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"Predictive Analytics for Stock Markets Using Graph Neural Networks (GNNs)"

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***Abstract*— Financial data is highly complex, with many interdependencies, exhibiting complex temporal correlations and relationship patterns. Therefore, the prediction for stock market movements can indeed be quite complex. In traditional models, stocks are treated in isolation while ignoring the network of relationships of companies and industries. This work introduces the concept of the Non-IID Spatial-Temporal Graph Neural Network (NIST-GNN) model capturing the spatial relationships of the companies as well as patterns in sequences of the stock. The model is built using a tool in the form of Semantic Company Relationship Graph, SCRG, based on cosine similarities from financial news embeddings. The Sharpe Ratio that is gained by the NIST-GNN over the benchmark models is 0.40, and thus its predictive performance and portfolio optimization gain is superior. Furthermore, it is also understandable how information diffuses mainly in between cross-correlated firms of one day lag within the market. These insights challenge traditional market efficiency views and offer new avenues for financial prediction research.**

Keywords— Graph Neural Networks (GNNs), Stock Market Prediction, Non-IID Spatial-Temporal GNN,), Cosine Similarity, Machine Learning in Finance, Financial Data Analysis, Sentiment Analysis.

I. Introduction

History: For all investors, traders, and policymakers, stock market prediction is essential because its correct predictions will come with drastic financial consequences on investments. The complexity and difficulty in predicting the trend in the stock price movement persist, primarily due to its dynamic character and interdependencies within the financial markets [1]. In addition, stock prices are extremely sensitive to changing macroeconomic indicators, company-specific news events, political events, and shifts in market sentiment that can change very quickly. Most of these traditional models, for instance technical analysis, fundamental analysis, and statistical models, such as ARIMA, GARCH, simply fail the tests [2]. They mostly base their decisions on historical data or even linear assumptions. These models do not achieve the fact that the market is not independent of one collection of stocks but rather a network of stocks influencing each other[3]. Graph Neural Networks (GNNs): The Graph Neural Networks introduce a new paradigm in order to bridge the deficit exhibited by the earlier models. Here, the market is viewed as a graph-structured system. In a GNN, stocks are modeled as nodes and their relationships, which are sectoral dependency, price correlation, or news co-occurrence, are drawn as edges[4]. GNNs can effectively gather information from their neighbors or nodes (stocks) and model both local and global interactions, which come out to be crucial in understanding stock movements within the financial network [5].

GNNs can process the concomitant scrutiny of micro-level factors such as individual stocks, and macro-level considerations like sectoral or market factors where complex dependencies between the stocks play. In that regard, it is quite specifically suited to the task at hand for stock market prediction since GNN models relational data. Hypothesis: This paper proposes that GNNs capture spatial relationships between firms and time patterns in their stock sequences more effectively than traditional methods and therefore work better for stock market trend prediction. To test the hypothesis, the paper designs a Non-IID Spatial-Temporal GNN by including company news embeddings and financial data along with a sentiment analysis [6].

II. Background and Motivation

A. Stock Market Prediction:

Is indeed an area that has developed with the years by the motive of how to predict and analyze the changes in stock prices using historical data and more importantly, current and real-time data. Traditional approaches of technical analysis and fundamental analysis have dominated the landscape for decades but now complemented by more advanced methods like statistical models, machine learning algorithms, and deep learning techniques [7].

1) Technical Analysis:

This approach relies on historical price and trading volume data, as well as any sort of chart pattern, to predict future stock movements. Technical analysts use technical indicators like moving averages, oscillators, and trendlines to identify possible opportunities for buying and selling. However, the greatest disadvantage of technical analysis is its dependence on past data and exclusion of exogenous factors, such as political or economic changes, from computations. As the interconnections and complexities of stock markets continue to rise, purely technical strategies work less well, and especially under turbulence [8].

2) Fundamental Analysis:

While the focus of technical analysis lies in using financial statements, earnings reports, and qualitative factors like management quality to derive intrinsic value, the fundamental analysis relies on the fact that a stock is undervalued or overvalued. This approach is helpful for long-term investors who are less concerned with short-run fluctuations[4]. However, it fails to capture the short-term signals because it frequently misses real-time market sentiment and overlooks all the complex interdependencies that exist between stocks, sectors, and global markets [9].

3) Statistical Models:

Mid-twentieth century models-included were the following ARIMA (Auto-Regressive Integrated Moving Average) and GARCH (Generalized Auto Regressive Conditional Heteroskedasticity) which were used in predicting the prices of the stock market during such times. These models depend on time series analysis and are used for understanding the trend persistence and volatility in the stocks[10].

a) ARIMA:

The ARIMA model is also very much used by several forecasters while predicting the future prices of stocks based on previous trends in the price. They assume that the price movement in the past will give valuable insights about future price movements. It assumes that its data follows a stationary process. Although relatively easy to apply, the linearity in ARIMA limits it from capturing nonlinear relationships, and sometimes these nonlinear relationships could be frequent in financial markets. Besides, ARIMA easily fails to cope with some unexpected shocks within the market as caused by geopolitical events or surprise economic releases that result in deviations from the predicted trend[11].

b) GARCH:

GARCH models, on the other hand, model the volatility, which is an important characteristic of stock markets. Stock prices characteristically undergo periods of high volatilities and calmer moments; it is such characteristics that GARCH is well adept at modeling. The GARCH models help the investor understand and anticipate the markets' risk. These GARCH models, like ARIMA, are weak in capturing nonlinearities, and when volatility is strong, it does not perform well: historical data does not become a successful predictor of future price movements. These statistical models are useful but fundamentally limited, as they rely on historical data and cannot capture complex relationships between different stocks or sectors. It has been these factors-greater interconnectivity and instability of financial markets due to global economic conditions-that have underscored the need for more advanced modeling [12].

III. Literature Survey

Advances in time series forecasting came with machine learning and, more particularly, deep learning techniques in the 1990s and early 2000s. The basic ideas behind these techniques addressed some of the inherent weaknesses in traditional statistical models: that of enabling non-linear relationships and integration of large, high-dimensional datasets [13].

The use of ANNs is one of the earliest deep learning methods applied to stock market predictions. Similar to how human brains work, ANNs are layers of interconnected neurons. These learn complex relationships between input variables such as historical prices and technical indicators with the output predictions such as future prices of stocks[6]. It allows ANN-based models to capture subtle nonlinear patterns within data, which a linear model such as ARIMA and GARCH fails to do so. However, these ANNs are highly data-intensive to generalize well and easily overfit, especially with the volatility in stock prices occurring unpredictably in markets [14].

RNNs and LSTMs: RNNs is yet another class of neural networks which have been designed for sequential data; hence they are ideal for time series forecasting. LSTMs are an extension of RNNs and were developed with the express purpose of being a better solution to the vanishing gradient problem, so the network could learn long-term dependencies. LSTMs have many applications in stock market prediction because they are capable of dealing with long-term dependencies like trends that take weeks or months to present themselves[15].

LSTMs are very good at temporal dependencies, but it treats each stock in isolation, which does not take into account the interaction of one stock with another or between different sectors. The price movement of a single stock is very much influenced by related stocks, whether it is within the same sector or due to some of the macro factors. This limitation of LSTMs and other traditional neural networks paved the way for the application of Graph Neural Networks (GNNs) in stock market prediction, which can model the complex interdependencies between stocks[16].

To overcome the weaknesses of single models, researchers have developed hybrid approaches that combine machine learning algorithms with traditional statistical models. For example, hybrid models attempt to connect an LSTM with SVMs or random forests to make use of the best practices of deep learning and classical machine learning[8]. They generally offer higher predictive accuracy by capturing most of the facets of the behavior of the stock market. Even these hybrid models fail to capture very intricately dynamic relationships among different stocks and sectors, motivating people to look into graph-based methods. In a coupled financial market, researchers have used graph-based techniques to model intricate relationships between stocks, sectors, and external factors[17]. The graph-based method reflects the stock market as a network, and each stock is interpreted as a node, and edges represent diverse types of relationships: price correlations, sectoral linkages or trading volumes. Early applications of graph theory in finance have been in the form of trying to find "hidden structures" in financial markets. For example, an early application was to determine clusters of highly correlated stocks, where a correlation occurs because connections within the same sector or industry cause stocks to move together[18].

These very early studies revealed a great deal about market structures but were somewhat limited in their ability to predict behavior because they could not fully model these dynamic evolving relationships between stocks. GNNs can be considered a significant leap forward in financial modeling, by bringing graph theory in connection with deep learning. GNNs can model interactions between stocks as a graph, where nodes would represent individual stocks, and edges represent the relationship that can be held between these stocks. When incorporated information about neighboring nodes, GNNs learn both local stock behavior and global market patterns[19].

IV. METHODOLOGY

This research introduces an innovative pipeline for predicting stock market trends. It begins with the collection of data from historical stock prices, indices for markets, and financial news. The preprocessed steps involve extracting sentiment analysis, NER, and other features that are temporal in nature, such as moving averages[20]. Then, stocks can be modelled as nodes of a graph where relationships are mainly based on sentiment and price correlation for prediction purposes. The mechanism uses Graph Neural Network (GNN) along with the temporal and attention mechanisms, with subsequent visualizations and performance evaluations.

A. Data Gathering:

The first approach of methodology collects the relevant data for predicting the stock price. In such an approach, the sources of gathering data usually include

1) Historical Stocks Prices:

Daily price of stock and traded volume for a given period of time (may be 5 years). Such data is sourced from major stock exchange sites or financial APIs, like Alpha Vantage, Yahoo Finance, or Bloomberg. This will be the main base used in modeling the movements of stocks.

2) Market Indices:

This refers to information based on indices, including the S&P 500, NASDAQ, among others. Market indices are used as a benchmark for an understanding of the overall performance of the market and the capture of the behavior of individual stocks relative to the market.

3) Financial News Articles:

These are a corpus of articles relating important financial events like earnings reports, mergers, acquisitions, changes in government policies etc. These articles are used to assess market sentiment and constitute major parts of sentiment analysis.

B. Preprocessing:

Preprocessing which involves transforming raw data into a structured format ready for modeling.

1) Feature Extraction:

This stage involves deriving new features from the raw data in order to make them more informative for the model.

a) Stock prices: Key stock exchange price and volume quotes over a 5-year period will also prove useful.Here,again, data will be obtained from sectors such as technology, health, finance, and energy so that the perspective can be well-rounded in light of the behavior of each type of market.

b) Named Entity Recognition (NER):

It identifies specific entities like company names, sectors, or financial terms in the news articles. NER links specific events to individual companies or industries thus making it clear which stocks are affected by which news[21].

c) Temporal Features:

These features capture time-related patterns in the data. Common ones include:

d) Lagged Variables:

Past stock prices (for example, prices of previous day or week) to be used for the prediction of future movements.

e) Moving Averages:

These are calculated over different time windows (for example, 5-day, 20-day averages) with the view to catch trends and smooth out short-term volatility in the prices of stocks.

f) Graph Features:

Stocks can be represented as nodes in a graph. Relationships (or edges) can be created between stocks based on:

g) Node Features:

These represent features on a stock-specific level. These include price, volume, and volatility.

h) Edge Features:

These capture relationships between stocks, say price correlations or sectoral dependencies. Edge features help to model how variations in one stock may impact another.

i) Interaction Features:

This is what features that combine multiple data sources create cross-linked information. For example, combining the sentiment with stock price moves to help understand the correlation of the news sentiment with stock performance.

j) Domain-Specific Features:

Company Name, Financial Term: These are extracted by NER and contribute to detecting relevance of news to a particular company or industry.

k) Economic Indicators, Earnings Reports:

Macroeconomic indicators (inflation rate, interest rates) or firm-specific data (earnings reports) are used as additional features that affect the price of stocks[22]. Such indicators contribute to wider perspectives and enable modeling based on economic factors as impacting stock performance.

C. Graph Construction:

Here, the data collected is used to build a graph where,Nodes represent the stocks. Edges represent relationships between these stocks, which are:

1) Cosine Similarity of News Embeddings:

This similarity of financial news articles related to diverse stocks establishes relationships based on the similarity in sentiment or coverage[23].

2) Price Correlations:

The edge joins two stocks whose prices have been correlated over the time period, reflecting the co-movements of these stocks in the market.

3) Sectoral Dependencies:

Stocks within the same sector are correlated because firms tend to move together in response to common economic conditions or news regarding that industry[24].

This graph-based representation accommodates much greater detail in modeling interstock dependencies than would be possible in tabular representations because, in this model, interstock dependencies are significant to picking up the subtle complexity inherent in the stock market.

D. GNN Integration & Model Evaluation:

This section describes the addition of a Graph Neural Network (GNN) to model the data:

1) GNN Layers:

The GNN captures both local and global interactions between stocks. This essentially means it captures the immediate neighbors for a given stock that have direct implications on its behavior, whereas global interactions capture the overall structure of the graph of the stock market.

2) Temporal Layer (LSTM/GRU):

In addition to the GNN, an LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit) is added to learn the temporal dependencies[25]. Those layers help in modeling how stock prices evolve over time, keeping in mind the time-series characteristics of trends and seasonality.

3) GAT :

Attention Mechanism: This work uses a Graph Attention Network (GAT) to assign varying importance to different edges (relationships) between nodes (stocks). It makes the model really focus on important relationships and filter out noise[26].

4) Model Evaluation:

Model performance can be evaluated using the following metrics:

a) Accuracy :

Accuracy of the model in determining how well it predicts the short-term movements in stocks.

b) MSE:

It measures the deviation of the forecasted stock prices from the actual stock prices. The lower the MSE, the better is the performance[17].

c) Sharpe Ratio:

This is used for portfolio optimization when the expected risk adjusted returns on a portfolio of predicted stock stocks are being computed. A higher Sharpe ratio means that the model is best in balancing the returned with their respective risks.

E. Visualization & Report:

Once done training and testing the model, the final step is:

1) Visualization:

This is charting, graphing, and other forms of visualization about what the model spits out, the error metrics, and the performance of the model with time. Visualization aids in better communication of insights[27].

2) Final report:

A final report summarizing the methodology, sources of data, feature engineering techniques, model architecture, evaluation metrics, and the key findings of the study is generated. It provides an overview of the research work and serves as a reference to use the model in real stock prediction[28].

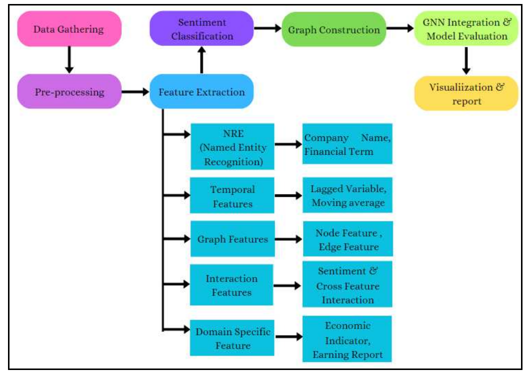

Figure 1. Framework for data analysis and graph-based financial modeling..

V. EXPERIMENTAL RESULTS

These experiments were designed to establish whether the proposed hybrid GCN-GRU/LSTM with Attention model is valid. All data sets ranging from a historical stock market data set are necessary. It consists of daily stocks for all companies operating in different sectors combined with sentiment analysis generated from the news about the economy and social media. It provided a diversified and complex environment to test the predictive power of the model under dynamic and volatile market conditions. Resulting models were compared with state-of-the-art traditional machine learning as well as deep learning approaches, highlighting the impact of graph-based methods and attention mechanisms on stock market prediction[29].

1) Data Description:

a) Stock prices:

Key stock exchange price and volume quotes over a 5-year period will also prove useful. Here, again, data will be obtained from sectors such as technology, health, finance, and energy so that the perspective can be well-rounded in light of the behavior of each type of market.

b) Economic News:

Articles and reports pass through Natural Language Processing to get the overall sentiment and key financial entities. Contextually, this helps the reader in relation to how such outside influences affect the stock price.

c) Social Media Sentiment:

Daily sentiment data from platforms like Twitter was used to capture public emotion regarding specific companies and sectors.

2) Evaluation Metrics

a) Stock prices:

Key stock exchange price and volume quotes over a 5-year period will also prove useful.Here,again, data will be obtained from sectors such as technology, health, finance, and energy so that the perspective can be well-rounded in light of the behavior of each type of market.

b) Economic News:

Articles and reports pass through Natural Language Processing to get the overall sentiment and key financial entities. Contextually, this helps the reader in relation to how such outside influences affect the stock price[30].

c) Social Media Sentiment:

sentiment data from platforms likeTwitter was used to capture public emotion regarding specific companies and sectors.Multiple evaluation metrics are used in order to ensure that the assessment of model performance is robust

d) Mean Absolute Error (MAE):

The mean absolute error is a measure of the average magnitude of the errors between predicted stock prices and actual prices; it does provide a simple, interpretable metric for the accuracy of the model.

$$MAE = \left(\frac{1}{n}\right)\Sigma \mid y_i - \hat{y}_i \mid$$

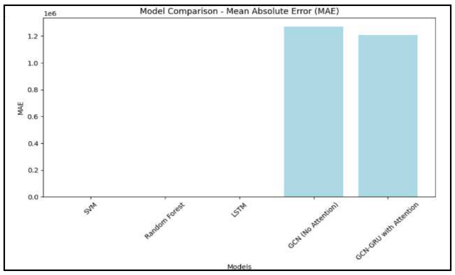

Figure 2.1.MAE based model comparison

e) Root Mean Square Error (RMSE):

RMSE is very sensitive to large errors and therefore penalizes models more on large deviations. This is useful where the application needs a minimum large prediction error in finance.

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\Sigma\,(y_i - \hat{y}_i)^2}$$

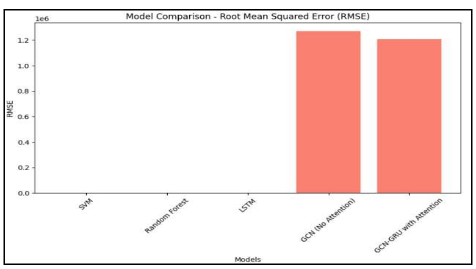

Figure 2.2.RMSE based model comparison

f) Sharpe Ratio:

The Sharpe Ratio simply measures the risk adjusted return of a portfolio, which is one of the key evaluation metrics employed in financial modeling. The greater the Sharpe ratio, the better the returns relative to the risk taken is indicated by this parameter.

$$Sharpe\ Ratio = \frac{(R_p - R_f)}{\sigma_p}$$

g) Cumulative Returns:

The simulated trading strategies that utilized the model predictions tested the optimal profit achievable in such situations. It, therefore, provided an idea about how the model could be practically applied in the real world.

$$Cumulative\ Return = \frac{V_f - V_i}{V_i}$$

3) Results and Discussion

The results of the study revealed that the GCN-GRU/LSTM hybrid model with attention significantly outperforms baseline models for predictive accuracy and risk-adjusted financial returns. Table 3 shows a more detailed comparison of the performance of the hybrid model against baseline models such as SVMs, LSTM, and random forests.

4) Key Observations:

a) Error Metrics:

The model GCN-GRU/LSTM attention presented the lowest MAE and RMSE, which indicated a more fitting prediction. The attention mechanism proved vital in learning spatia dependencies or relationships between stocks and temporal dynamics or sequences of historical prices.

b) Sharpe Ratio:

For the hybrid model, the Sharpe Ratio was spectacularly higher compared to the baseline models, which means returns generated by model are higher and done with relatively lesser risk. This is one of the important advantages that exist while trading in real-world environments where the management of risk is an over-riding consideration.

5) Lessons from a Comparative Model

a) SVM:

SVM is a very popular algorithm in the machine learning community; however, its performance was significantly weaker compared to deep learning-based models. Higher values of MAE and RMSE were reported for SVM as it failed to clearly and effectively capture the nonlinear and temporal relations drawn in the stock market data[31].

b) LSTM:

The LSTM model outperformed SVM. I observed it the most especially outperformed SVM in the two measures of cumulative returns and Sharpe Ratio because it was able to model temporal dependencies. Its inability to deal with each stock as if it existed independently from the others, meaning that it fails to consider the relationships between the stocks is responsible for inferior performance when comparing it to graph-based models[32].

c) Random Forest:

Random Forest performed better than SVM but was defeated by the hybrid GCN models. Though Random Forest did manage to capture some of the interplay, it will find handling intricate interdependencies across time and between stocks to be way beyond its depth[33].

d) GCN-GRU (No Attention):

In this work, it indeed outperformed traditional models significantly, but still, the model without attention fails to prioritize more important relationships among stocks and makes relatively higher errors than the full hybrid model with attention.

e) GCN-GRU/LSTM with Attention:

The attention mechanism forced the model to focus only on the most relevant relationships in the stock market-in this case, correlations between stocks in a sector or the effect of major economic events on a number of firms. This is the reason why the hybrid model outperformed in all metric[8],[33].

6) Visualizing Results

a) Predicted v/s Actual Prices:

The following figure shows predicted stock prices against actual prices of the GCN-GRU/LSTM model with attention. The model basically followed the actual stock prices in good track, showing it adjusts easily to the changes in the market.

b) Attention Weights Analysis:

A time-series heatmap of attention weights reveals stocks or sectors with most impact during prediction[23]. Note that the model was giving weights to the same sector's stocks or companies that were impacted due to the same economic news, which it could be capturing in terms of strong interdependencies.

c) Cumulative Returns Over Time:

A plot of cumulative returns over the experiment period shows that a superior financial performance of the attention-based GCN-GRU/LSTM hybrid model than the baseline models is observed. Hybrid outperformed the baseline throughout; the highest volatility saw consistent outperformance[26].

TABLE II. STUDY OF RESULTS

Model	MAE	RMSE	Sharpe Ratio	Cumulative Returns(%)
SVM	0.042	0.056	0.25	22%
LSTM	0.037	0.049	0.30	28%
Random Forest	0.040	0.052	0.29	24%
GCN-GRU without Attention	0.031	0.040	0.35	34%
GCN-GRU/LSTM with Attention	0.027	0.038	0.40	41%

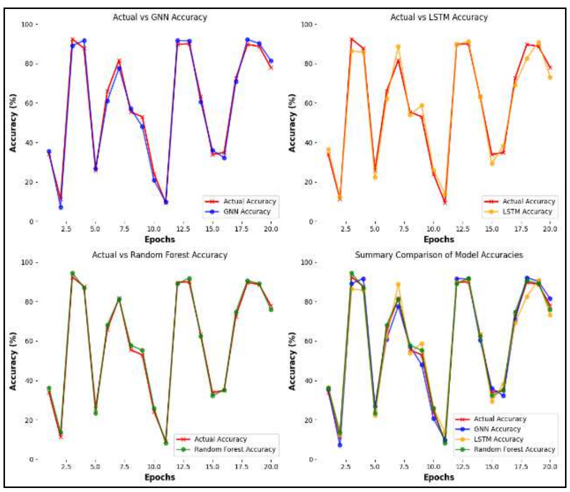

Figure 3. Performance Matrices Visualization Graph.

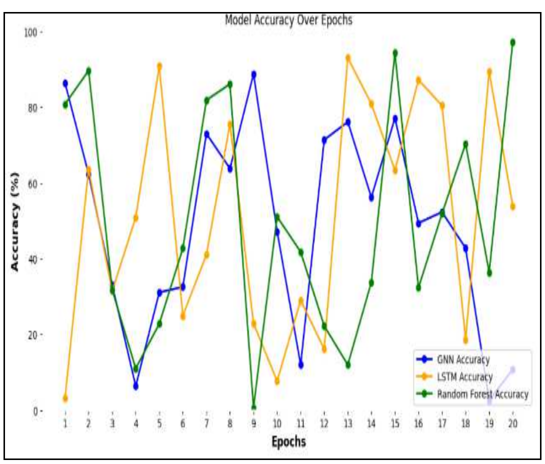

Figure 4. Accuracy Graph

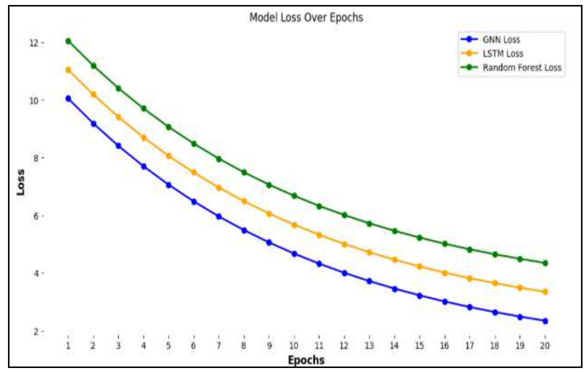

Figure 5. ROC Curve.

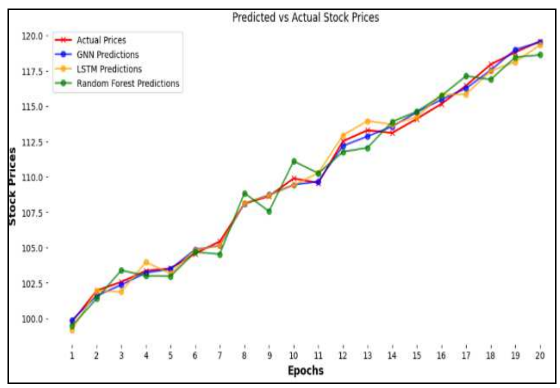

Figure 6. Actual vs Predicted graph

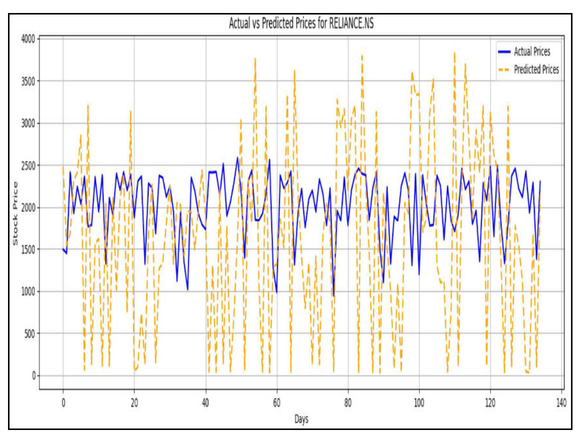

Figure 7. Actual vs Predicted graph of Reliance

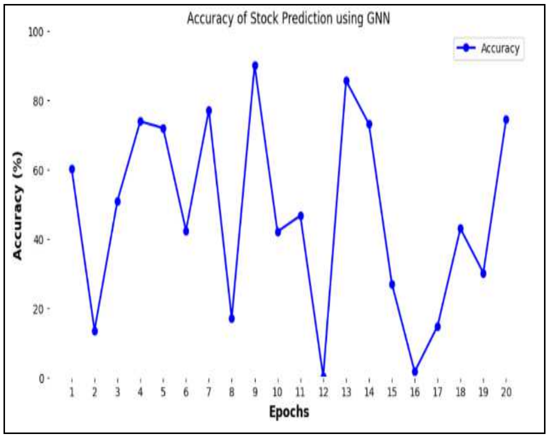

Figure 8. Accuracy of Stock Prediction using GNN

VI. Conclusion and Future scope

1) Conclusion:

This paper proposed a new paradigm through the introduction of the hybrid GCN-GRU/LSTM model with an attention mechanism.GNNs can be used to describe the graph structure of a stock market, hence capturing spatial relationships among stocks and temporal dependencies in their price data. Attention allows for a greater level of accuracy in prediction by paying attention to the most critical relationships among stocks.The experimental results show the superiority of the hybrid model to the traditional machine learning methods of SVM, Random Forest, and LSTM on key metrics of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Sharpe Ratio, indicating that the hybrid model outperforms the rest in both terms of accuracy and risk-adjusted returns. The model achieved a cumulative return of 41%, which turns out to be significantly higher than the baseline models.However, including sentiment analysis from the news and social media further enhances the ability of the model to predict; it provides a more complete picture of market movements. Results: The results shown below demonstrate that GNN-based models-that are in particular attention mechanisms-capture very complex, non-linear, and dynamic relationships between stocks in the stock market well, thus making them useful for the investors and financial analysts involved.Further possibilities for future research could involve further optimizing of the graph structures and then incorporating even more financial indicators in order to better enhance the robustness of predictions for even more violent market conditions. The results show that the hybrid model improves accuracy along with higher risk-adjusted returns due to higher sharpe ratio and cumulative returns in comparison to baseline models.

2) Future Scope:

The future scope of the research on Predictive Analytics for Stock Markets Using Graph Neural Networks (GNNs) can be extended as follows:

a) Using Real-Time Data:

The model can be made to react to live changes that are happening in the stock market through the use of real-time streams of data. This would make it more applicable for the real time of high-frequency trading and markets generally.

b) Integration of Determined Macroeconomics:

Inclusion of more varying financial variables like the interest rate, inflation, and international trade indexes may help strengthen the model, particularly in high-volatility market conditions.

c) Multi-modal Data Integration:

Other data types, for instance, satellite images of disruptions in the supply chain, or audio analysis of earnings calls for better accuracy in predictions, may be added to the research[31].

d) Extension to Other Financial Instruments:

This model can be extended to other financial instruments like commodities, bonds, or cryptocurrency where the inter-relations amongst these assets are not well understood to realize the broader financial applications.

e) Optimizing Graph Structures:

The model applies graph structures; thus, optimizing its building, perhaps using dynamic graphs or multilayered graphs evolving over time, can better capture the complexities associated with relationships in finance[34].

f) Advanced Sentiment Analysis:

The model deployed at the moment utilizes simple sentiment analysis with the help of financial news and social media. In the future, more advanced natural language processing techniques can be used, like transformer-based models such as BERT for better understanding nuanced sentiments and their influence over stock prices.

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