Geopolitical Risk Analysis and its Impact on Market Volatility

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***Abstract*—This study addresses the influence of geopolitical risks on financial markets, as noticed in recent events like the COVID-19 pandemic and the Russia-Ukraine war. This study showcases a model combining financial indices with the Geopolitical Risk Index (GPRI), employing Bi-LSTM networks with attention mechanisms to analyze the data. This approach captures the nuanced effects of geopolitical events on market volatility. Focused on the pandemic period, our model offers insights into market dynamics during times of geopolitical unrest and serves as a predictive tool for market behavior in response to global events.**

***Index Terms*—GPR Index, Volatility Spillover**

I. Introduction

In an increasingly interconnected global economy, financial markets are susceptible to a range of influences, with geopolitical risks being a particularly impactful factor. The recent COVID-19 pandemic, Russia-Ukraine war and riots in France (Nahel Merzouk riots) [3] has underscored this interdependence, leading to heightened volatility.

Events of social unrest play a vital role in forecasting the dynamics of financial markets during times of geopolitical unrest. This is primarily because market movements are reactionary and anticipatory. In periods of geopolitical tension, markets often respond to both the immediate impact of social disturbances and the expectations of what might unfold next. It can be said that a direct correlation exists between price movements and ongoing events as well as the public's speculation. Understanding this dual nature of market responses—reactive to present situations and potential developments—is essential for accurately predicting market trends in such volatile periods. [1]

The objective is to develop a predictive model that analyses the impact of geopolitical risks on market volatility i.e., during and post COVID era, during and post Russia-Ukraine war era etc. By examining historical financial data and the Geopolitical Risk Index (GPRI) [2], the model forecasts market behavior in response to events of major social unrest helping to decipher how financial markets might behave in response to both current and the incoming future during geopolitical events.

This study introduces novel contributions in predicting financial market behavior both during and after significant global events of tension. The novelty of this research lies in its ability to forecast market trends in these critical periods. The methodology involves compiling an extensive dataset that includes essential financial indices and the Geopolitical Risk Index (GPRI), serving as a gauge for geopolitical instability.

To analyze this data, the study employs sophisticated machine learning models, namely:

- Bi-directional Long Short-Term Memory (Bi-LSTM) networks.
- Bi-LSTM networks with an added attention layer.
- Dual Bi-LSTM layers coupled with an attention layer.

These models are adept at capturing both the chronological sequences and the subtle influences of major events on market volatility. This approach allows for a nuanced understanding of how markets respond to geopolitical crises, including both immediate reactions and subsequent developments. By focusing on the predictive capabilities during and after periods of unrest, this study offers valuable insights into the dynamics of financial markets in the face of geopolitical challenges. This analysis will enable investors and analysts to differentiate between typical market movements and those triggered by geopolitical unrest, guiding informed financial decisions in times of unrest and enabling long-term understanding.

II. Related Work

Chiu-Lan Chang et al.[4] employ statistical methodologies, specifically the Pooled and Grouped Benjamini-Hochberg procedures, to identify stock return anomalies during the COVID-19 pandemic. The method addresses the limitations of conventional error rate control in large datasets and evaluates the effectiveness of these procedures in detecting erroneous null hypotheses.

Combining predictive modeling and explainable AI to assess market fear, Indranil Ghosh et al.[5] use Implied and Historical Volatility metrics during the pandemic. The study highlights the use of feature selection and advanced algorithms, focusing on model interpretability to elucidate the underlying factors driving predictions.

Concentrating on the Indian market Hawaldar et al.[6] examine, the interplay between crude oil price fluctuations and stock market returns. Utilizing correlation and beta analysis, discussing the indirect effects of oil price changes on economic aspects like fiscal deficits and exchange rates.

Zhixuan Wang et al.[8] using the Event Study Method (ESM), analyze the response of China's stock market to the pandemic-induced supply chain disruptions. The study examines abnormal returns and employs a variety of models for a thorough analysis, addressing challenges like event window determination and cross-sectional dependencies in returns. The paper also notes unexplored areas, including the long-term consequences of the pandemic and the applicability of their methods to other markets or situations.

III. Data Source

This study uses a dataset comprising key global financial indices: S&P 500 (United States), GDAXI (Germany), FCHI (France), FTSE (United Kingdom), IMOEX (Russia), NIFTY (India), SSE (China), and the Geopolitical Risk Index (GPRI). Sourced mainly from Yahoo Finance and GPR Index, the dataset encompasses movements from 28th October 2013 to 28th October 2023 and has 1842 rows and 8 columns as seen in Fig 1.

Date	S&P500	FTSE	GDAXI	NIFTY	IMOEX	SSE	GPRI
142	2023-01-31	7771.70	7771.70	15128.26953	7,771.70	7,771.70	3255.669922
143	2023-01-31	7771.70	7771.70	15128.26953	7,771.70	7,771.70	3255.669922
144	2023-01-31	7771.70	7771.70	15128.26953	7,771.70	7,771.70	3255.669922
145	2023-01-31	7771.70	7771.70	15128.26953	7,771.70	7,771.70	3255.669922
146	2023-01-31	7771.70	7771.70	15128.26953	7,771.70	7,771.70	3255.669922

Fig. 1. Snapshot of the dataset

The data was segmented based on significant geopolitical events: the COVID-19 pandemic (November 1, 2020 - May 1, 2023) and the Russia-Ukraine war (January 24, 2022 - July 1, 2023). This temporal partitioning facilitates focused analysis of market reactions during these periods [12]. This was done to cater to the Bi-LSTM models used for analysis, which are adept at capturing time-based market trends.

IV. Methodology and Experimental Setup

A. Data Preprocessing

To preserve the temporal information essential for understanding market dynamics, the data was transformed into sequences. This sequencing approach is particularly beneficial for feeding into Bi-LSTM models, which are designed to capture temporal dependencies and trends in time-series data. By structuring the data in this manner, the study achieves a more accurate and nuanced analysis of how markets react over the course and post a period of global unrest.

B. Feature Selection

Discrepancies in date formats between the financial indices and GPRI data were standardized to a uniform format. The standardized data was aligned by dates, ensuring that financial indices corresponded accurately with GPRI values.

C. Predictive Model Building

The bi-directional Long Short-Term Memory (bi-LSTM) network is favoured as this scenario requies understanding of both past and future context within the data sequences, due to its dual-direction processing capability. This attribute allows bi-LSTMs to learn more complex patterns and capture long-term dependencies more effectively, which can be advantageous in predicting price movements (time series prediction tasks) where both preceding and subsequent events influence the outcomes. This study employs three distinct models for predictive analysis.

- Bidirectional Long Short-Term Memory (bi-LSTM) network is utilized as seen in Fig. 2. This model is specifically chosen for its proficiency in capturing temporal dependencies and its ability to process data in both forward and backward directions, which is pivotal in enhancing the accuracy of predictions in time-series data.

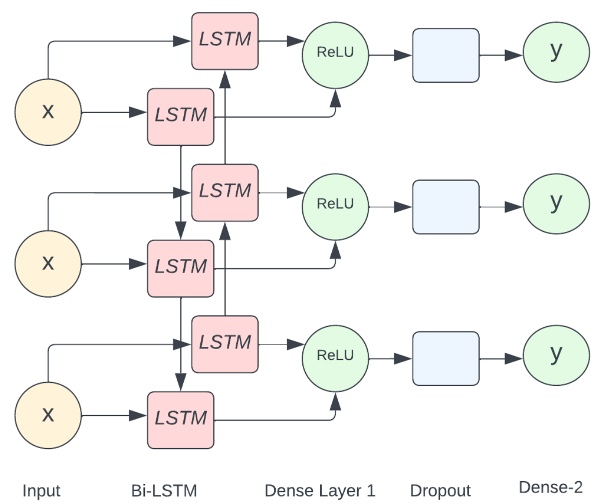

Fig. 2. Bi-LSTM Architecture

- Bi-LSTM network as seen in Fig. 3 augmented with an attention layer. The addition of the attention mechanism enables the LSTM to focus selectively on crucial segments within the data sequences. As not all elements within the data sequences are equally informative regarding price movements. In this case the attention layer plays a pivotal role in identifying and focusing on those segments of the data that contribute significantly more to understanding and predicting these movements.
- Dual-layered Bi-LSTM network, each augmented with an attention mechanism as seen in Fig. 4. This architecture

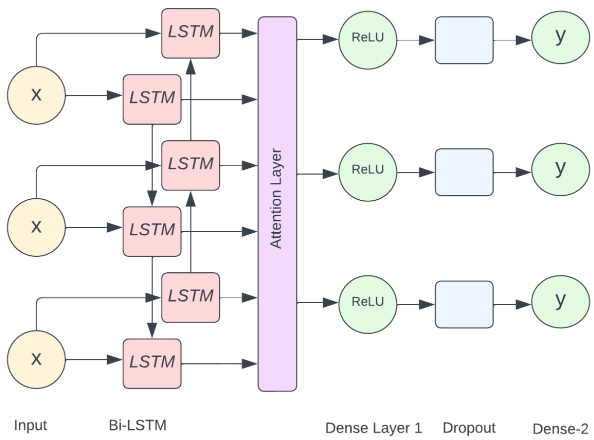

Fig. 3. Bi-LSTM with Attention Augmentation

is designed to enhance the depth and complexity of the analysis. This configuration allows the model to capture more nuanced patterns and dependencies within the dataset, which is crucial for accurately predicting the Geopolitical Risk (GPR) index. The attention layers ensure that the model's predictions are not only based on the general trends in the data but also on the most significant events that have a higher impact on the GPR index. This architecture is optimized for both capturing deep temporal dependencies and focusing on the most relevant data points for GPR prediction

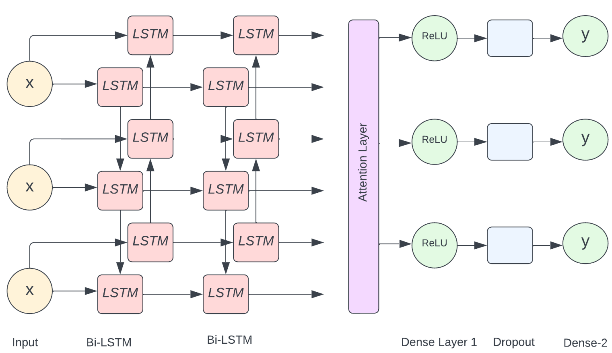

Fig. 4. Dual Bi-LSTM augmented with attention layer

D. Model Evaluation

Each model was compiled using the Adam optimizer with mean squared error as the loss function, optimizing for predictive accuracy. Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) were calculated to quantitatively assess prediction accuracy.Residuals were calculated, plotted, and then used to create a plot with confidence intervals [10], providing insights into prediction variability and systematic errors.

V. Results and Analysis

A. Bi-LSTM Network

The bi-LSTM model demonstrates effective learning, as evidenced by the consistent decrease in training loss, indicating improvement in performance over time as seen in Fig. 5. The

Fig. 5. Bi-LSTM Training loss vs. Validation loss

model demonstrates an ability to capture the general trend of the actual data, evident from instances where the predicted values (blue line) align with the actual values (red line), though deviations are noticeable (Fig. 6). This alignment indicates the model's predictive capability, particularly in segments where the predicted and actual values closely correspond. However, the model exhibits challenges in accurately capturing rapid changes or outliers in the dataset. Additionally, the predictions tend to be smoother compared to the actual data, suggesting a potential over-smoothing issue. This could indicate that the model is averaging the input data excessively, a phenomenon commonly observed in many time series forecasting models. The residuals (Fig. 7) are centered around zero, which is

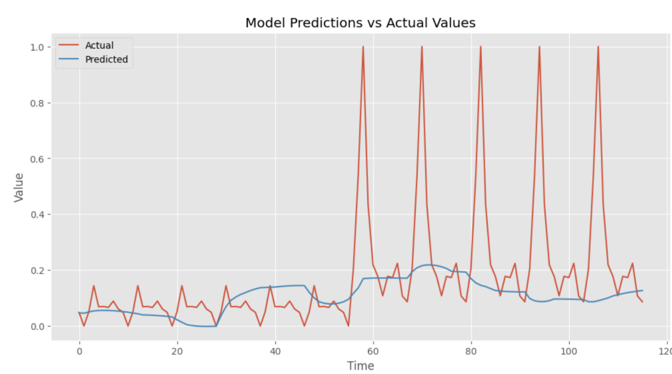

Fig. 6. Bi-LSTM: Actual vs Predicted values

a positive indication that the model does not systematically over-predict or under-predict. The absence of a clear pattern in the residuals suggests that the model effectively captures the variance in the data. Furthermore, the residuals display homoscedasticity, meaning their spread is consistent across the time axis. This homogeneity indicates that the model performs uniformly across different data points and does not struggle with values that deviate from the mean.

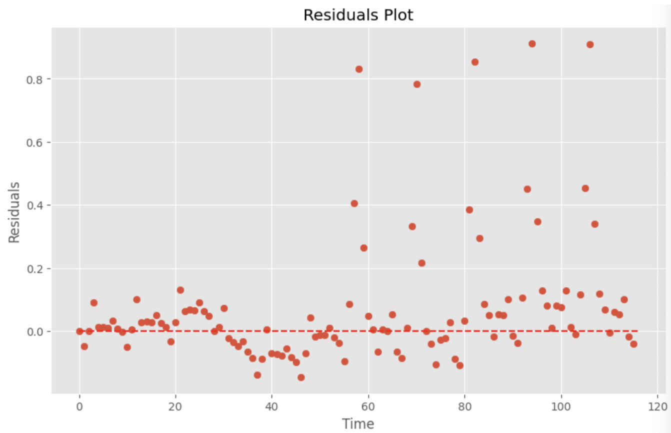

Fig. 7. Residuals plot

The values of MAE, RMSE, and MSE are all relatively low, as seen in Table I, indicative of the fact that the model's predictions are close to the actual values The RMSE is noticeably higher than MAE suggesting there might be some larger errors in the predictions.

Metric	Value
Mean Absolute Error	0.119007
Root Mean Squared Error	0.215807
Mean Squared Error	0.046572

TABLE I
BI-LSTM ERROR METRICS

B. Bi-LSTM Augmented with Attention Layer

The model's predictions as seen in Fig. 8 are less smoother and more responsive to sharp peaks and troughs in the actual stock price movements. This might suggest the model is not averaging the input data over the sequence, preserving detail on rapid market changes.

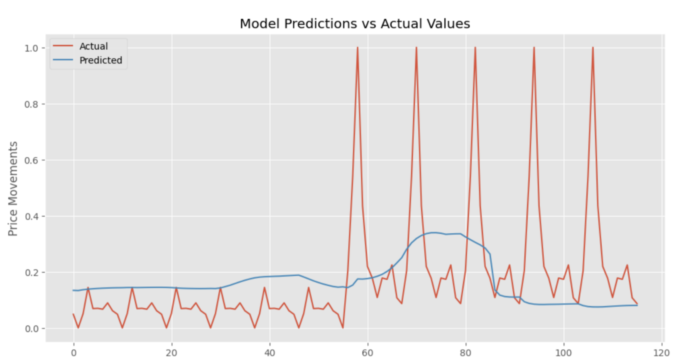

Fig. 8. Bi-LSTM with Attention augmentaion: Actual vs Predicted values

In comparison to the Bi-LSTM model, the relatively low MAE seen in Table II suggests that, on average, this Bi-LSTM with Attention layer can achieve predictions closer to the actual index values demonstrating desired performance.

Metric	Value
Mean Absolute Error	0.111731
Root Mean Squared Error	0.214112
Mean Squared Error	0.045843

TABLE II
BI-LSTM WITH ATTENTION ERROR METRICS

C. Dual Bi-LSTM Augmented with Attention Layer

This model exhibits a trend-following behavior as seen in Fig. 9, with its predictions (blue line) aligning with the overall trajectory of the actual GPRI (red line). Typically, most models are designed to eliminate outliers in their learning process. However, in this case, the objective is to predict outliers [19], specifically the behavior of the financial market during volatility spillover. This makes the task inherently more challenging, as it requires the model to identify and respond to unusual and extreme variations in the data.

Despite these challenges, the model demonstrates a commendable ability to follow the overall trend of the actual GPRI, as shown by the blue line aligning with the broader movements of the red line over time. This indicates the model's success in learning the general direction and trends of the GPRI, even in the presence of extreme market behaviors. Moreover, the model's baseline predictions effectively capture the periods of stability or less erratic behavior in the GPRI, reflecting its understanding of the underlying patterns during these phases.

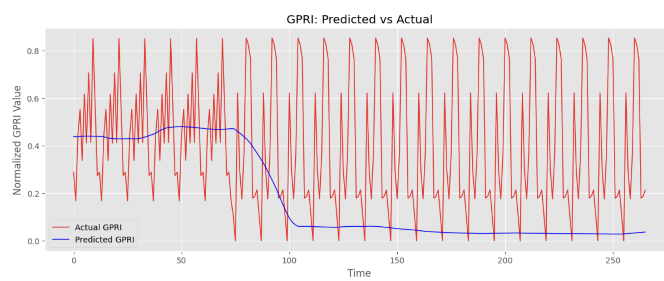

Fig. 9. Dual Bi-LSTM Predictions vs Actual Movements

Although the model does not precisely capture the sharp spikes characteristic of volatility spillovers, its reactivity to changes in the GPRI is a significant achievement. The model's predictions mirror shifts in the actual GPRI, indicating its responsiveness to market changes. The smooth nature of the model's predictions points to its capacity to filter out noise, focusing on underlying factors driving GPRI movements. This characteristic could be particularly advantageous for specific types of risk assessment or long-term strategic planning.

The double Bi-LSTM with an Attention layer shows the lowest RMSE as seen in Table III, suggesting that it is better at handling large errors and is noticeably more effective in minimizing the costly large prediction errors. This is valuable in financial contexts where large prediction errors can be more damaging than several small errors.

Metric	Value
Mean Absolute Error	0.120211
Root Mean Squared Error	0.207384
Mean Squared Error	0.043008

TABLE III
DOUBLE BI-LSTM MODEL ERROR METRICS

VI. CONCLUSION AND FUTURE SCOPE

This study's exploration into the application of bi-directional LSTM networks (augmented with attention layers) in the prediction of price movements, reveals significant insights. The basic bi-LSTM model showed proficiency in capturing general trends and temporal dependencies in the data but faced challenges in responding to rapid changes and outliers. The addition of an attention layer in the same model enhanced its ability to focus on critical segments within the price movements, improving its responsiveness to sharp fluctuations which is common during periods of geopolitical tension. The dual-layered bi-LSTM with attention mechanisms further excelled in capturing intricate patterns and dependencies during the same periods, crucial for accurate GPR index predictions.

These models demonstrated their effectiveness in closely aligning predictions with actual values on both tested and untested data, with the dual-layered approach showing the most promise in minimizing large prediction errors. This aspect is particularly vital in financial contexts, where large errors can have more severe consequences than multiple smaller ones.

Looking forward, the application and improvement of these models hold immense potential. Adapting the bi-LSTM models for real-time data analysis can provide more timely and relevant insights especially during a time of unrest. This enhancement would enable the models to process and analyze data as it becomes available, offering immediate predictions and responses. Furthermore, integrating these models with other advanced AI techniques, such as reinforcement learning or genetic algorithms, could significantly enhance their robustness. Such integration would allow the models to learn and evolve in more dynamic and complex environments similar to a stock market's behaviour, potentially improving their predictive accuracy and reliability. Additionally, conducting longitudinal studies on these models is vital. By evaluating their performance over extended periods, deeper insights can be gained into their long-term effectiveness, stability, and areas requiring refinement. This continuous evaluation will not only validate the models' current capabilities but also guide future improvements and innovations in predictive modeling.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to Prof. RimJhim Singh for her invaluable guidance and input throughout our project. Her timely advice and expert recommendations were especially helpful in navigating the challenges we encountered.

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