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TIME SERIES APPROACH FOR STOCK MARKET PRICE PREDICTION USING DEEP LEARNING TECHNIQUES

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***ABSTRACT*:**

Cybersecurity has become a major concern in modern digital environments due to the widespread use of internet services, cloud computing, and interconnected network devices. As cyber-attacks grow in frequency and complexity, traditional Intrusion Detection Systems that rely on fixed rules or known attack signatures struggle to identify new and evolving threats. This project focuses on developing a Time Series–based Intrusion Detection System that analyzes network traffic patterns over time to detect abnormal behavior. By studying temporal trends and deviations in network data, the proposed system improves the identification of suspicious activities without depending solely on predefined attack signatures. The proposed system combines data preprocessing, feature extraction, and time series–based analysis to distinguish between normal and malicious network activities. Standard benchmark datasets such as NSL-KDD and CIC-IDS-2017 are used for training and evaluation. Preprocessing steps including data cleaning, normalization, feature selection, and dimensionality reduction are applied to enhance detection performance and reduce computational overhead. By analyzing temporal patterns and variations in network traffic over time, the system effectively identifies anomalies while minimizing false alarms and improving overall detection accuracy.

KEYWORDS: *Stock Market Prediction, Time Series Analysis, Deep Learning, Price Forecasting, Financial Data Analysis, Neural Networks, Market Trend Analysis.*

1. INTRODUCTION

Stock market price prediction has become increasingly important with the expansion of global financial markets and the widespread use of online trading systems. Stock prices are influenced by numerous factors and exhibit complex, non-linear behavior, which makes accurate forecasting difficult when using conventional statistical approaches. This project adopts a time-series-based deep learning framework to predict stock prices by learning patterns from historical market data. By examining past price movements over time, the system aims to identify meaningful trends and enhance the reliability of future price predictions.

Traditional stock market prediction techniques primarily depend on statistical models and rule-based methods that utilize historical averages and predefined indicators. Although these methods are capable of identifying general market trends, they often perform poorly during periods of high volatility and sudden price changes. Conventional machine learning models offer partial improvement; however, their ability to adapt to rapidly changing market conditions remains limited. These shortcomings emphasize the need for advanced prediction models that can effectively capture non-linear behavior and long-term dependencies in financial time-series data.

Recent advancements in machine learning and artificial intelligence have led to the development of deep learning models specifically designed for sequential data analysis. Unlike traditional approaches, deep learning-based time series models can automatically learn complex temporal relationships directly from historical stock price data. Their ability to recognize evolving patterns and long-term trends makes them particularly suitable for forecasting stock prices in highly dynamic and uncertain financial markets.

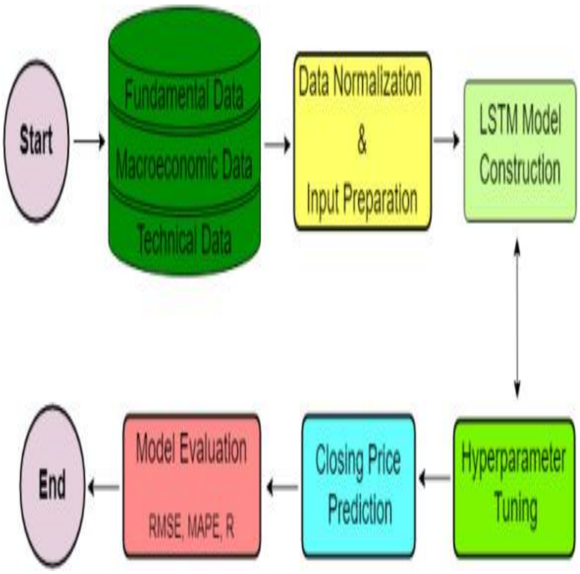

Fig.1: Conceptual Architecture of Time Series–Based Stock Market Price Prediction Using Deep Learning

1.1 OBJECTIVES

To examine the drawbacks of conventional statistical and machine learning approaches in accurately predicting stock market prices.

To analyze historical stock price data using time-series methods in order to identify underlying temporal patterns and market trends.

1.2 PROBLEM STATEMENT

Stock prices exist in a highly dynamic, non-linear, as well as unpredictable, manner, thus rendering a predictive procedure very challenging. This can be attributed to the fact that conventional statistical models, as well as machine learning models, lack adaptability, thus failing to tackle complex patterns as well as suddenstock fluctuations that tend to exist within the stock market. Thus, a model that can adapt to the stock price pattern using a time series technique based on a deep model has been a burning need for stock price predictions.

1.3 EXISTING SYSTEM

In the existing stock market prediction models, price predictions are generally done through conventional statistical analysis and basic machine learning algorithms. In these models, predictions are done through averages or pre-defined indicators, hampering adaptability to non-linear changes and unexpected variations in the stock markets. Though some basic machine learning algorithms can be upgraded and achieve greater accuracy in predictions, they are always bounded by static patterns and devoid of adaptability to stock market variations. Hence, there are limitations to the accuracy of predictions in existing models.

2. LITERATURE SURVEY

Recent advancements in financial data analysis have emphasized the importance of accurate stock market price prediction for investment decision-making and risk management. Traditional stock prediction approaches are mainly based on statistical models such as moving averages, autoregressive models, and linear regression techniques. Although these methods perform reasonably well under stable market conditions, they fail to capture non-linear price movements and sudden fluctuations in dynamic market environments [1], [2], [3]. As a result, their forecasting accuracy remains limited when applied to real-world financial data.

To overcome these limitations, machine learning techniques have been increasingly adopted for stock market prediction. Models such as Support Vector Machines (SVM), k-Nearest Neighbor (k-NN), Decision Trees, Random Forests, and Naïve Bayes classifiers have been widely used to analyze historical stock prices and technical indicators [4], [5], [6]. These methods improve prediction accuracy by learning complex patterns from data; however, they often rely on handcrafted features and static training datasets. Consequently, their performance degrades when market conditions change rapidly, leading to reduced adaptability and generalization issues [7], [8].

With the rapid growth of deep learning and time series modeling, researchers have shifted towards neural network–based approaches for stock price forecasting. Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models have shown strong capability in capturing temporal dependencies and long-term patterns in financial time series data [9], [10], [11]. These models outperform traditional techniques by learning sequential information directly from historical price data without manual feature engineering. However, challenges such as overfitting, high computational cost, and sensitivity to noisy data still affect their prediction reliability [12], [13].

Recent studies have also explored hybrid deep learning architectures that combine convolutional layers with recurrent networks to improve feature extraction and trend learning in stock market time series [14], [15]. Although these hybrid models achieve better accuracy, they require careful tuning and large volumes of high-quality data. Furthermore, real-world stock markets are influenced by multiple external factors such as economic indicators, investor sentiment, and global events, which are difficult to model effectively [16], [17]. These challenges indicate the need for robust time series–based deep learning models that can handle market volatility, reduce prediction errors, and adapt to continuously evolving financial environments [18], [19], [20].

3. PROPOSED SYSTEM

This article presents a deep learning-based approach to stock market prediction using time series analysis that provides an alternative to the traditional statistical and machine learning approaches to stock market prediction. This article proposes a new methodology that does not utilize fixed indicators or linear modeling. Instead, the proposed methodology utilizes a deep learning approach to develop Deep Neural Networks that will learn how to produce accurate predictions of future stock prices based on complex temporal dependencies between historical stock prices, [9],[11]. The proposed system has four main components: data acquisition, feature pre-processing, time series modeling and price prediction.

The first phase of the proposed system is the pre-processing of historical stock prices and financial indicator data through cleaning, normalization, feature selection and dimensionality reduction into a structure that is appropriate for input into a deep learning model [6],[12] . After the pre-processing of the data, the outputs are used as input to the time series model (LSTM or GRU Networks) to model the temporal patterns and sequential dependencies of the market data. During the training of the system to minimize the error in predicting future stock prices, weights for each of the features are updated and adjusted by backpropagation and iterative optimisation as the system continues to learn and improve the accuracy of predictions over time [10],[13].

To provide enhanced model stability and reduce overfitting in the proposed model, additional techniques such as stacking layers, dropout regularisation and sequence-to-sequence modelling were incorporated into the model to provide additional robustness to the model [14],[18]. The goal of the proposed model is to enhance the accuracy of future stock price predictions, reduce error in predicting future stock prices and develop a model that will be able to adapt to the changing conditions of the market [14],[18]. The proposed model is developed to be applied to real businesses.

3.1. SYSTEM ARCHITECTURE

Proposed system architecture consists of four major functional categories: Data Collection, Feature Preprocessing, Time Series Modeling and Price Prediction. First, benchmark datasets containing historical stock prices along with other related financial indicators are sourced (or collected) and organised into structured feature sets. The structured features must be 'cleaned, normalised and selected' to produce high-quality input sequences for deep learning models. The cleaned and selected data go to a time series prediction model e.g. LSTM or GRU - this model becomes the core of the System; the model learns the temporal patterns/sequential dependencies from historical data and produces predictions of future stock prices based upon these learned patterns. It also produces price predictions based on the learned patterns, which may be useful in making trading, investing and market analyses decisions.

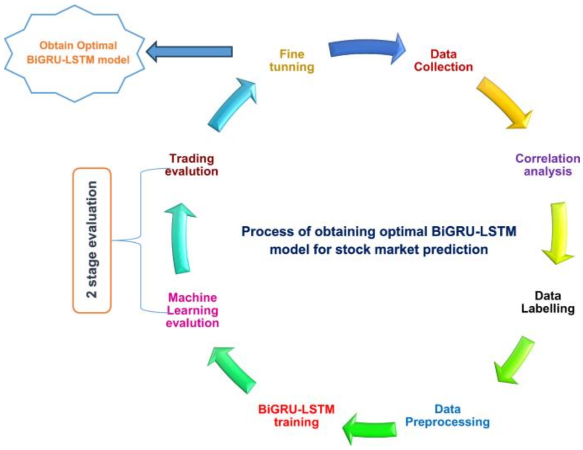

Fig.2: Conceptual Model for Stock Market Price Prediction Using LSTM/GRU Networks.

3.2. WORKING PRINCIPLE

The operation of the stock market price prediction system proposed will be done according to the following five phases:

1. The stock prices and financial data have been gathered from various datasets.
2. The data has had the data processed via Feature Extraction, Normalisation, Cleaning and Time Series Sequencing applied as part of the preparation for Time Series Modelling.
3. Time Series Sequences will be interpreted and analysed by either an LSTM Model or GRU Model so that (a) the temporal relationships within the sequence can be learned; and, (b) to obtain sequential dependencies.
4. The Model makes future stock price predictions based on the learned temporal relationship patterns contained within the model (the input data).
5. Model Predictions are compared to actual stock prices; and the Model's parameters will be updated during the back propagation phases of training to continue increasing overall prediction accuracy.

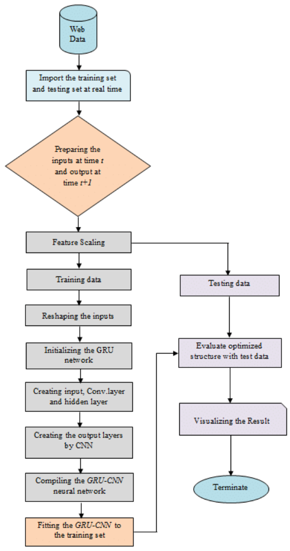

Fig.3: Operational Flowchart of the Proposed Time Series–Based Stock Price Prediction System.

3.3 ADVANTAGES

1. **Adaptive Learning**: As new data from the markets is collected, adaptive learning adjusts prediction based on this information.
2. **High Detection Accuracy**: Capable of identifying very complex relationships, it has very accurate predictions based on analysis of large amounts of historical data.
3. **Reduced False Positives:** By minimizing the error between predicted and actual values, reduced forecasting errors are possible through sequence modelling**.**
4. **Scalability:** This model can accommodate an enormous amount of both historical and live financial data**.**
5. **Real Time Detection:** Predictive capacity continues uninterrupted so that trade/investment decisions can be made based on most current available data**.**
6. **Minimal Human Intervention Required:** This system uses previous days/hours of market data plus the present day/hour's data to "learn". In doing so, very little if any manual labour is required to create useable features or provide supervision. It learns continuously and allows Traders and Analysts to depend on this model for accurate predictions without the need for extensive human interaction.

4. DATASET AND PRE-PROCESSING

4.1 DATASET

In order to assess how well the proposed system performs stock market price prediction system, publicly available **financial datasets** are used. Using standard datasets ensures consistent benchmarking and allows comparison with existing forecasting models.

4.1.1 Historical Stock Price Dataset

Historical stock price data for selected companies or indices is collected from sources such as Yahoo Finance, Google Finance, or Kaggle. The dataset includes features such as:

- Open price
- Close price
- High and low prices
- Trading volume
- Adjusted close price

These historical data features act as input sequences, enabling the model to learn temporal patterns and trends in stock price movements.

4.1.2 Technical Indicators and Economic Data

In addition to the raw price data, technical indicators such as Moving Averages, RSI (Relative Strength Index), MACD (Moving Average Convergence Divergence), and Bollinger Bands are calculated to improve feature representation. Other data, including economic indicators, sentiment scores, or additional financial metrics, can also be included to provide the model with richer context. Each feature sequence is then preprocessed into normalized, time-lagged sequences suitable for LSTM or GRU input. The dataset consists of historical stock price sequences recorded at consistent intervals—daily, hourly, or minute-wise. Each sequence includes multiple features such as open, high, low, and close prices, trading volume, and computed technical indicators, forming a structured input for the time series prediction model.

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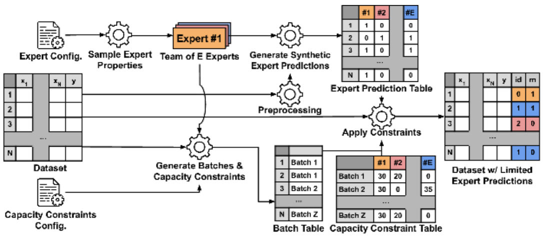

Fig.4: Benchmark Financial Datasets Used for Training and Evaluation figure

4.2 PRE-PROCESSING STEPS

Before training, the financial dataset undergoes several preprocessing operations to ensure data quality and consistency. Missing values are handled, and features are normalized or scaled to a common range. Time series sequences are generated using sliding windows to capture temporal dependencies in the stock prices. The dataset is then split into training and testing subsets to evaluate the model's forecasting performance. These preprocessing steps help stabilize the learning process of LSTM/GRU networks and improve prediction accuracy.

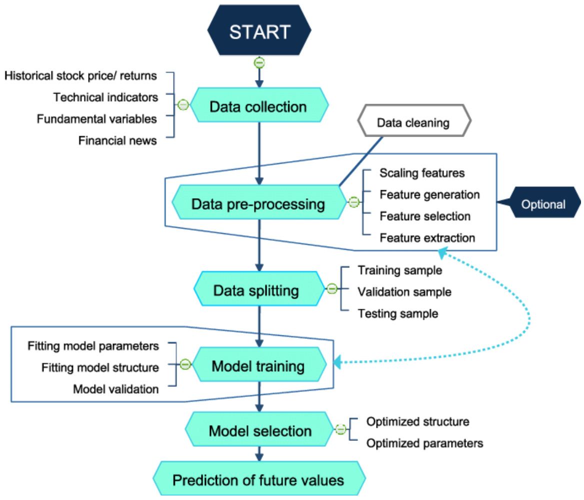

Fig.5: Workflow of Preprocessing Steps Used in the Proposed Stock Price Prediction Mode

5. ALGORITHM

The proposed stock price prediction system leverages deep learning–based time series models, such as LSTM and GRU, to forecast future prices by learning temporal relationships from historical data. Rather than depending on fixed indicators or linear models, these approaches can automatically identify complex sequential patterns and trends within financial time series.

5.1 Q-Learning Algorithm

The LSTM/GRU-based prediction model learns to forecast stock prices by minimizing the difference between predicted and actual values. The expected output $\hat{y}_t$ for time step t is computed from the input sequence using the network. The **prediction error** is calculated using the **Mean Squared Error (MSE)**:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

Where,

- y_t = actual stock price at time step t
- $\hat{y}_t$ = predicted stock price at time step t
- *n represents the total number of time steps in the sequence.*

5.2 LSTM/GRU-Based Deep Learning Model

LSTM/GRU networks extend traditional RNNs by effectively capturing long-term dependencies in sequential data using gated mechanisms.

In the proposed stock market price prediction system:

- **Input layer:** receives sequences of historical stock prices and technical indicators.
- **Hidden layers:** LSTM or GRU units learn temporal patterns and trends in the financial time series.
- **Output layer:** predicts the stock price for the next time step or multiple future time steps.

○ **Prediction Error Policy**

- The model uses a **prediction error–based mechanism** to guide learning:
- **Accurate prediction → Low error:** The model's parameters are reinforced, reducing the loss.
- **Large prediction error → High loss:** The network adjusts weights to minimize the deviation between predicted and actual prices.
- **Slight deviation → Moderate adjustment:** Small weight updates are applied to fine-tune the network without overcorrection.

5.4 TRAINING WORKFLOW

- The dataset is first pre-processed to remove noise, normalize feature values, and convert traffic records into numerical feature vectors.
- These processed feature vectors are treated as states and supplied as inputs to the Reinforcement Learning (RL) agent.
- For each traffic instance, the RL agent selects an action (normal or malicious classification) using an ε-greedy exploration policy.
- A reward is assigned for correct classification, while a penalty is given for wrong prediction, guiding the learning process.
- The Q-values or network weights are updated after every interaction to improve the decision-making policy.

- This procedure continues for multiple training episodes until the model converges to an optimal policy.
- Deep Q-Learning Methods like experience replay and target networks are employed to stabilize the training process.

  Finally, the trained LSTM/GRU model is evaluated using the test dataset to assess forecasting accuracy, and it can be deployed for **real-time stock price prediction** to support trading, investment decisions, and market analysis.

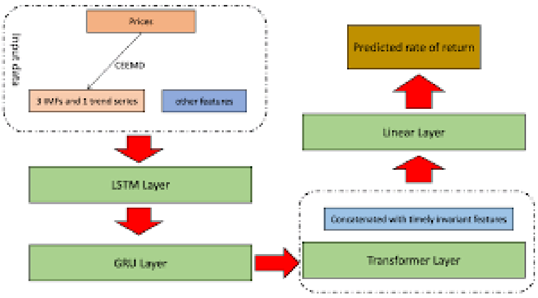

Fig.6: Workflow of the LSTM/GRU–Based Stock Price Prediction Model

6. RESULT AND DICUSSION

6.1 PERFORMANCE METRICS

To measure the effectiveness of the proposed **time series–based stock price prediction system**, several standard forecasting performance metrics are used:

- Mean Squared Error (MSE) – Measures the average squared difference between predicted and actual stock prices. Lower values indicate better accuracy.
- Root Mean Squared Error (RMSE) – The square root of MSE, providing error in the same units as stock prices.
- Mean Absolute Error (MAE) – Measures the average absolute difference between predicted and actual prices, reflecting overall prediction accuracy.
- R-squared (R^2 Score) – Indicates how well the model captures the variance in actual stock prices. Values closer to 1 signify better prediction.
- Mean Absolute Percentage Error (MAPE) measures the average percentage difference between predicted and actual prices, with lower values indicating greater prediction accuracy
- Fig. 6: Performance Metrics used for evaluating the Stock value Prediction Model

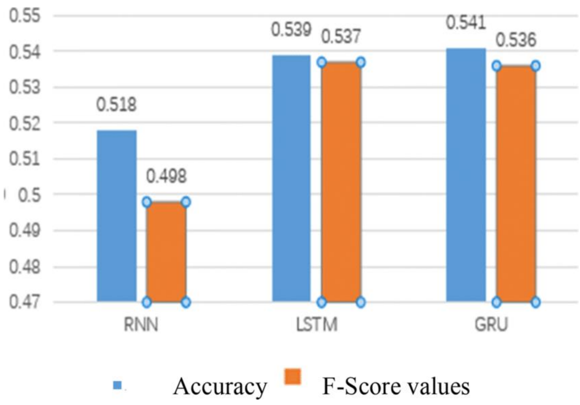

Fig.7: Performance Metrics of the LSTM/GRU Stock Price Prediction Model

6.2. EXPERIMENTAL RESULTS

The proposed **LSTM/GRU-based stock price prediction model** was evaluated using historical stock market datasets after completing the training process. The dataset was divided into **training and testing subsets** to ensure unbiased evaluation. The model was trained over multiple epochs until the **loss function converged** and stable prediction performance was achieved.

Forecasting performance metrics such as **MSE, RMSE, MAE, R^2, and MAPE** were computed on the test data to assess accuracy and reliability.

The results show that the LSTM/GRU model achieved **high prediction accuracy** while maintaining **low forecasting errors** compared with traditional statistical and shallow machine learning methods. The model demonstrated **stable learning behavior**, with the loss decreasing steadily over successive training epochs, indicating effective learning of temporal patterns in the stock price sequences. The evaluation metrics further confirm that the system is capable of accurately predicting both short-term fluctuations and long-term trends in stock prices, making it suitable for real-world trading and investment analysis.

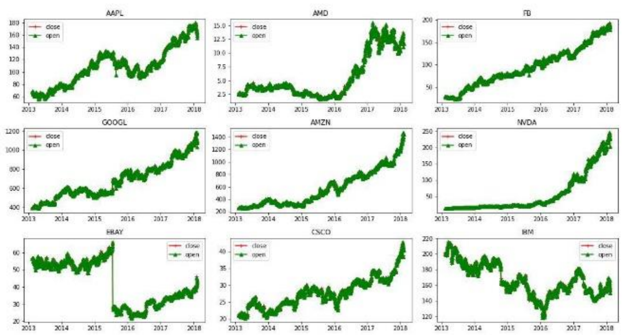

Fig.8: Predicted vs Actual Stock Prices for the Test Dataset.

7. CONCLUSION AND FUTURE WORK

This project presented a **Time Series–based Stock Market Price Prediction System** using deep learning techniques such as LSTM and GRU networks. The proposed system effectively captures temporal dependencies in historical stock price data and generates accurate forecasts for future prices.

The findings demonstrate that the LSTM/GRU model can:

1. Capture complex temporal patterns in stock price sequences.
2. Adapt to changing market trends by learning from historical data.
3. Provide accurate short-term and long-term predictions.
4. Minimize forecasting errors, improving reliability for trading and investment decisions.

Compared to traditional statistical or shallow machine learning methods, the deep learning–based time series model offers a more robust, self-learning approach for stock price forecasting, making it suitable for real-world financial applications.

Future research may focus on:

- Implementing real-time online prediction for live trading environments.
- Integrating additional financial and macroeconomic indicators to enhance forecasting accuracy.
- Optimizing model architectures and hyperparameters for improved performance.
- Reducing computational complexity to enable faster predictions.
- Combining LSTM/GRU with attention mechanisms or transformer models for capturing long-term dependencies more effectively.
- Exploring multi-step ahead forecasting and risk-sensitive prediction strategies.

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