while BERT, through early fusion, comprehends nuanced news impacts. Rigorous experiments will ascertain that the early fusion of these models outperforms individual ones, showcasing their complementary strengths [9]. This tailored ensemble, through the strategic integration of diverse data types at an early stage, significantly advances stock prediction in Bangladesh.

Overall, this research makes significant theory and practice contributions. It pushes forecasting boundaries through domain-adapted NLP and deep learning ensembles [10] [11]. The methodology combining LSTM and Bangla BERT [12] illuminates the value of news analytics for low-resource time series modelling [13] [14]. This innovative approach not only advances academic discourse but also facilitates data-driven financial decisions in emerging markets, demonstrating substantial gains from multimodal learning [15].

II. Literature review

Khan et al. [16] propose using deep reinforcement learning (DRL) to address challenges in stock price forecasting, successfully combining deep learning and reinforcement learning. Their approach, trained on U.S. equity data, consistently predicts stock prices, demonstrating effectiveness with stable loss functions and rewards.

Razib et al. [17] tackle stock market trend prediction using Long Short-Term Memory (LSTM) networks. Employing LSTM on Stock Bangladesh data (1999-2021), their methodology involves training, and optimizing epochs, resulting in an 88% accuracy. Notably, BEXIMCO exhibits over 90% accuracy, while other companies like ACI, ISLAMI BANK, and NAVANA CNG average 85%.

Ansari et al. [18] introduce a deep reinforcement learning decision support system for stock trading, utilizing a GRU-based forecasting network to consider past and future trends. The system demonstrated profitable outcomes when tested on diverse markets, including Tesla, IBM, Amazon, CSCO, SSE Composite Index, NIFTY 50 Index, and the US Commodity Index Fund. The study analyzes data from ten markets, collected between January 1, 2017, and January 1, 2022, employing Deep-Q Network and DNN models.

Vargas et al. [22] employ Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to predict intraday movements of the S&P 500 index using financial news and technical indicators. CNN proves adept at capturing semantic information, while RNN excels in modelling contextual details and temporal characteristics, contributing to enhanced stock market forecasting compared to similar studies.

Althelaya et al. [23] investigate deep learning methods, focusing on variants of Deep Recurrent Neural Networks (LSTM and GRU), for stock market time-series forecasting. Bidirectional and unidirectional stacked architectures with multivariate inputs are evaluated, showing that a stacked LSTM model achieves superior forecasting performance for both short- and long-term periods when compared to shallow neural networks, using historical S&P500 index data.

Lin et al. [24] emphasize sentiment analysis in stock market forecasting, specifically in non-native English-speaking regions, leveraging electronic word-of-mouth data from social media. Employing Long Short-Term Memory (LSTM) models with a genetic algorithm for parameter selection and multilingual sentiment analysis, their approach exhibits superior forecasting accuracy across diverse data types, promising advancements in stock market predictions.

Akita et al. [25] introduce a unique method employing Paragraph Vector and Long Short-Term Memory (LSTM) for financial time series forecasting. Integrating numerical factors and textual information from newspaper articles, the approach, evaluated on Tokyo Stock Exchange data for fifty companies, effectively forecasts opening prices by leveraging distributed representations and modelling temporal effects.

Manuel et al. [26] utilize deep learning models to predict daily stock price movements, incorporating financial news titles and technical indicators. A hybrid model (SI-RCNN) merging Convolutional Neural Network (CNN) for news and Long Short-Term Memory (LSTM) for indicators outperforms an LSTM-only model (I-RNN), emphasizing the vital role of financial news in result stability. The models inform trading agent decisions, enhancing trading precision.

A. W. Li et al. [27] explore the role of intelligent models in mitigating investment risks in stock market forecasting. Emphasizing Deep Learning models, particularly LSTM (73.5%), the systematic review evaluates predictor techniques, trading strategies, profitability metrics, and risk management, revealing areas for further research and development. Limitations include insufficient consideration of profitability (35.3%) and limited implementation of risk management in reviewed articles.

III. Dataset

The numerical datasets about the stock markets of multiple companies were procured from Mendeley Data [29]. This comprehensive compilation encompasses nearly three hundred and fifty separate CSV files, each corresponding to distinct companies. The primary focus of our analysis is on the stock information of the "BEXIMCO" company, spanning from January 1999 to September 2020. The dataset is characterized by its inclusion of crucial stock market indicators, featuring key columns such as Date, Open, High, Low, Close, and Volume. These columns provide essential information, including the specific date, opening and closing prices, the highest and lowest prices observed during the trading day, and the associated trading volume. This meticulous collection of data serves as the foundation for our in-depth examination of the stock market dynamics, ensuring a comprehensive understanding of the temporal evolution of "BEXIMCO" company shares over the specified timeframe.
The textual corpus, comprising news headlines, was meticulously curated from Bengali-language newspapers, specifically "The Daily Prothom Alo." This comprehensive dataset encapsulates news headlines obtained from the aforementioned newspaper, coupled with their corresponding publication dates, spanning the period from July 2014 to December 2023. This collation provides a succinct yet comprehensive overview of news articles disseminated by these reputable sources, thereby facilitating a nuanced temporal analysis of information dissemination trends. Following the amalgamation of these datasets, our research selectively focuses on both the stock data about the "BEXIMCO" company and the associated news headlines, encompassing the timeframe from July 2014 to September 2020. This judicious selection serves as the empirical foundation for our investigation, enabling a synergistic exploration of the dynamic interplay between stock market fluctuations and the contextual news landscape within this specified temporal domain. Our dataset is classified as 'positive,' 'neutral,' or 'negative,' corresponding to numerical values of 3, 2, and 1, respectively.

Date	headline	Volume	Open	High	Low	Close
06-07-2022	জিপি ও রবির দাপটে লেনদেন বাড়ল ৪৫%	4159876	133.000000	135.00000	132.000000	132.900000
30-06-2022	৬ মাসে বন্ধ কোম্পানির শেয়ারের দাম বেড়ে ৫ গুণ	2808804	131.900000	132.00000	129.400000	129.800000
26-06-2022	ডিএসইতে লেনদেন কমেছে ১১%	1460443	135.800000	135.90000	132.200000	132.200000
16-06-2022	‘কালোটাকা বিনিয়োগের সুযোগ বিবেচনাযোগ্য’	5257953	131.800000	135.40000	131.100000	134.600000
15-06-2022	টানা দরপতন চলছে শেয়ারবাজারে	4967167	128.300000	132.80000	128.000000	131.300000

Fig. 1. Merged Dataset

IV. Methodology

The methodology section of this research paper describes how the research was conducted, including the type of data used, the process of data collection, and the approach taken to analyze the data. Our model architecture is an Early Fusion model, which combines both text and numerical inputs. Here's a breakdown of our architecture:

A. Text Processing Branch

The text processing branch of our model begins with an input layer (`text_input`) designed to accommodate pre-encoded text tensors. These tensors are reshaped using a `Reshape` layer to add a channel dimension, facilitating Conv1D processing. Following this, a Convolutional layer (`Conv1D`) with 32 filters and ReLU activation is applied to extract relevant features from the text data. Subsequently, a MaxPooling1D layer (`MaxPooling1D`) is employed to down-sample the feature maps, enhancing computational efficiency and reducing overfitting.

B. Price Processing Branch

The price processing branch of our model is responsible for handling the temporal sequence of stock prices. It starts with an input layer (`price_input`) designed to accept single-timestep price data. These inputs are reshaped using a `Reshape` layer to include a timestep dimension, enabling subsequent processing using an LSTM layer (`LSTM`) with 32 units. This LSTM layer is adept at capturing temporal dependencies within the price data, crucial for accurate prediction.

C. Fusion Layer

To combine the information gleaned from both the text and price processing branches, we employ a fusion layer. Here, the output from the LSTM layer in the price processing branch is repeated using a `RepeatVector` operation to match the sequence length of the text inputs. This repeated output is then concatenated with the pooled text features after zero-padding (`ZeroPadding1D`) to ensure dimensional compatibility. This fusion mechanism allows for the seamless integration of textual and numerical information, enhancing the model's predictive capabilities.

D. Output Layer

The fused representation is passed through a dense output layer (`Dense`) with a single unit and linear activation function. This configuration is tailored for regression tasks, enabling the model to generate continuous predictions of stock prices.

E. Model Compilation

Finally, the model is compiled using the Adam optimizer and the Mean Squared Error (MSE) loss function. This compilation step configures the model for training, specifying the optimization algorithm and the metric used to evaluate performance.

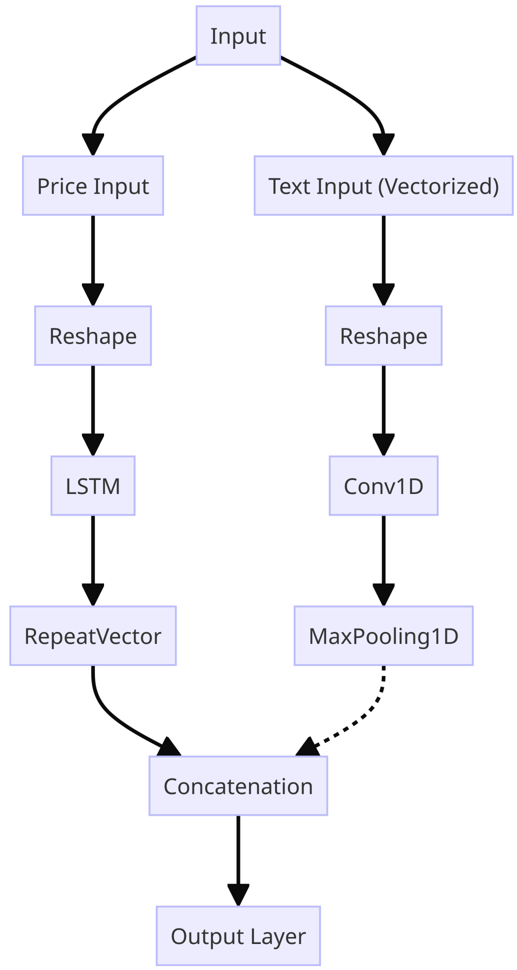

Fig. 2. Structure of Multimodal Methodology

V. Result Analysis

The Mean Squared Error (MSE) value of 2504.23 indicates the average squared difference between predicted and actual values. A lower MSE suggests that the model has better accuracy in predicting the stock market values.

TABLE I
Error Analysis of BEXIMCO

Error	Score
Mean Squared Error (MSE)	2504.23
Mean Absolute Error (MAE)	28.50
Root Mean Squared Error (RMSE)	3913.34

The Mean Absolute Error (MAE) of 28.50 represents the average absolute difference between predicted and actual values. A lower MAE indicates a closer match between predicted and actual values, signifying better predictive accuracy.

The Root Mean Squared Error (RMSE) value of 3913.34 is the square root of the MSE, providing a measure of the spread of errors. A lower RMSE signifies a more accurate model, as it indicates smaller errors between predicted and actual values.

TABLE II
ERROR ANALYSIS OF DACCADYE

Error	Score
Mean Squared Error (MSE)	1474.95
Mean Absolute Error (MAE)	7.69
Root Mean Squared Error (RMSE)	704.64

In summary, the MSE, MAE, and RMSE values collectively suggest that the model exhibits reasonable accuracy in predicting stock market values, with low errors and a close match between predicted and actual results. However, further context regarding the specific domain and dataset characteristics would be necessary for a more comprehensive analysis.

Here are other companies MSE shown below :

Company	Loss	Company	Loss
COPPERTECH	3676.3701171875	DELTASPINN	2299.0712890625
DACCADYE	697.7158813476562	BXSYNTH	1368.7296142578125
EMERALDOIL	1668.7244873046875	CITYGENINS	1913.43017578125
EASTLAND	955.0673217773438	CONFIDCEM	5183.931640625
DESCO	3441.3203125	FARCHEM	1099.353515625
DBH	4648.8525390625	DHAKABANK	1139.431884765625
ECABLES	16513.33984375	BPPL	54990.4921875
CVOPRL	61835.171875	DHAKAINS	1439.9873046875
CROWNCEMNT	22674.333984375	DSHGARME	16711.75390625
CITYBANK	1034.007080078125	EBL	981.372802734375
DOMINAGE	1762.115478515625	CENTRALINS	1460.9859619140625
ENVOYTEX	1276.8028564453125	BSRMSTEEL	2805.183837890625

Fig. 3. Mean Square Error of 24 different Companies

VI. Conclusion and Future Work

This research introduces an innovative approach to stock market forecasting for the Dhaka Stock Exchange (DSE) using a multimodal ensemble framework called ”Early Fusion”. By combining LSTM networks with Bangla BERT, a specialized NLP model, we achieved improved predictive accuracy.

Experimental results demonstrate the effectiveness of our ensemble approach, outperforming individual models and providing more accurate predictions of stock prices. By leveraging the complementary strengths of LSTM and Bangla BERT, our model enhances decision-making for stakeholders in financial markets.

This study contributes significantly to the progression of forecasting methodologies through the integration of domain-specific NLP and deep learning ensembles, specifically emphasizing the paradigm of early fusion. This research offers tangible practical benefits for stakeholders in emerging markets, such as Bangladesh, where informed and data-driven financial decisions play a crucial role in fostering economic progress.

For future work, we would like to incorporate more technical indices such as the moving average (MA) and the moving average convergence divergence (MACD) for better profit-making capabilities. The authors would thank to the Lecturers Mr Md. Reasad Zaman and Mr Mohammad Marufur Rahman of Ahsanullah University Of Science And Technology for valuable discussions.

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