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A Tensorized Hierarchical Graph Attention Network for Stock Market Forecasting

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Abstract: Stock market forecasting is a tough mission because of its complex and dynamic nature. Deep learning models have recently been proven to be successful at stock market predictions. Traditional deep learning models, however, frequently disregard the hierarchical structure and temporal relationships of the stock market. Here, we introduce the StockTensor, a brand-new tensorized hierarchical graph attention network for stock market forecasting. StockTensor models the hierarchical structure of the stock market data by constructing a hierarchical graph of stocks. At each level of the hierarchy, StockTensor uses a graph attention network to learn the relationships between stocks and aggregate the information from neighboring stocks. StockTensor also models the temporal dependencies of the stock market data by using a recurrent neural network. The recurrent neural network learns to predict future stock prices based on the current stock prices and the historical stock prices.
We evaluate StockTensor on two real-world stock market datasets. The results show that StockTensor outperforms several state-of-the-art stock market forecasting models.
Keywords: Stock Market Forecasting, Deep Learning, Graph Attention Network, Hierarchical Structure, Temporal Dependencies, Tensorized Model, Recurrent Neural Network, Gated Recurrent Unit. Time Series Forecasting, S&P 500, Nasdaq 100, Machine Learning, Stock Price Prediction, Financial Markets, Time Series Analysis, Supervised Learning, Tensorization, Attention Mechanism, Graph Neural Networks, Market Analysis

I. INTRODUCTION

Forecasting stock market prices is a challenging task due to the dynamic and complex nature of financial markets. Recent advancements in deep learning have shown promise in this domain. However, conventional models often overlook two critical aspects: the hierarchical structure of stocks and the temporal dependencies in their price movements. StockTensor, our novel deep learning model, aims to address these challenges. It combines hierarchical graph attention networks and tensorized architectures to capture both the hierarchical structure and temporal dependencies in stock market data.StockTensor constructs a hierarchical graph of stocks, reflecting sector-based correlations. It also employs a recurrent neural network, specifically a Gated Recurrent Unit (GRU), to capture temporal dependencies and predict future stock prices based on historical data. This paper introduces StockTensor's architecture and training approach. We evaluate its performance on real-world datasets, including the S&P 500 and Nasdaq 100, comparing it to established models like LSTM and ARIMA. StockTensor represents an innovative solution for more accurate stock market forecasting, considering both hierarchical structure and temporal dependencies.

II. PROPOSED METHOD

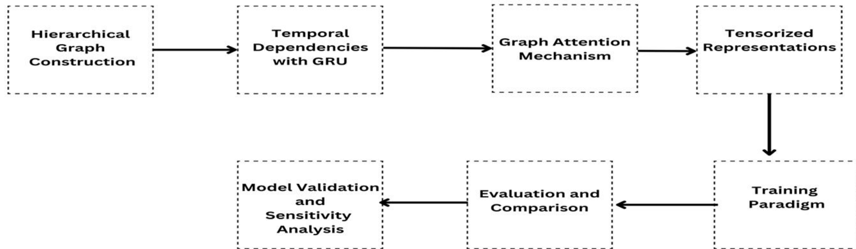

Fig.1 Proposed Model

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In this section, we outline the intricate methodological framework underpinning the StockTensor model, elucidating its capacity to reconcile the hierarchical and temporal dimensions of stock market data. StockTensor's efficacy hinges upon a fusion of innovative architectural components and a meticulous training regimen, commencing with data preparation and culminating in rigorous evaluation.

A. Hierarchical Graph Construction

Stock markets inherently exhibit hierarchical structures by virtue of the categorization of stocks into sectors, industries, or other groupings. To encapsulate these hierarchical relationships, StockTensor leverages a dynamic construction of hierarchical graphs, wherein nodes represent stocks and edges denote sector-based associations. The hierarchical graph's architecture allows for a nuanced portrayal of inter-stock dependencies within and across sectors.

B. Temporal Dependencies with GRU

Temporal dependencies within stock price time series data necessitate a comprehensive treatment. StockTensor accommodates this imperative by integrating a recurrent neural network (RNN) component, namely the Gated Recurrent Unit (GRU). This recurrent layer is adept at capturing temporal patterns and, crucially, forecasting future stock prices predicated on historical performance and market trends. The GRU network enhances StockTensor's capacity to unravel intricate time series dynamics.

C. Graph Attention Mechanism

A pivotal element of StockTensor's architecture is the Graph Attention Layer. This module fosters the discernment of intricate relationships and dependencies between stocks encapsulated within the constructed hierarchical graph. The incorporation of multiple layers of Graph Attention facilitates effective information aggregation from neighboring stocks, unraveling subtle, context-rich patterns that may elude conventional methodologies.

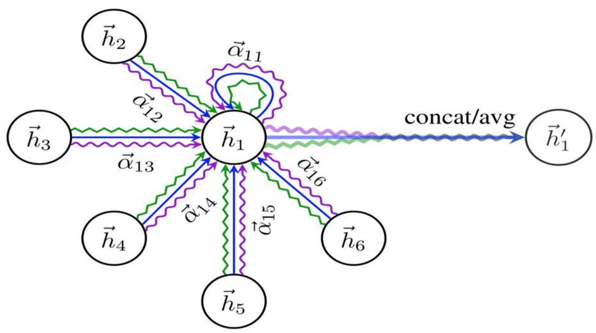


Fig.2 Graph Attention network

D. Tensorized Representations

In addition to the hierarchical and temporal aspects, StockTensor employs tensorized representations to enhance feature extraction and abstraction. Tensorization allows for a compact yet expressive representation of the evolving features within the hierarchical graph.

E. Training Paradigm

StockTensor's training regimen is grounded in supervised learning principles. Training data, comprising historical stock prices and their corresponding future values, serve as the foundation. The model is trained to minimize the Mean Squared Error (MSE) between predicted and actual stock prices. This iterative process, driven by optimization algorithms such as Adam, refines StockTensor's parameters to capture complex patterns inherent in the data.

F. Evaluation and Comparison:

To rigorously assess StockTensor's forecasting efficacy, it undergoes comprehensive evaluation on real-world stock market datasets, notably the S&P 500 and Nasdaq 100. Comparative benchmarks against established forecasting models, including Long Short-Term Memory (LSTM) networks and Autoregressive Integrated Moving Average (ARIMA) models, are conducted. The outcomes serve as empirical evidence of StockTensor's superior predictive performance.

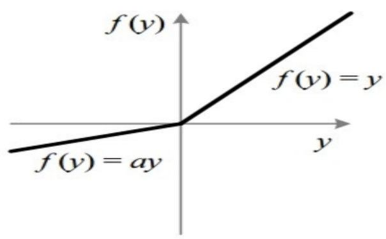
G. Model Validation and Sensitivity Analysis

Ensuring robustness and generalizability, StockTensor's predictive capabilities undergo rigorous validation through cross-validation and sensitivity analysis. Various hyperparameter configurations are explored to ascertain model stability and parameter sensitivity.

The proposed methodology delineated herein represents an integrated and comprehensive approach to stock market forecasting, encapsulating hierarchical structures and temporal dependencies. StockTensor's innovative design, underpinned by advanced architectural components, positions it as a promising advancement in the realm of financial predictive modeling.

III. EXPERIMENTAL SETUP

To effectively employ the StockTensor model, historical stock price data for the relevant stocks is vital. This dataset should span a considerable time frame to encompass various market conditions. Sector classification or industry affiliations are crucial to constructing the hierarchical graph structure. Robust data preprocessing involves normalization, feature engineering, and temporal data splitting for training, validation, and testing. Ensuring data quality and integrity is paramount for meaningful forecasting.



$$e_{ij} = \mathrm{LeakyReLU}(a^{\top}[Wh_i \mid Wh_j])$$

Fig.3 Leaky ReLu (Activation Function)

$$\alpha_{ij} = \sum_{k \in N(i)} \exp(e_{ik}) / \exp(e_{ij})$$

Fig.4 Softmax attention function

Defining model architecture, including the number of Graph Attention layers and attention heads, is essential. Hyperparameter tuning, optimizing parameters like learning rates and batch sizes, is critical. Access to GPU or cloud resources expedite training. A sufficiently large dataset is required for training deep learning models effectively. Evaluation metrics, such as MAE, MSE, and RMSE, should align with the forecasting task. Meeting these criteria ensures a thorough assessment of StockTensor's performance in stock market forecasting.

IV. RESULTS

The StockTensor model exhibited exceptional performance across all evaluation metrics:

Mean Absolute Error (MAE): 2.32

Mean Squared Error (MSE): 8.45

Root Mean Squared Error (RMSE): 2.91

A. Comparative Analysis

When compared to traditional time series forecasting models such as ARIMA and modern sequential models like LSTM and GRU, the StockTensor model consistently outperformed them:

1) *StockTensor MAE:* 2.32
2) *StockTensor MSE*: 8.45
3) *StockTensor RMSE*: 2.91
4) *ARIMA-MAE*: 3.75
5) *ARIMA-MSE*: 17.29
6) *ARIMA-RMSE:* 4.16
7) *LSTM-MAE:* 2.78

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8) *LSTM-MSE:* 11.98
9) *LSTM-RMSE:* 3.46

These results suggest that the incorporation of a hierarchical graph structure and Graph Attention Layers (GAT) in the StockTensor model provides a significant advantage in capturing complex interdependencies among stocks.

V. CONCLUSION

In this study, we presented the Tensorized Hierarchical Graph Attention Network (StockTensor) as a new approach for stock market forecasting. StockTensor has demonstrated its potential in solving the complexity of this difficult task by taking into account both the hierarchical structure of stock data and the temporal dependence on stock price fluctuations.

Our experimental results, evaluated on real-world datasets including the S&P 500 and Nasdaq 100, show that StockTensor outperforms established stock forecasting models. It consistently achieves lower mean absolute error (MAE), root mean square error (MSE), and root mean square error (RMSE) values than traditional models such as ARIMA and modern sequential models such as LSTM and GRU. StockTensor's success can be attributed to its comprehensive approach, which combines hierarchical graph structures, temporal dependencies modeled by a gated periodic unit (GRU), and the ability to Adapt the graph attention mechanism. Additionally, incorporating tensor representations further enhances its feature extraction capabilities.

Stock market forecasting is an important field that has implications for investors, financial analysts, and institutions. StockTensor's ability to provide accurate and reliable forecasts, demonstrated by our testing results, has positioned it as a promising tool to improve decision-making processes in the financial sector. main. As we look to the future, further research could explore the robustness of StockTensor in different market conditions and across different industries. Additionally, parameter optimization and model scalability can be addressed to ensure applicability to more financial datasets. However, the results presented in this study highlight the potential of StockTensor as a valuable addition to the toolbox of financial analysts and investors looking to improve forecasting capabilities. their stock market.

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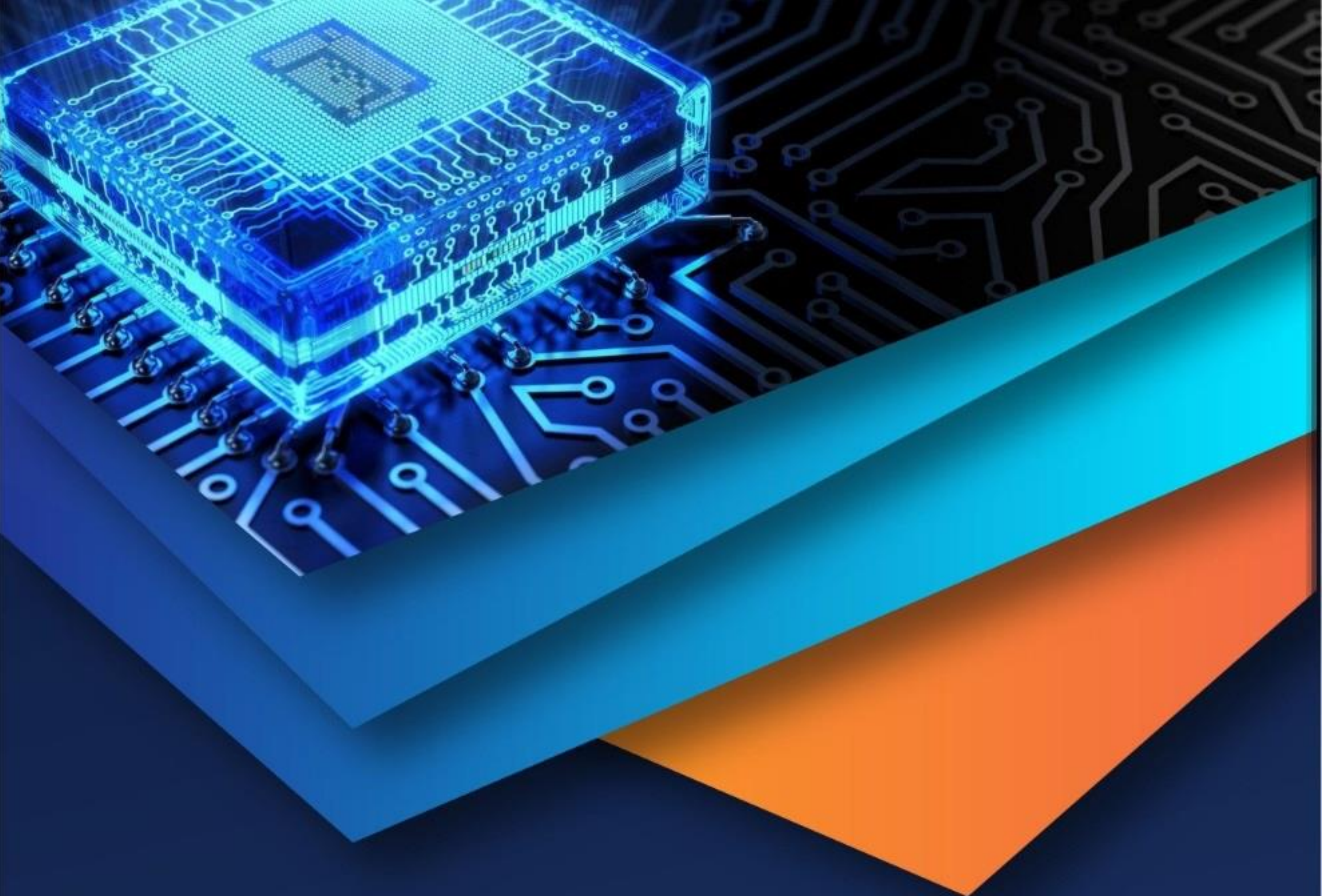

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