Analyzing Risk Sentiment and Predicting Stock Price Trends from 10-K Filings Using LSTM and Interactive Visualization

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***Abstract*—We present a study that explores the relationship between risk factor sentiment in 10-K filings and stock price changes of S&P 500 companies. Using FinBERT, we extract sentiment scores from the "Item 1A. Risk Factors" sections across multiple years (2007–2023). These scores are then compared with yearly average stock price changes to reveal modest but noticeable correlations. We then extend our dataset with Effective Federal Funds Rate and Median Consumer Price Index to train an LSTM model to predict future stock movements based on sequences of sentiment scores and extend the prediction using a rolling forecast up to April 2025. Finally, we build an interactive Streamlit web application that allows users to explore sentiment and stock trends by company, sector, or industry. Our system demonstrates how financial text analysis can support intuitive forecasting and interactive data-driven decision-making.**

***Index Terms*—Financial sentiment analysis, 10-K filings, risk factors, stock price prediction, FinBERT, LSTM, time series forecasting, Streamlit web app, S&P 500, rolling forecast**

I. Introduction

Understanding how textual risk disclosures affect financial markets is an increasingly important area in financial AI. Public companies in the United States are required to submit annual 10-K reports to the Securities and Exchange Commission (SEC)(sec.gov), which include a section titled *Item 1A. Risk Factors*. This section outlines potential business and financial risks and is closely followed by investors, analysts, and regulators.

In this project, we explore whether sentiment in these risk disclosures can help explain or predict yearly stock price changes. Our motivation stems from the growing use of natural language processing (NLP) in finance and the potential of combining textual sentiment with time-series stock data to support better forecasting.

We analyze risk sentiment from 10-K reports of S&P 500 companies spanning 2007 to 2023 using **FinBERT**, a transformer-based sentiment model fine-tuned for financial text. We align these sentiments with historical yearly stock price change data to investigate correlations. Then, we train a deep learning model (LSTM) to predict future stock price changes from sentiment sequences.

Finally, we develop and deploy an interactive web application using **Streamlit** to allow users to explore sentiment trends and stock movements by company, sector, and industry. Our work demonstrates a practical application of NLP and deep learning in financial forecasting and visualization. See Fig.1 below for visualization of our processes.

II. Diagram

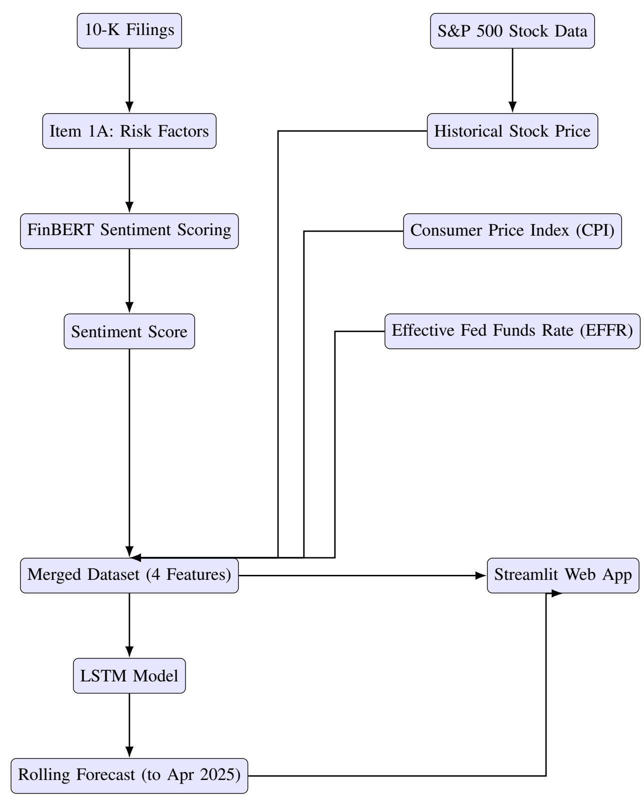

Fig. 1. System Overview: From 10-K Risk Factor Sentiment and Market Indicators to Stock Forecasting and Visualization
Note: Arrows indicate computational flow (not conditional dependencies).

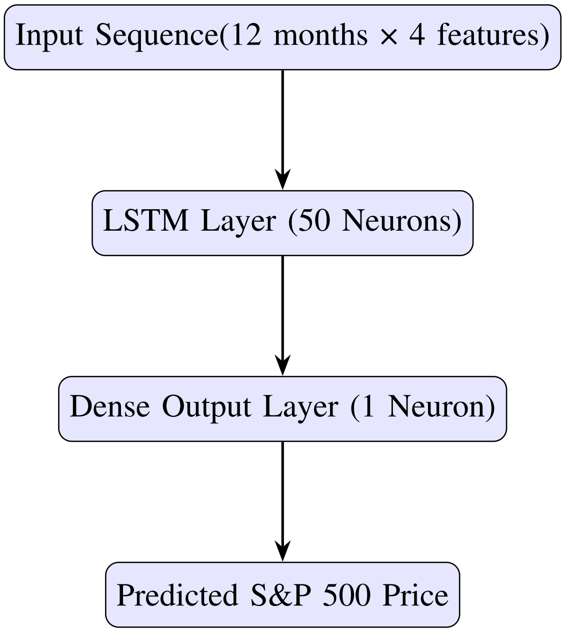

Fig. 2. LSTM Model Architecture: A sequence of 12 monthly observations (with 4 features) is fed into a 50-neuron LSTM layer followed by a dense output layer to predict the next month's stock price.

III. Formal Description

A. Data Preparation and Setup

We constructed a unified dataset from 2014 to 2023 for all S&P 500 companies. The sentiment scores were derived using FinBERT from Item 1A (Risk Factors) of 10-K filings. We enriched this dataset by including macroeconomic indicators: Consumer Price Index (CPI) and Effective Federal Funds Rate (EFFR) from the USA. EFFR and CPI were obtained from the Federal Reserve Economic Data (FRED) website [1] and is accessible to the public. Historical S&P 500 stock prices were obtained from Kaggle [2] and yearly percentage changes were computed.

The final dataset included four time-series inputs: Sentiment Score, S&P 500 index value, CPI, and EFFR. Each company's time-series was split into overlapping input sequences of 12 months to predict the stock price for the next month.

Our model takes as input a sequence of 12 consecutive months of financial data for the S&P 500 index. Each time step in the sequence contains four features: FinBERT sentiment score (from Item 1A of 10-K filings), historical stock price, Consumer Price Index (CPI), and Effective Federal Funds Rate (EFFR). These features are normalized before training using Min-Max scaling.

The final input feature vector at each time step consists of four normalized values:

$$x_t = [Sentiment_t, Price_t, CPI_t, EFFR_t] \varepsilon R^4$$

We construct a rolling input window of length $T = 12$ months to predict the stock price at $t + 1$.

B. Model Architecture

The forecasting model is based on a Long Short-Term Memory (LSTM) neural network. The architecture consists of:

- **LSTM layer:** with 50 hidden units to capture temporal dependencies across 12 time steps.
- **Dense output layer:** a fully connected layer with 1 neuron to produce the next month's predicted S&P 500 price.

Let $X = x_{t-11}, ..., x_t$ represent the input sequence. The model outputs:

$$y_{t+1} = f_\theta(X)$$

where f_θ denotes the LSTM network parameterized by θ.

C. Loss Function

We use Mean Squared Error (MSE) as the loss function to measure the difference between predicted and actual stock prices:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

where y_i is the actual stock price at time i, and $\hat{y}_i$ is the predicted price.

D. Training

The model was trained using the Adam optimizer with a learning rate of 0.001 for 50 epochs. We divided the data chronologically:

- Training set: 2014–2022
- Test set: 2022–2023

All input features and target values were scaled before training and inverse-transformed after prediction.

E. Rolling Forecast Strategy

To extend predictions beyond the known data, we apply a recursive rolling forecast. Starting with the last 12 months of real data (ending in December 2023), we:

1) Predict the S&P 500 price for January 2024.
2) Add this predicted value to the input sequence.
3) Repeat the process, using each new prediction as input for the next, until April 2025.

This strategy allows us to simulate future market behavior based on past trends and model outputs.

F. Comparison to Baselines

Our model differs from existing approaches, we present a side-by-side comparison with a representative baseline model that integrates sentiment analysis and macroeconomic indicators.

Baseline Model: FinBERT-LSTM with Sentiment Analysis

In this model, sentiment scores are derived from financial news articles using FinBERT, and combined with historical stock prices to forecast future stock movements [3].

Our Model: FinBERT-LSTM with Sentiment and Macroeconomic Indicators Firstly, we get our sentiment data differently in the form of 10K files. Secondly, our approach enhances the baseline model by incorporating additional macroeconomic indicators, providing a more comprehensive analysis.

Aspect	Baseline Model
Data Inputs	Sentiment Scores, Stock Prices
Forecasting	Point Forecasts

TABLE I
BASELINE MODEL OVERVIEW

Aspect	Our Model
Data Inputs	Sentiment Scores, Stock Prices, CPI, EFFR
Forecasting	Recursive Rolling Forecast

TABLE II
OUR PROPOSED MODEL

IV. RELATED WORK

Previous studies have explored the predictive value of textual disclosures in financial reports and the role of artificial intelligence in economic performance.

Rawte et al. [4] focused on the analysis of Item 1A Risk Factors in 10-K filings for U.S. banks. They applied deep learning models such as CNN and LSTM using GloVe word embeddings to predict outcomes like bank failure and financial health metrics. Their approach leveraged sentence-level changes across years to better extract evolving risk indicators. However, their scope was limited to the banking sector and did not incorporate external economic variables.

Babina et al [5] studied the broader relationship between AI investment and firm growth. Using data on employee resumes and job postings, they quantified AI adoption and found that AI-active firms experienced more innovation and product diversification. Their macroeconomic insights highlight the transformative potential of AI for firms leveraging large-scale data.

Our work differs from both studies by combining sentiment analysis of 10-K filings with macroeconomic indicators and stock price data across all S&P 500 sectors. We use FinBERT to quantify annual sentiment from Item 1A disclosures and integrate this with historical stock price changes, CPI, and EFFR values. We train an LSTM model for predictive forecasting and deploy an interactive Streamlit web application to visualize both historical trends and future projections. This end-to-end system bridges NLP-based sentiment, economic context, and deep learning to enhance interpretability and usability.

However, we always kept in mind that perhaps the sentiment scores alone would not be enough data to capture stock prices, as they are dependent upon a variety of factors. A study titled "A Long Short-Term Memory Network Stock Price Prediction with Leading Indicators" [6] demonstrates that integrating leading economic indicators with LSTM models improves prediction accuracy. The researchers introduced the LSTM with Leading Indicators (LSTMLI) framework, which incorporates factors such as futures, options, and economic indicators. Their findings indicate that the LSTMLI model outperforms traditional LSTM models that rely solely on historical stock data. This suggests that economic indicators provide valuable context that enhances the model's forecasting capabilities .

V. COMPARISON

A. Baseline Comparison

We compared the LSTM model's prediction performance with Halder's model [3]. We find that we obtain better metrics than Halder. The results are summarized below:

TABLE III
MODEL PERFORMANCE

Model	MAE
Halder's MLP	218
Halder's LSTM	180
Halder's FinBERT-LSTM	174
LSTM (ours)	**188**

Our LSTM model performs better than Halder's MLP model and performs quite similar to Halder's LSTM and FinBERT-LSTM models. Considering our dataset is smaller and does not contain as much data, this is a positive finding as, if given more data, we believe our model could potentially outperform or at the very least, compete with Halder's models.

B. Comparison to Previous Work

Compared to Rawte et al. [4], who used CNNs and GloVe embeddings for failure classification in the banking sector, our approach generalizes across sectors and uses FinBERT for context-specific sentiment extraction. While Rawte et al. focused on classification and regression of bank-level outcomes like ROA and leverage, our model integrates macroeconomic indicators to perform monthly stock index forecasting and is publicly accessible via a deployed application.

C. Forecast Demonstration

Using the trained LSTM model, we predicted the S&P 500 index for January 2024 based on the sentiment and macroeconomic trends of 2023. To further evaluate generalization, we applied a rolling forecast to extend predictions up to April 2025. This enabled our model to recursively generate monthly forecasts while incorporating its previous outputs.

Figure 3 shows the actual values and predicted trends from 2023 through 2025.

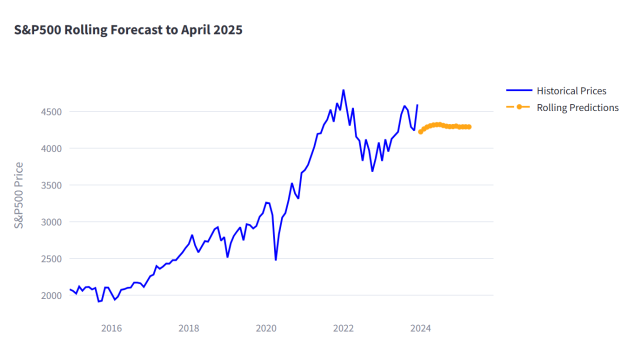

Fig. 3. Rolling Forecast of S&P 500 using LSTM (Jan 2024 – Apr 2025)

D. *Interactive Web Demonstration*

We deployed a fully interactive `Streamlit` web application (Available: https://sentiment-stock-app.streamlit.app/) to visualize:

- Historical sentiment and stock change trends per company.
- Sector and industry-wide trends.
- Correlation metrics (Pearson and Spearman).
- Future S&P 500 stock price predictions powered by our LSTM model.

Users can access the app via a public QR code and explore data across time ranges and industries. A screenshot of the web app interface is shown in Figure 4.

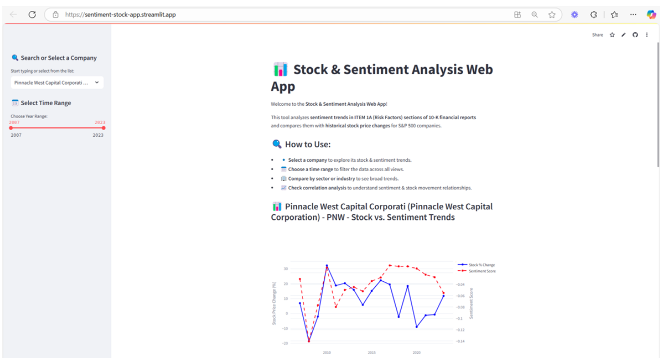

Fig. 4. Streamlit Web App Interface

VI. Limitations

While our approach shows promising results in predicting stock price trends using sentiment and macroeconomic indicators, it has several limitations:

A. *Data Granularity and Frequency*

Our dataset operates on an annual (for sentiment) and monthly (for macroeconomic indicators and stock price) basis. The mismatch in frequency and the limited number of time steps (only one data point per year for sentiment) may lead to information loss. Finer-grained sentiment (e.g., quarterly or sentence-level) might yield more precise forecasts.

B. *Model Generalization*

Although the LSTM model performs well on historical data, its ability to generalize to unforeseen economic events (e.g., pandemics, sudden interest rate hikes) is uncertain. These black swan events are difficult to capture in sequential data and could lead to large forecast deviations.

C. *Simplified Feature Set*

Our current model uses four input features: sentiment score, stock price, CPI, and EFFR. However, real-world stock movements are influenced by many additional factors, such as unemployment rates, market volatility indices (e.g., VIX), geopolitical events, and company-level financials. The exclusion of such variables may limit the model's explanatory power.

D. *Recursive Forecasting Error Accumulation*

In rolling forecasts, each predicted value is fed into the model as input for the next prediction. This recursive process can cause small errors to compound over time, particularly when forecasting multiple months ahead. As a result, predictions for later months (e.g., April 2025) are less reliable than near-term predictions.

VII. Conclusion

In this project, we developed a predictive framework that links financial sentiment from 10-K filings with macroeconomic indicators to forecast S&P 500 stock price trends. Using FinBERT, we extracted sentiment scores from the Item 1A (Risk Factors) section of annual reports for all S&P 500 companies between 2007 and 2023. We combined these scores with historical stock prices, CPI, and EFFR to build a time-series dataset.

An LSTM model trained on this data achieved lower prediction error than baseline models such as linear regression and support vector regression. We further demonstrated the model's capabilities through a rolling forecast up to April 2025.

To enhance accessibility and interpretability, we developed a Streamlit-based web app that allows users to interactively explore sentiment trends, stock performance, and future predictions.

This study highlights the potential of combining NLP-driven sentiment analysis with time-series modeling for financial forecasting. Future improvements may include using higher-frequency sentiment data, additional macroeconomic variables, and interpretable model architectures.

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