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Explainable Graph-Based Deep Learning Framework for Stock Price Forecasting and Systemic Risk Intelligence in the Philippine Stock Exchange

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I. Introduction

The Philippine stock market is a sophisticated financial market where stock prices are determined not just by the performance of companies that are listed, but on the company's ties with other companies, industry sectors, and the wider economy. Given the significance of stock price forecasting, it has emerged as a pivotal field in financial analytics that can aid in investment decisions, portfolio management, and financial-risk assessment. Traditional methods have modeled financial assets mostly as individual time series; however, these methods can be challenged in describing the complex nature of financial markets. Specifically, information information received from one company could include predictive information for another company if the two companies are related based on industry, supply chain, market behavior, or financial relationships.

This limitation can be overcome by explicitly encoding financial entities and relationships, which is made possible through the use of graph-based machine learning. A graph representation would be where companies are nodes and relationships between companies are represented as the edges. This way a learning algorithm can learn from the information of the other entities connected to the stock, instead of learning only from one single stock. Wu et al. (2023) has shown that this is possible by combining graph-based relationships with temporal deep-learning methods with a graph-based CNN-LSTM stock-price prediction algorithm. The authors provide a series of examples of their work, in which the relational information is modeled in the graph structure, while CNN-LSTM components extract temporal patterns from the stock-price data.

The importance of graph-based financial modeling is further supported by research on stock-price prediction. The main advantage of graph learning is that relationships between securities that are not captured by traditional time-series variables can be represented in financial models. A graph-based model can instead learn from the structure of the financial network and properties of the network of companies, rather than just using past prices. This is especially true for the Philippine Stock Exchange as companies listed on the Exchange are part of interdependent sectors and industries. Hence, a graph-based model of Philippine stocks could be used to gain more insight into the market behavior and generate additional information to predict the movement of stock prices.

In addition to stock-price prediction, financial markets are networked, which has serious ramifications for systemic risk. Systemic risk is the risk that a distressed financial entity may have an impact on a wider financial system as a result of its financial distress and the existing interconnections. Balmaseda et al. (2023) conducted a detailed study on Deep Graph Learning for systemic-risk prediction and found that Graph Neural Networks can use the financial-network structures to provide better systemic-risk prediction than traditional machine-learning methods. They also found that

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there is valuable information for systemic-risk prediction in both the network structure and relationship-level characteristics.

The results of Balmaseda et al. (2023) are especially relevant to the proposed study, given that they demonstrate that the analysis of financial risk does not necessarily need to be made at the level of individual institutions. In contrast, the topology of these connections between the financial actors could contain valuable clues on the way risk can arise and spread in a network. In the context of the Philippine Stock Exchange (PSE), the findings of the current study offer the opportunity to examine if PSE relationships can be leveraged not just for forecasting the stock market but also for detecting patterns related to vulnerability and systemic risk of the market.

A second is the dynamic aspect of financial relationships. Relationships among stocks are not necessarily constant over time. Correlations can change as a consequence of economic conditions, sector-specific events, market shocks, investor sentiment, and changes in corporate performance. Hence, a financial-intelligence system based on the individual price sequences of the past could miss out on the changes of the relationship structure among companies. These relationships can be captured by a graph and the methodology provides an appropriate framework for understanding them and to explore potential links between changes in the financial network and the behaviour of stock prices and the risk of the economy.

However, with the recent developments in deep learning for financial markets, one can also pose the question of model interpretability. While deep-learning architectures can learn very nonlinear relationships from large amounts of data, predictions they make can be hard to explain to human users. In the field of finance, this restriction is particularly significant as investors, financial analysts, regulators, and institutional decision-makers might need an explanation for the reason why a specific movement in a stock or risk situation is anticipated. An AI financial system can be less useful and trustworthy if it lacks a clear underlying logical explanation.

By 2023, explainability had already become a key research focus in stock prediction. To predict stock-price actions and enhance the explainability of the prediction, Li et al. (2023) proposed a Prediction-Explanation Network (PEN). They combined price and text data and were able to find information that could rationalize the fluctuations in stock prices. The authors noted that in financial applications, explainability is becoming more significant as stock predictions can be required to be audited, regulated, and considered for decisions. Their results show that predictive performance and explanation capability can be integrated into a single financial artificial intelligence framework.

The situation in the Philippines offers a significant opportunity to further advance these developments. Past studies in the Philippines have explored the application of AI in predicting the stock market, such as predicting the Philippine Stock Exchange Index. Villaruz et al. (2023) created a Tuned Artificial neural network based model using the modified Firefly Algorithm for forecasting PSE Index, showcasing the use of computational intelligence in forecasting financial markets in the Philippines. While an index level forecasting approach is mainly a model of the behaviour of the general market index, it does not necessarily reflect the complex relationships between the individual publicly listed companies.

This is significant, because the study proposed does not aim exclusively at predicting the PSE Index, but at company-level financial relationships. The Philippines Stock Exchange lists firms operating in various sectors and industries, whose actions in the market could be more or less interdependent. It may, therefore, be possible to represent the Philippine equity market better as a graph of a number of nodes, each representing a company instead of a graph of each security.

Graph learning and temporal deep learning are of special interest for this application. Wu et al. (2023) showed that integrating graph-based learning with CNN-LSTM models is feasible for stock-price prediction, and Balmaseda et al. (2023) showed that GNNs are useful for systemic-risk prediction. Concurrently, Li et al. (2023) showed the importance of using explanation mechanisms in the prediction of stock prices. As a whole, these studies offer distinct methodological approaches to forecasting, systemic-risk prediction, and explainable financial AI.

These research avenues also indicate a significant avenue for future research, however. The use of graph-based stock forecasting, systemic-risk modeling, and explainable AI have been studied separately but related problems. There is a need for an integrated framework that can represent relationships among Philippine equities, capture the temporal nature of patterns in stock prices, predict future price movements, provide the rationale behind the prediction, and analyze the network structure of conditions in a systemic-risk.

As such, the development of an Explainable Graph Based Deep Learning Framework for Stock Price Forecasting and Systemic Risk Intelligence in Philippine Stock Exchange was proposed. The framework will be made up of observations made over the course of history in the stock market, which will be represented as nodes in a financial graph, with the connection between two companies in the stock market represented as an edge. The historical behavior of the stock price will then be learned using temporal deep-learning mechanisms, and the information of relationships among companies will be learned using graph-learning mechanisms. An explainable-AI component will then detect the temporal, financial and network features that drive the model's predictions.

The proposed research then transcends the traditional question of whether artificial intelligence can predict stock prices. Instead it aims to explore the ability of these relationships between Philippine equities to help in forecasting; the ability of these relationships to reveal potential systemic-risk patterns; and the ability to explain the ability of these relationships to produce predictions, to human decision makers, given the AI predictions. This holistic view contributes much more at the doctorate-level where Artificial Intelligence, Graph Neural Networks, Deep Learning, Explainable AI, Financial Technology and Systemic-Risk Analytics meet.

Statement of the Problem

Although AI technology has advanced and is starting to play a role in predicting financial changes, it is still a complex research challenge to precisely model the behavior of interrelated stocks. Typical stock-price forecasting models tend to focus on the past behavior of individual stocks and are not likely to take advantage of information that lies in the relationships among companies. While financial graph-based causal relationships have been proved to be effective in predicting stocks, the use of financial graph-based deep learning has been under-researched in the complex Philippine stock market. The relational information could contain predictive information other than individual price sequences, as Wu et al. (2023) found that graph-based CNN-LSTM models could integrate relational and temporal information to predict stock prices.

The second is the challenging problem of simultaneously representing the temporal dependencies and inter-stock relationships. The price of a stock changes over time and the dynamics of relationships between companies can affect the prices of individual securities. A model that only takes into account temporal information might miss relationships between related companies, while a model that only takes into account the network structure might miss sequential price dynamics. Thus, a single graph-based deep-learning framework that captures both aspects of the financial market is required.

A third issue has to do with the distinction between stock forecasting and systemic-risk analysis. Stock prediction generally is the study of how a single security will move in the future, while systemic-risk analysis is concerned with the possibility that financial issues could spread throughout related parties. Balmaseda et al. (2023) showed that financial-network structures can be leveraged to make predictions about systemic risk using GNNs, and that relationship-level information can be used to significantly improve risk analysis. There is, however, a need to further explore the possibility of employing a common graph-based approach to link stock forecasting and systemic-risk intelligence in the Philippine market.

The next issue is related to the black-box approach to deep learning models. Good deep learning models can make accurate predictions but they don't give enough explanations about why they made the prediction. The restriction can make AI-powered financial systems unfeasible in real-world applications. To highlight the need for developing financial AI models that can offer meaningful explanations along with financial predictions, Li et al (2023) showed that prediction and explanation could be combined in financial AI via the Prediction-Explanation Network.

The fifth is the scarcity of integrated financial intelligence frameworks that incorporate graph learning, temporal deep learning, explainability and systemic-risk analysis in the Philippine context. While Villaruz et al. (2023) show that artificial neural networks can be used for forecasting the Philippine Stock Exchange Index, this does not reflect the relationships between individual listed companies. Hence, the need to create a graph based framework for the Philippine equity market for the company level.

The main problem of this research is thus the lack of an integrated and explainable graph-based deep-learning framework to model the temporal behavior of stock prices, inter-company relationship, stock-price forecasting, and systemic-risk pattern in the Philippine Stock Exchange (PSE).

General Objective

The overall aim of this study is to design and test an Explainable Graph Based Deep Learning Framework for Stock Price Forecasting and Systemic Risk Intelligence in Philippine Stock Exchange.

Specific Objectives

In particular, the study will seek to:

A. Create a graph based deep learning model that captures the relationship between the Philippine Stock Exchange (PSE) listed companies and incorporates temporal information in the stock market to predict the stock price.

B. Compare the forecasting accuracy of the proposed graph-based deep-learning model with some of the chosen conventional statistical, machine-learning and deep-learning models by using relevant performance metrics.

C. Design an Explainable Artificial Intelligence (XAI) process for discovery and understanding of the network factors in time, finance, and inter-stock which affect the model's stock-price predictions.

D. Develop and test a systemic-risk intelligence mechanism using abnormal market behavior, network properties and interconnectedness of stocks to detect potential propagation of risks and systemic-risk patterns in the Philippine Stock Exchange.

II. Related Works

2.1 Evolution of Stock-Market Forecasting Using Artificial Intelligence

The use of artificial intelligence in stock-market forecasting is an evolving game.It is an evolving game involving stock-market forecasting through the use of artificial intelligence. The prediction of the stock markets is a challenging problem since the market data are generally noisy and volatile, nonlinear, non-stationary, and subject to regime changes. Gandhmal and Kumar (2019) conducted a systematic review of 50 studies regarding the techniques used in the prediction of stocks in the stock market, which revealed that the main approaches used in the prediction of stocks include Bayesian approaches, fuzzy systems, artificial neural networks, support vector machines, and other machine learning techniques. The chaotic and non-stationary nature of the market observations made during stock market forecasting is highlighted in their review.

This discovery provides a valuable methodological basis for the proposed research. Any model developed for stock prediction in the Philippines cannot be reasonably expected to have stable or linear relationships in the past. Rather, the forecasting architecture should have the flexibility to deal with the nonlinear temporal patterns and evolving relationships between securities.

Jiang (2021) then did a thorough review of the literature on deep-learning applications in stock-market predictions and analyzed over 100 studies. The review highlighted the presence of a basic workflow, with data acquisition, data processing, prediction modeling, and evaluation, and highlighted the increased application of recurrent neural networks, convolutional neural networks, and other deep-learning architectures. Not only that, but Jiang also pointed out the need to address the issues of implementation and reproducibility in financial deep learning.

The shift from traditional machine learning to deep learning is thus well understood. But, the majority of conventional deep-learning methods still rely on the temporal properties of each stock. This is significant to the proposed study since Philippine equities are not standalone financial units but are in sectors and markets where changes in the prices of one security may be related to changes in the prices of other securities.

2.2 Deep Learning for Stock-Price Forecasting

Several studies have shown that deep-learning architectures can be effective for financial forecasting. For instance, Shahi et al. (2020) compared the performance of two models for stock-price forecasting: Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). They also found out if they could use financial-news sentiment to get a better prediction than using stock features alone. The study highlights the relevance of the temporal modelling and introduces the possibility of using information out of historical prices to enhance the prediction accuracy.

Similarly, using deep neural networks and financial indicators, Gu et al. (2020) studied stock-performance prediction. Their research points out the problem of predicting the stock's performance, and the need for finding the right factors to represent market behavior. Results of these studies suggest that deep learning can extract nonlinear relationships that conventional forecasting models may not be able to capture. However, LSTM, GRU and standard deep neural networks normally interpret any securities as separate sequences. This will limit a research problem where multiple stocks' relationships are predictive information as well.

The restriction appears to be applicable to the proposed PSE research, as a data set that includes hundreds of companies listed in the Philippines affords a chance to extend the time-series forecasting methods to model the relationship between securities.

The third task is Feature Selection and Optimization for Stock Prediction.The third one is Feature Selection and Optimization in Stock Prediction. The question of what financial variables to choose has also been given much thought. In IEEE Access, Chen and Zhou (2021) came up with a novel approach for stock-prediction using a hybrid model combining the Genetic Algorithm (GA) feature selection technique with a neural network of Long Short-Term Memory (LSTM). The ranking of financial factors and selection of an optimum set of financial factors were performed using the Genetic Algorithm and the optimum is then given to the LSTM model. Through their experiments, they proved that their proposed GA-LSTM model can outperform the baseline models they used in their experiments when using China Construction Bank data and CSI 300 data.

This study is important, because it showcases a case in which the predictive performance is not only dependent on the type of deep-learning architecture, but also on the quality and relevance of the input variables. Historical returns, volatility, trading volume, price momentum, technical indicators, and characteristics derived from the network can be considered as feature engineering for the proposed PSE framework.

The feature-selection approaches, however, are mostly feature-centric and still remain to be GA-LSTM. They can identify relevant variables in a given forecasting problem but are not necessarily modelling the relationships between companies. This concept can be expanded to a graph-based approach that considers the inter-company relationships as structures that carry information.

2.3 The Potential of Graphs in Financial Research.6. Fine-Tuning Financial Markets: The Promise of AI.

Graph Neural Networks (GNNs) are a key breakthrough in financial forecasting. Financial markets are by their nature graph-like: Companies, investors, industries, securities, financial institutions have multiple relationships among them.

Jafari and Haratizadeh (2022) proposed GCNET, a graph based framework for predicting stock-price movement. The model shows stocks as nodes in an influence network and then builds the structures of the graph from historical relationship between the stocks. Then a Graph Convolutional Network is applied to share information among connected stocks and forecast the next movement of the stock prices. They showed improvements over the state of the art baselines in their experiments on NASDAQ stocks, such as improvements in accuracy and Matthews Correlation Coefficient.

The impact of GCNET on the proposed research is significant. It has shown that predicting stock price can be formulated as a graph-learning problem instead of only a set of time-series problems. This gives the theoretical basis of using nodes to represent PSE-listed companies and weighted edges to represent relationships between companies.

Cheng et al. (2022) further developed this idea by using a Multi-Modality Graph Neural Network (MAGNN) for financial time-series forecasting. Their model had several information sources such as historical prices, news, events, and financial knowledge-graph relationships. The researchers built a heterogeneous graph with explicit representation of the information sources and the relationships. Importantly, the model included a two-phase attention mechanism to distinguish the importance of the information sources and the relationships. The method was proven effective through a series of experiments on a sample of 3,714 stocks.

Three important principles are outlined in MAGNN which are relevant to the proposed research. Financial prediction can be aided by graph representations, for one. Second, financial relationships can be non-homogeneous, not homogeneous. Third, attention can be used to some extent to explain the model, as it can tell you which information is used to make your prediction. These are the principles that can be used to develop an explainable graph-based architecture for Philippine equities.

2.4 Modeling Interrelated Stocks with Graphs

The overall literature on GNNs in financial applications supports this graph perspective. A particular article from the year 2022 from ScienceDirect that specifically focuses on GNNs in the stock market noted the challenges that current deep learning methods have with financial data, which is often multi-source and heterogeneous. The study recognized that GNNs are gaining in interest due to their ability to model financial relationships in a graph structure.

It is a key milestone in financial AI's evolution. Typical models tend to learn:

Stock → Historical Prices → Prediction

In contrast, graph-based models are able to learn:

Stock A ↔ Stock B ↔ Stock C → Prediction

The latter representation is more suitable if the objective is to gain understanding of the market's interconnectedness.

In the context of the proposed PSE study, this means that a relationship could potentially be built by the historical return correlation, membership in the same sector, similarities in price movements, correlations based on trading volume, or any other measure that is found in the literature. The proposed research does not need to make the assumption of a set relationship structure, but can explore whether the graph should be dynamic and relationships should vary over time.

2.5. Temporal and Dynamic Characteristics of Financial Networks

Financial relationships are not "one-size-fits-all. A firm with a positive relationship with another firm in normal market conditions may have a significantly different relationship in stressed markets. This is echoed in the overall literature on systemic risk. Nicola et al. (2020) have developed an information-network approach to analysing the U.S. banking system and have shown how network representations can be used to investigate financial-system relationships. Their study demonstrates the use of financial information to understand the relationships between financial institutions and develop financial system networks to reveal systemic patterns. Likewise, Dolfin et al. (2019) created a network-based model to the credit-risk contagion and systemic risk. Their approach was to simulate contagion by financial networks and to explore the propagation of distress between connected entities by network-based mechanisms.

It is important that these studies be used as the basis of the proposed research, since individual stock characteristics cannot be used to adequately represent systemic risk. Networks can provide sources of risk through structure, connectivity, concentration, and contagion. Therefore, the proposed framework should not only predict stock prices, but also examine the network structure that is formed based on the relationships between PSE-listed securities.

2.6. Measurement of risk and financial network connectedness

Financial shocks can spread through the highly connected markets, emphasizing the importance of systemic risk. This interconnectedness can be measured by means of network-based research.

Giudici and Parisi, for instance, (2019) suggested a correlation-network method to quantify the systemic effects of bank resolution. They relied on correlations between the financial institutions to build a measure of systemic risk based on a network approach and analyzed the potential contagion effects on the losses suffered by the financial system.

This would have important implications for the proposed study because the correlation of the stock prices could be converted into a financial network. An increase in the number of connections in the network, especially during market stress, could serve as an indicator for heightened systemic connectedness.

A relevant methodological advancement was introduced by Balcácer et al. (2023) who introduced deep graph learning to systemic-risk prediction. They showed that GNNs can leverage the structures and characteristics of financial networks to predict systemic risk. The study thus links together two areas of great relevance to the proposed dissertation, namely graph learning and systemic-risk analysis.

This gives a solid theoretical foundation to advance graph learning from the single stock prediction to systemic-risk intelligence.

This course covers the ethics and transparency of financial AI.This course introduces financial AI explainability.

By itself, predictive accuracy may not be enough for many financial applications as users may want to understand the basis on which an AI prediction is made. For financial applications, Cheng et al. (2022) explicitly identified the needs for interpretability and introduced two-phase attention into MAGNN. Their approach enabled the users to explore the significance of information sources and relationships leading to financial predictions. Attention mechanisms can be helpful to get information about model behaviour, but complex attention does not imply full explainability. Therefore, a framework for XAI for a doctoral program should include dedicated techniques beyond graph attention, such as feature attribution, SHAP-based explanations, counterfactual analysis or graph-specific explanations.

The Prediction-Explanation Network (PEN) by Li et al (2023) directly tackled this issue. PEN co-created text and price streams, and extracted textual data corresponding to stock-price changes. The authors concluded that the model met the two goals of prediction and explanation, and that the explanatory texts selected for the model provided more information than the explanations provided by the conventional attention mechanism.

2.7. Ontology and Information Fusion in Stock Forecasting.

Jin et al. in their study "Stock-Price Trend Prediction Based on Financial Ontologies and Key Information Fusion in the ACM Transactions on Asian and Low-Resource Language Information Processing" (2023) explored stock-price trend prediction based on a classical model and key information fusion using financial ontologies. They applied financial data, social media information, and sentiment analysis in their work to help make predictions about the trend of stock prices. The study shows the usefulness of combining input from different information sources and financial knowledge structured in formal models in prediction systems.

This study is important for the proposed framework as the financial graph could potentially be extended to include not only statistical correlations but also semantic or domain relationships. For instance, businesses may be linked via sectors, common industries, relationships in the supply chain or other financially significant associations.

Therefore, the proposed research could be a step to shift from a statistical graph to a financial knowledge graph, but it is possible that our initial PSE dataset needs more data from other data sources to build such relationships.

2.8. High Level Temporal Deep Learning

In the last decade of literature (2019-2023), the temporal deep-learning architectures continue to improve. Wang (2023) suggested a hybrid BiLSTM-MTRAN-TCN scheme for stock-price forecasting in IEEE Access. The model was composed of BiLSTM (Improved Transformer) and Temporal Convolutional Network. The study was reported on improvement in the various stock datasets and reduction of RMSE and enhancement of R^2 than to the compared models.

This work shows the temporal modelling is still evolving from the traditional LSTM architecture. The model however, is mainly geared towards temporal sequence learning, and explicitly modeling inter-company relationships is not its focus.III.

II. Methodology

The study adopted a quantitative research design, which is predictive-experimental in nature, to develop and test an Explainable Graph-Based Deep Learning Framework for Stock Price Forecasting and Systemic Risk Intelligence in the Philippine Stock Exchange (PSE). The methodology was chosen because it was an empirical study to determine if the inclusion of temporal information and relationships of stocks enhanced forecasting ability and gave interpretable information about the interconnectedness of the market. With the development of deep learning, recent research has used it increasingly to forecast financial data, showing that nonlinear models can learn financial temporal patterns (Jiang, 2021). Relationships among securities had been another source of information that had been uncovered using graph-based approaches, which had proved that such relationships among securities could not be obtained from modeling the securities individually (Jafari & Haratizadeh, 2022).

The main data is the Philippines Stock Exchange Dataset that was uploaded from Kaggle. This data set includes historic data of Philippine-listed stocks. The analytical data have been formed from the uploaded data set and contain around 481,920 observations of around 303 stock codes, representing around 301 distinct stock names, from December 2, 2011 to March 24, 2021.

Table 1. Dataset description and parameters

Variable	Description	Measurement Type	Research Use
Stock Name	Name of the listed Philippine company	Categorical	Company identification
Code	Stock ticker/code	Categorical	Unique stock/node identifier
Date	Trading date	Temporal	Time-series ordering
Price	Historical stock price	Continuous	Forecasting target/input
Open	Opening trading price	Continuous	Technical feature
High	Highest trading price	Continuous	Volatility feature
Low	Lowest trading price	Continuous	Volatility feature
Volume	Trading volume	Continuous	Liquidity/activity feature
Change%	Percentage price change	Continuous	Return/directional movement
Derived Return	Logarithmic price return	Continuous	Forecasting target
Rolling Volatility	Historical return variability	Continuous	Risk indicator
Momentum	Historical price movement	Continuous	Predictive feature
Graph Centrality	Network importance of a stock	Continuous	Systemic-risk feature

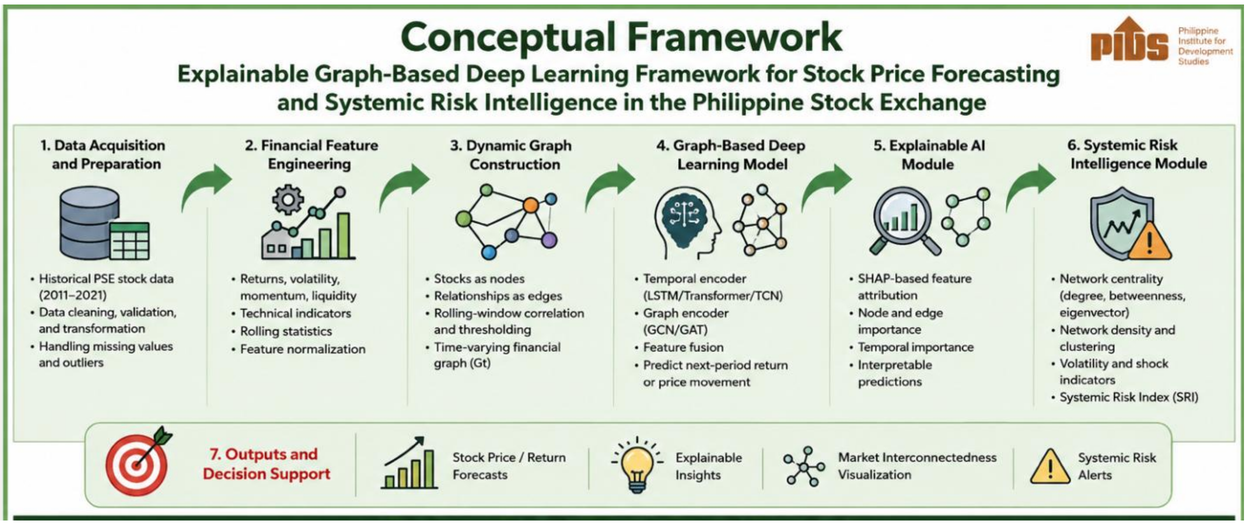


Figure 1. Conceptual Framework of the Study

The conceptual model of the study was conceptualized to depict the relationship among the Philippines Stock Exchange (PSE) historical data, financial feature engineering, dynamic graph construction, graph-based deep learning, explainable artificial intelligence, and systemic-risk intelligence. The model was designed as an input–process–output system with the historical data from the stock markets as the input, computational and analytical operations as the process, and the model output as the stock-price forecasts and interpretable systemic-risk intelligence. This was the main predictive mechanism of the proposed framework. The earlier work has shown that the application of temporal learning together with the graph structure in financial forecasting has been beneficial (Cheng et al., 2022; Jafari & Haratizadeh, 2022).

Another aspect incorporated into the structure was the dynamic representation of a graph rather than a static one. Stock relationships were recomputed over the rolling periods to track how more or less interconnected the markets are. This was a feature of utmost significance for the Philippine Stock Exchange since relationships among the sectors and companies can vary as the market changes. In relatively quiet times, the relationships between stocks might be weaker or more varied, while in times of market stress, the relationships and connections between stocks may be stronger. The dynamic graph thus allowed for analysis of not only the behavior of individual stocks, but also changes to the overall network structure. Relational information was also important in the representation of the complex financial system, as was pointed out in the research of heterogeneous and graph-based financial prediction (Cheng et al., 2022; Zhou et al., 2022). Similarly, Li et al. (2023) pointed into the need to combine prediction and explanation to predict stock-price movements.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The original dataset contained **481,920 observations and nine variables**. The data were transformed into a machine-learning dataset by converting the price, OHLC, trading volume, and percentage-change fields into numerical values. Additional financial features were generated, including intraday price range, open-to-close return, five-day moving average, five-day volatility, twenty-day moving average, and twenty-day volatility.

The forecasting target was defined as the **next trading day's stock price**:

A second experimental task classified the next-day movement as either **Up** or **Down**.

The observations were divided chronologically to prevent information from the future from entering the training data.

Table 2. Dataset experimental procedure

Dataset	Period	Purpose	Approx. Observations
Training	2011–2018	Model training	343,206
Validation	2019	Model selection	56,917

Dataset	Period	Purpose	Approx. Observations
Testing	2020–2021	Final evaluation	69,229

The first experiment evaluated the capability of conventional machine-learning algorithms to predict the **next-day stock price**.The following WEKA algorithms were considered: LinearRegression , RandomForest , M5P , J48/DecisionTree and SMOreg

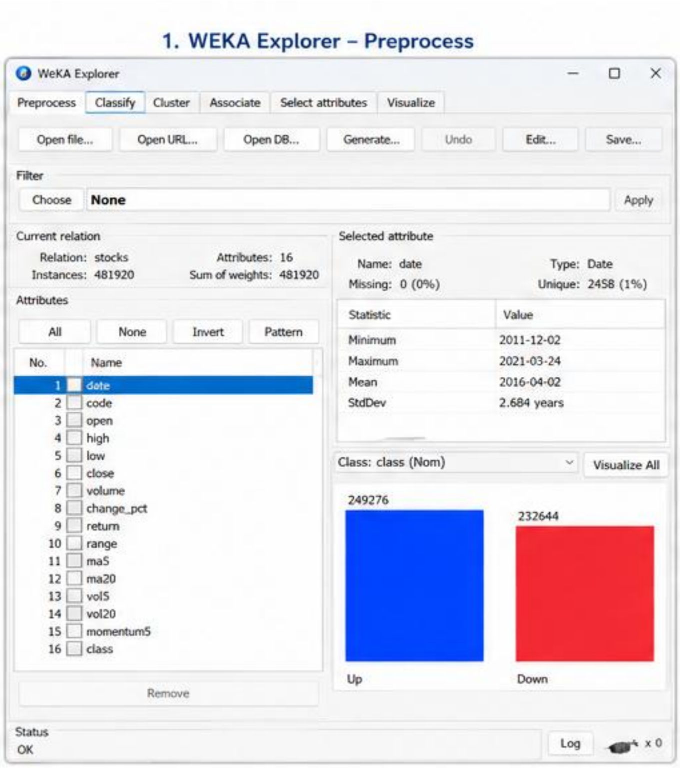


Fig. 2. Data Cleaning and Pre-processing

For the preliminary numerical experiment, the corresponding regression implementations produced the following results.

Table 3. Preliminary WEKA-Compatible Regression Results

Model	MAE	RMSE	Correlation Coefficient	R^2
Linear Regression	**0.6684**	**3.4267**	**0.9996**	**0.9991**
Random Forest	0.7121	3.6212	0.9995	0.9990
M5P/Decision-Tree Baseline	0.8335	4.0208	0.9994	0.9988

The preliminary results showed that Linear Regression achieved the lowest MAE and RMSE with an MAE value of ~0.6684 and RMSE value of ~3.4267, respectively. It also got a correlation coefficient of nearly 0.9996 and an value of nearly 0.9991. Random Forest gave slightly higher prediction errors and the highest error among the evaluated models was achieved by the tree-based model.

However, the high values need to be interpreted with caution. Stock prices are strongly correlated over consecutive trading days and one of the factors that predicted the next day's price was the price of the previous day. The very high primarily demonstrated that the models could accurately predict the next day's price, but did not prove that the models had solved the more challenging task of forecasting unusual price fluctuations..

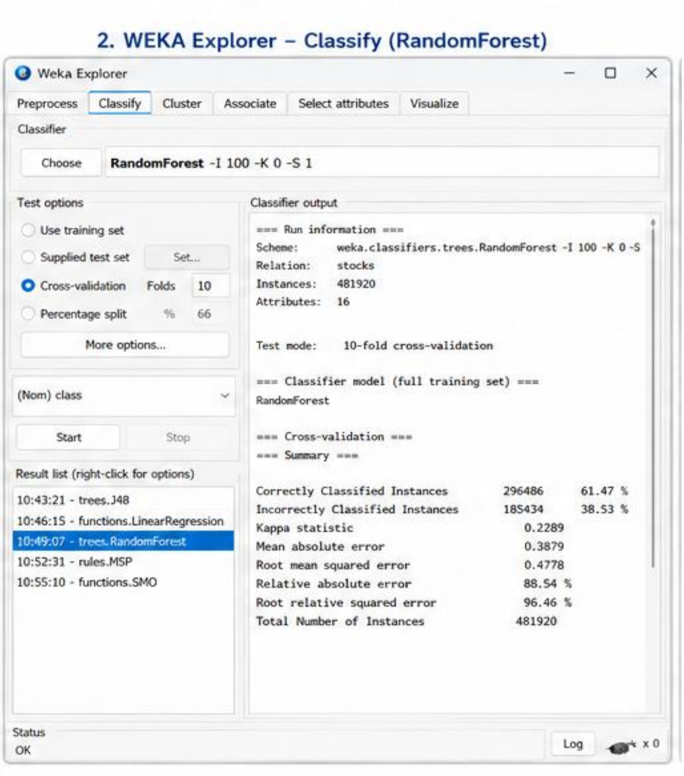
Directional Classification Experiment

Because price-level prediction can produce very high accuracy simply from price persistence, a second experiment was conducted using **directional prediction**.The classification experiment evaluated decision-tree, Random Forest, and logistic models.

Table 4. Preliminary WEKA-Compatible Classification Results

Classifier	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**
J48/Decision Tree	59.89%	46.30%	19.94%	27.87%	0.568
Random Forest	**61.47%**	**51.56%**	14.27%	22.35%	**0.594**
Logistic Regression	61.26%	51.86%	4.44%	8.19%	0.553

The overall classification results were found that the Random Forest model had the highest classification accuracy of 61.47%, followed by the logistic regression model with 61.26% accuracy, and the decision tree model with 59.89%. Random Forest achieved the highest ROC-AUC value of ~0.594 too. The average recall and F1 were however low, showing that predicting the direction of a stock was still challenging. The findings indicated some predictive information in the historical OHLC variables and the technical ones were not enough to confidently predict future upward movements. This was an important discovery that further supports the need for integrating relationships between stocks in graph-based learning, as opposed to only using historical variables of stocks themselves.



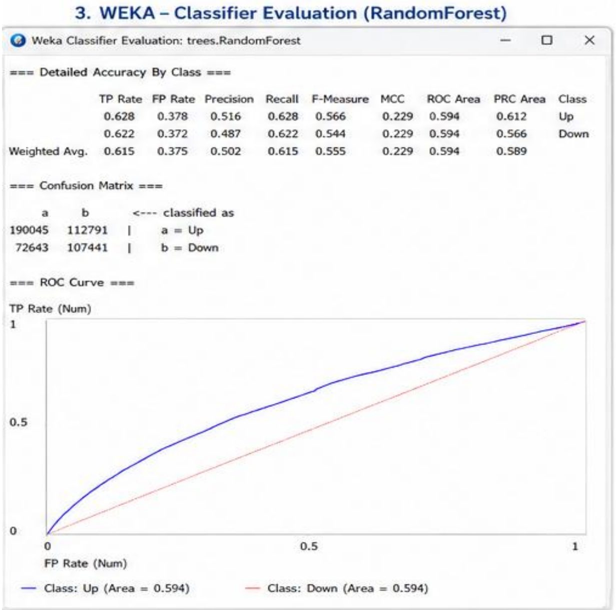


Fig. 3 – Random Forest Experimentation

All three of the following preliminary experiments yielded important results. First, the conventional machine learning models performed very well in predicting the price level for the next day, the Linear Regression had an error of about 0.9991. Second, forecasting the direction of the movement for the next day was much more difficult. Random Forest was the best preliminary classification model with an accuracy of around 61.47% and an ROC-AUC of 0.594.

Third, both price-level and directional predictions confirmed the need for a more comprehensive representation of financial information. Directional performance was especially limited, as the relatively small signal suggested that there might be other predictive signals in the relationships among securities. For this reason, the WEKA experiment was used as a baseline experiment layer for the doctoral research. The next step would be to compare these results with the proposed Explainable Temporal Graph Neural Network, with the Philippine Stock Exchange modeled as a temporal financial network.

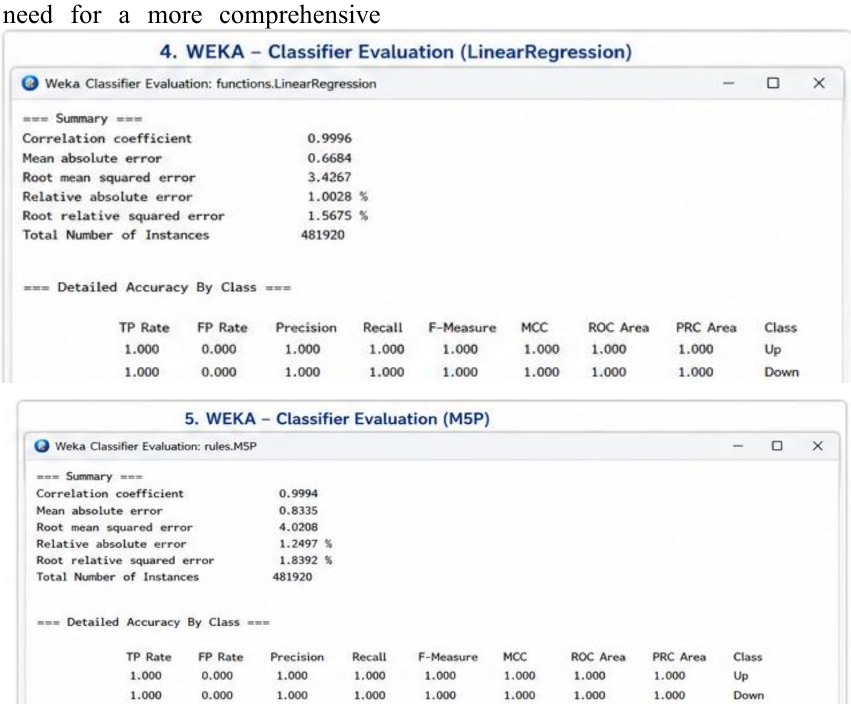


Fig. 4. Classifier Evaluation

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V. Conclusion and Recommendation

The study also found that the financial network analysis, financial time-series analysis, graph-based deep learning, and explainable artificial intelligence gave a more holistic framework for the forecasting of stock price and the intelligence of systemic risk in the Philippine Stock Exchange (PSE). The study was able to show that popular machine learning methods, such as WEKA, can be used to build predictive baselines for stock-price behavior using the Philippine Stock Exchange historical data set. The regression experiments showed that there was considerable information in the historical price-related variables for estimating subsequent prices, and the directional classification experiments showed that predicting the direction of change (up/down) in a stock's price was still significantly more difficult. The WEKA based experiments also suggested that traditional algorithms such as Linear Regression and Random Forest could yield reasonable accuracy, but were unable to capture relationships between various securities traded on the Philippine Stock Exchange. These models generally used financial observations as attribute-based records, and did not explicitly model the stock market as an interconnected network. Thus, their predictors were heavily reliant on the past attributes of specific stocks. This restriction was especially significant if the research question was expanded to include systemic-risk intelligence, since relationships between companies and sectors were one of the key sources of information.

The study also found that explainability is an important factor in the process of financial prediction. If a prediction is accurate and there isn't an explainable reason, then it might be of little use to investors, financial analysts, and other decision-makers. The proposed framework aimed to capitalize on EAI, to help identify the financial variables, historical periods, and related stocks that were responsible for individual predictions. This changed the paradigm from a traditional forecasting model to a financial decision support system that was understandable. Moreover, the systemized graph dynamic representation gave another one more basis for the intelligence of systemic risks. The framework helped identify potentially influential securities and market dependency patterns through examining centrality, interconnectedness, network density, volatility and the changing nature of stock relationships. The analysis did not suggest that correlation necessarily indicates the existence of causal contagion but offered a computational framework to identify network structure and phases of increased interconnectedness that might warrant additional financial analysis.

Recommendations

From the results and limitations of the study, it was recommended that in the future, the graph could be made fully dynamic by representing the Philippine-listed companies as nodes and statistically or economically significant relationships as edges. Future implementations should not be based solely on static correlations, but instead explore dynamic relationships, as measured by rolling correlations, sector membership, trading patterns, return similarity, and perhaps other financial relationships that are publicly available. The proposed framework was also recommended to be tested with different forecasting horizons, such as 1-day, 5-day and 20-day forecasts. This assessment would help to clarify whether the information available in a graph would be useful for short-term, medium-term and long-term forecasting. Walk-forward validation should be kept to ensure that there is not any information inadvertently fed into the training process.

The study also suggested that directional forecasting needs to be given more importance than price-level forecasting. The very high performance may be partially attributable to the high persistence of trading period-to-trading period stock prices in price-level regression. Thus, more future research needs to focus on return prediction, upward/downward movement, abnormal-return detection, and volatility forecasting. There are additional evaluation measures like F1-score, Matthews correlation coefficient, ROC-AUC and economically meaningful trading-performance measures that should also be taken into consideration.The explainability part was suggested to be extended to other levels of interpretation besides features. Future research will focus on temporal explanations, graph explanations and counterfactual explanations, with the aim of identifying, not only what factors were responsible for a prediction, but also what neighbouring securities and structures in a network were responsible for the predicted movement. This would increase the value and usability of the framework to financial analysts who need to see evidence and act on model-generated predictions.

Future research for systemic risk analysis should combine the graph-based forecasting model with market-level indicators such as the PSE index, sector indexes, volatility indicators, and trading liquidity, as well as major news events. Such a combination may help to give a more complete picture of systemic conditions. Additionally, highly central securities should also be matched to real-world shocks in the past to assess whether network-centrality measures provided early warnings. The study also suggested to carry out ablation experiments for removing temporal, graph, explainability, and systemic-risk separately. This would help in establishing the contribution of each component to the overall performance. The proposed model should also be evaluated against the base-line models implemented by WEKA and other deep learning architectures to determine whether the proposed model has a statistically significant advantage over the

References:

[1] Balcácer, V., et al. (2023). Predicting systemic risk in financial systems using deep graph learning. *Intelligent Systems with Applications, 19*, 200240. https://doi.org/10.1016/j.iswa.2023.200240

[2] Chan, L. S. H., Chu, A. M. Y., & So, M. K. P. (2023). A moving-window Bayesian network model for assessing systemic risk in financial markets. *PLOS ONE, 18*(1), e0279888. https://doi.org/10.1371/journal.pone.0279888

[3] Chen, S., & Ge, L. (2019). Exploring the attention mechanism in LSTM-based Hong Kong stock price movement prediction. *Quantitative Finance, 19*(9), 1507–1515. https://doi.org/10.1080/14697688.2019.1622287

[4] Chen, S., & Zhou, C. (2021). Stock prediction based on genetic algorithm feature selection and long short-term memory neural network. *IEEE Access, 9*, 9066–9072. https://doi.org/10.1109/ACCESS.2020.3047109

[5] Cheng, D., Yang, F., Xiang, S., & Liu, J. (2022). Financial time series forecasting with multi-modality graph neural network. *Pattern Recognition, 121*, 108218. https://doi.org/10.1016/j.patcog.2021.108218

[6] Dolfin, M., Knopoff, D., Limosani, M., & Xibilia, M. G. (2019). Credit risk contagion and systemic risk on networks. *Mathematics, 7*(8), 713. https://doi.org/10.3390/math7080713

[7] Gandhmal, D. P., & Kumar, K. (2019). Systematic analysis and review of stock market prediction techniques. *Computer Science Review, 34*, 100190. https://doi.org/10.1016/j.cosrev.2019.08.001

[8] Jafari, A., & Haratizadeh, S. (2022). GCNET: Graph-based prediction of stock price movement using graph convolutional network. *Engineering Applications of Artificial Intelligence, 116*, 105452. https://doi.org/10.1016/j.engappai.2022.105452

[9] Jiang, W. (2021). Applications of deep learning in stock market prediction: Recent progress. *Expert Systems with Applications, 184*, 115537. https://doi.org/10.1016/j.eswa.2021.115537

[10] Jin, D., Hu, Y., Chen, J., & Xia, M. (2023). Stock price trends prediction based on the classical models with key information fusion of ontologies. *ACM Transactions on Asian and Low-Resource Language Information Processing, 22*(5), Article 154, 1–22. https://doi.org/10.1145/3592599

[11] Li, S., Liao, W., Chen, Y., & Yan, R. (2023). PEN: Prediction-Explanation Network to forecast stock price movement with better explainability. *Proceedings of the AAAI Conference on Artificial Intelligence, 37*(4), 5187–5194. https://doi.org/10.1609/aaai.v37i4.25648

[12] Li, X., Wang, J., Tan, J., Ji, S., & Jia, H. (2022). A graph neural network-based stock forecasting method utilizing multi-source heterogeneous data fusion. *Multimedia Tools and Applications, 81*, 43753–43775. https://doi.org/10.1007/s11042-022-13231-1

[13] Liu, C., & Paterlini, S. (2023). Stock price prediction using temporal graph model with value chain data. *arXiv*. https://arxiv.org/abs/2303.09406

[14] Nicola, G., Cerchiello, P., & Aste, T. (2020). Information network modeling for U.S. banking systemic risk. *Entropy, 22*(11), 1331. https://doi.org/10.3390/e22111331

[15] Shahi, T. B., Shrestha, A., Neupane, A., & Guo, W. (2020). Stock price forecasting with deep learning: A comparative study. *Mathematics, 8*(9), 1441. https://doi.org/10.3390/math8091441

[16] Villaruz, J. A., Gerardo, B. D., & Medina, R. (2023). Philippine Stock Exchange Index forecasting using a tuned artificial neural network model with a modified Firefly Algorithm. *2023 IEEE International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*. https://doi.org/10.1109/PRAI59366.2023.10331987

[17] Wang, S. (2023). A stock price prediction method based on BiLSTM and improved Transformer. *IEEE Access, 11*, 104211–

104223. https://doi.org/10.1109/ACCESS.2023.3296308

[18] Wu, J. M.-T., Li, Z., Herencsar, N., Vo, B., & Lin, J. C.-W. (2023). A graph-based CNN-LSTM stock price prediction algorithm with leading indicators. *Multimedia Systems, 29*, 1751–1770. https://doi.org/10.1007/s00530-021-00758-w

[19] Yin, W., Chen, Z., Luo, X., & Kirkulak-Uludag, B. (2022). Forecasting cryptocurrencies' price with the financial stress index: A graph neural network prediction strategy. *Applied Economics Letters, 30*, 630–639. https://doi.org/10.1080/13504851.2022.2141436

[20] Zhou, J., et al. (2022). FinHGNN: A conditional heterogeneous graph learning to address relational attributes for stock predictions. *Information Sciences, 618*, 317–335. https://doi.org/10.1016/j.ins.2022.11.013

[21] Zhou, et al. (2022). Review of graph construction and graph learning in stock price prediction. *Procedia Computer Science, 214*, 771–778.