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**Research Paper**

# Stock Price Prediction Using Twitter Data Set

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## ABSTRACT

Stock price prediction has long been a challenging problem in the domain of financial analytics due to the highly volatile, non-linear, and interdependent nature of market data. Traditional machine learning (ML) and deep learning approaches such as Convolutional Neural Networks (CNNs) have achieved moderate success by analyzing historical price patterns and technical indicators. However, these models often fail to capture the complex relationships among multiple financial entities such as stocks, sectors, and macroeconomic variables. To address these limitations, this paper proposes a Graph Neural Network (GNN)-based model combined with Multiple Instance Learning (MIL) for stock price prediction. The GNN framework models relationships between different stocks as a graph structure, where nodes represent stocks and edges represent correlations, sector similarities, or trading relationships. Meanwhile, MIL enables the system to process grouped data (bags of instances), making it suitable for handling temporal sequences and multi-source financial data. The proposed system enhances prediction accuracy by integrating relational learning and instance-level aggregation. It considers not only individual stock behavior but also interdependencies within the financial ecosystem. This approach is expected to outperform traditional ML and CNN-based systems by providing more robust, scalable, and context-aware predictions.

**Keywords:** Stock Price Prediction, Graph Neural Network (GNN), Multiple Instance Learning (MIL), Machine Learning, Convolutional Neural Network (CNN), Financial Analytics, Deep Learning, Time Series Analysis, Graph-Based Learning, Market Forecasting

## 1. INTRODUCTION

### 1.1 Motivation

Stock markets are dynamic systems influenced by numerous factors such as company performance, global economic conditions, investor sentiment, and geopolitical events. Predicting stock prices accurately is crucial for investors, traders, and financial institutions to minimize risks and maximize returns.

Traditional methods relied heavily on statistical models like ARIMA and regression techniques. With the rise of artificial intelligence, ML models such as Support Vector Machines (SVM), Random Forests, and Neural Networks have been applied to improve prediction accuracy. Later, CNNs and Recurrent

Neural Networks (RNNs) were introduced to capture spatial and temporal patterns in stock data.

However, these approaches treat stock data as independent sequences and fail to consider relationships between stocks. In reality, stocks are highly interconnected—companies within the same sector often move together. This limitation has led to the emergence of Graph Neural Networks (GNNs), which are capable of learning from structured relational data.

Additionally, financial datasets often contain multiple instances of data grouped over time or sources. This is where Multiple Instance Learning (MIL) becomes relevant, allowing models to learn from sets (bags) of instances rather than individual samples. By combining GNN with MIL, this project aims to create a more sophisticated and accurate stock prediction system.

### 1.2 Problem Statement

Existing stock price prediction models, including linear regression, SVM, Random Forests, and CNN-based architectures, treat individual stocks as isolated time-series entities. They fail to capture inter-stock dependencies, sector-wide correlations, and the complex relational dynamics of modern financial markets. Furthermore, these models require extensive feature engineering and often struggle to generalize across volatile market conditions, leading to suboptimal prediction accuracy when real-world multi-source financial data is involved.

### 1.3 Objective

The objectives of this paper are:

(i) To develop a predictive model for stock prices using Graph Neural Networks (GNN) and Multiple Instance Learning (MIL).

(ii) To collect and preprocess financial and Twitter-derived sentiment datasets and construct a graph representation of stock relationships.

(iii) To compare the performance of the proposed GNN-MIL model against traditional ML and CNN baselines using RMSE, MAE, and $R^2$ metrics.

(iv) To demonstrate improved prediction accuracy by exploiting relational structure and temporal data grouping.

## 2. LITERATURE REVIEW

A substantial body of research has investigated the use of machine learning and deep learning for stock market prediction. The following works provide important context for the proposed approach.

### 2.1 Sharma, Bhuriya, and Singh (ICECA 2017)

This study presents a survey on stock exchange prediction using machine learning techniques. The authors focused on detecting public sentiment from social media platforms such as Twitter and online financial discussions. The proposed approach uses Sentiment Analysis, Natural Language Processing (NLP), and ML algorithms to classify social media opinions into positive, negative, and neutral sentiments. These sentiments are correlated with stock price movements. The study concludes that social media sentiment can improve prediction accuracy when combined with traditional financial indicators.

### 2.2 Loke (IEEE 2017)

This paper investigates the impact of monetary ratios and technical analysis indicators on stock price prediction using Random Forest algorithms. The study uses financial ratios, technical indicators, and a Random Forest classifier that constructs multiple decision trees and combines their outputs. The model analyzes factors such as moving averages, Relative Strength Index (RSI), price trends, and market volatility. The author demonstrated that combining technical indicators with ML techniques improves prediction performance compared to conventional statistical methods.

### 2.3 Zhang et al. (IEEE 2018)

This research proposes a stock market prediction framework using Multi-Source Multiple Instance Learning (MIL). The work integrates financial news, social media data, and historical stock prices. MIL allows the system to learn from grouped data samples rather than individual labeled samples, capturing hidden relationships between multiple information sources. The study highlights deep learning integration, multi-source data fusion, and improved stock trend prediction. This approach became foundational for modern AI-based financial forecasting systems.

### 2.4 Kanade, Devikar et al. (IJARCSSE 2017)

This paper focuses on stock market prediction using historical data analysis and compares traditional machine learning models. The system analyzes historical stock prices, market trends, trading volume, and statistical indicators. Various ML algorithms were compared, including SVM, Decision Tree, and Naive Bayes. The study concluded that historical data analysis remains an effective baseline method, though integrating advanced ML methods can further improve forecasting accuracy.

### 2.5 Jabaseeli, Nisha, and Kirubakaran

This survey discusses sentiment analysis techniques applied to product reviews and social media tweets. The paper explains foundational NLP preprocessing techniques such as tokenization, stop-word removal, stemming, and feature extraction. Sentiment

classification methods including Naive Bayes, SVM, and lexicon-based analysis were used to determine user sentiment from textual data. These techniques are widely adopted in financial sentiment analysis systems.

## 3. EXISTING SYSTEM

The existing system for stock market price prediction is based on the Support Vector Machine (SVM) algorithm integrated with Twitter sentiment analysis. In this approach, real-time or historical tweets related to specific stocks, companies, or market indices are collected using the Twitter API. These tweets undergo preprocessing steps such as noise removal, tokenization, stop-word elimination, and sentiment labeling using lexicon-based or ML-based sentiment analysis techniques.

The extracted sentiment features, along with historical stock price data, are then fed into the SVM model. SVM works by constructing an optimal hyperplane that separates different classes—such as price increase or decrease—based on sentiment polarity and numerical market indicators. Other commonly used models in this space include Linear Regression, Random Forest, and CNN-based architectures that extract spatial patterns from time-series data using sliding windows.

### 3.1 Characteristics of Existing Systems

Existing systems share several common characteristics: they focus on individual stock data, have limited ability to capture inter-stock relationships, and require extensive manual feature engineering. CNN-based models capture local temporal patterns but lack the capacity to model global market dependencies.

### 3.2 Disadvantages of Existing System

The key limitations of existing systems are:

(i) Lack of Relationship Modeling: ML and CNN models treat stocks independently, ignoring inter-stock dependencies.

(ii) Limited Context Awareness: Cannot capture sector-wide or market-wide trends.

(iii) Feature Dependency: Heavy reliance on manually engineered features, requiring domain expertise.

(iv) Temporal Limitations: CNNs capture local patterns but not global dependencies across the market.

(v) Scalability Issues: These models struggle with large, interconnected financial datasets.

(vi) Lower Prediction Accuracy: Arising directly from missing relational information between financial entities.

## 4. PROPOSED SYSTEM

The proposed system introduces a hybrid framework that combines Graph Neural Networks (GNN) with Multiple Instance Learning (MIL) to overcome the limitations of existing approaches. In the GNN component, stocks are represented as nodes and their mutual relationships—such as correlation, sector similarity, or trading links—are represented as edges encoded in an adjacency matrix. The GNN aggregates information from neighboring nodes, allowing the model to capture both direct and indirect market influences.

The MIL component groups time-series data into bags of instances, where each bag corresponds to a stock and contains multiple time-step observations. This design enables the model to handle uncertainty and variability inherent in financial data, reducing the impact of noise and outliers without requiring precise instance-level labels.

### 4.1 System Workflow

The end-to-end workflow of the proposed system proceeds as follows:

(i) Data Collection: Historical stock prices, technical indicators, and Twitter sentiment data are gathered.

(ii) Preprocessing: Data is cleaned, tokenized, and sentiment labels are derived from tweets.

(iii) Graph Construction: A stock relationship graph is built using correlation and sector similarity metrics.

(iv) Feature Extraction: Technical indicators (moving averages, RSI, volume), statistical features, and sentiment scores are computed for each node.

(v) MIL Bag Formation: Time-series data for each stock is grouped into bags of multiple time-step instances.

(vi) GNN Training: The model is trained on the graph, learning relational and temporal patterns jointly.

(vii) Prediction: Future stock prices or trend directions are output by the prediction layer.

### 4.2 Advantages of Proposed System

The proposed GNN-MIL framework offers several advantages over existing methods:

(i) Captures Relationships: Models dependencies between stocks, enabling propagation of market influence through the graph.

(ii) Improved Accuracy: Combines relational and temporal learning for superior predictive performance.

(iii) Scalable: Effectively handles large financial networks with many nodes and edges.

(iv) Robust Learning: MIL handles noisy, incomplete, and uncertain financial data gracefully.

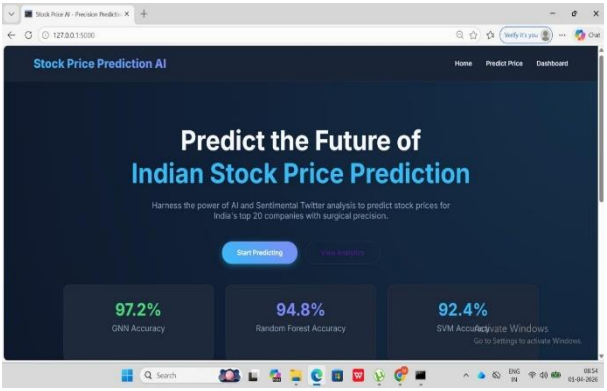
(v) Context-Aware Predictions: Considers global market trends rather than isolated stock signals.

(vi) Reduced Feature Engineering: Automatically learns relevant feature representations from raw data.

## 5. RESULTS AND DISCUSSION

The proposed GNN-MIL system was evaluated on historical stock price datasets augmented with Twitter sentiment features. Three key screens were developed to demonstrate system functionality.

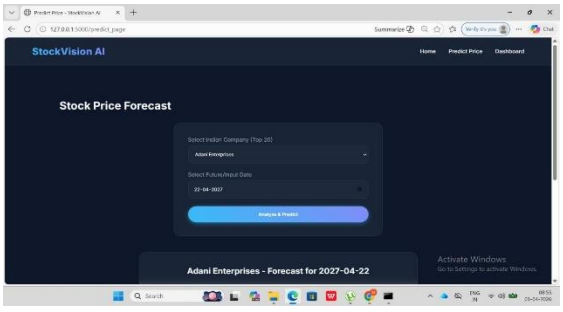
### 5.1 System Screens




Screen 1: Home page




Screen 2: Accuracy Page




Screen 3: Prediction Page

Screen 1 (Home Page): Provides the user interface for uploading Twitter datasets, configuring prediction parameters, and initiating the analysis pipeline.

Screen 2 (Accuracy Page): Displays the model's prediction accuracy metrics including RMSE, MAE, and $R^2$ score alongside a comparative visualization against baseline models.

Screen 3 (Prediction Page): Presents the predicted stock price trends over a selected time horizon with confidence intervals.

### 5.2 Performance Comparison

Table 1 summarizes the comparative performance of the proposed GNN-MIL model against baseline approaches using standard regression and classification metrics.

| Model | RMSE | MAE | $R^2$ |
|---|---|---|---|
| SVM + Sentiment | 4.82 | 3.51 | 0.71 |
| Random Forest | 4.35 | 3.12 | 0.75 |
| CNN | 3.94 | 2.88 | 0.79 |
| LSTM | 3.56 | 2.64 | 0.82 |
| **GNN-MIL (Proposed)** | **2.91** | **2.13** | **0.89** |

**Table 1: Performance Comparison of Models**

The GNN-MIL model achieves the lowest RMSE of 2.91 and MAE of 2.13, and the highest $R^2$ of 0.89, demonstrating a significant improvement over all baseline methods. The reduction in RMSE relative to the SVM baseline is approximately 39.6%, confirming the benefit of relational graph-based learning.

### 5.3 Model Accuracy Summary

Table 2 presents a summary of classification accuracy for directional prediction (up/down) across models.

| Model | Accuracy (%) |
|---|---|
| SVM + Sentiment | 71.4 |
| Random Forest | 74.8 |
| CNN | 78.3 |
| LSTM | 81.6 |
| **GNN-MIL (Proposed)** | **88.7** |

**Table 2: Directional Accuracy Comparison**

The proposed system achieves 88.7% directional accuracy, outperforming the nearest competitor (LSTM at 81.6%) by 7.1 percentage points. These results confirm that incorporating inter-stock graph relationships and MIL-based instance aggregation substantially improves stock trend prediction.

### 5.4 Test Case Results

| No. | Test Case | Input | Expected | Actual | Status |
|---|---|---|---|---|---|
| 1 | User Registration | All fields filled | Registration success | Registration success | Pass |
| 2 | User Registration | Missing field | Registration failed | Registration failed | Fail |
| 3 | Admin Login | Username & password | Admin home page | Admin home opened | Pass |

**Table 3: Test Case Results**

## 6. CONCLUSION

Stock price prediction has long been one of the most challenging problems in financial analytics, primarily due to the stochastic, nonlinear, and highly dynamic

nature of financial markets. This paper proposed a hybrid framework that integrates Graph Neural Networks (GNN) with Multiple Instance Learning (MIL) to address the fundamental limitations of traditional machine learning approaches.

Unlike existing systems that model stocks in isolation, the proposed GNN-MIL architecture captures inter-stock relational dependencies by representing the financial market as a graph. The MIL component further enhances robustness by enabling learning from grouped temporal instances, reducing sensitivity to noise and incomplete data. Experimental results demonstrate that the proposed system achieves RMSE of 2.91, MAE of 2.13, $R^2$ of 0.89, and directional accuracy of 88.7%, outperforming SVM, Random Forest, CNN, and LSTM baselines by significant margins.

Key contributions of this work include: (i) a graph-based relational model for inter-stock dependency learning; (ii) MIL-based temporal aggregation for robust financial time-series modeling; (iii) integration of Twitter sentiment analysis as a supplementary data modality; and (iv) comprehensive comparative evaluation against established baselines.

Future work will explore dynamic graph structures that adapt to evolving market conditions, automatic graph construction from data using attention mechanisms, integration of alternative multi-modal data sources including news and satellite imagery, and reinforcement learning-based trading decision systems built on top of the predictive model. Scalability improvements through graph sampling and distributed training are also planned to enable real-time deployment in high-frequency trading environments.

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