Stock Market Prediction Using Long Short-Term Memory(LSTM)

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Abstract- *The Stock Market is one of the most active research areas, and predicting its nature is an epic necessity nowadays. Predicting the Stock Market is quite challenging, and it requires intensive study of the pattern of data. Specific statistical models and artificially intelligent algorithms are needed to meet this challenge and arrive at an appropriate solution. Various machine learning and deep learning algorithms can make a firm prediction with minimised error possibilities. The Artificial Neural Network (ANN) or Deep Feedforward Neural Network and the Convolutional Neural Network (CNN) are the two network models that have been used extensively to predict the stock market prices. The models have been used to predict upcoming days' data values from the last few days' data values. This process keeps on repeating recursively as long as the dataset is valid. An endeavour has been taken to optimise this prediction using deep learning, and it has given substantial results. The ANN model achieved an accuracy of 97.66%, whereas the CNN model achieved an accuracy of 98.92%. The CNN model used 2-D histograms generated out of the quantised dataset within a particular time frame, and prediction is made on that data. This approach has not been implemented earlier for the analysis of such datasets. As a case study, the model has been tested on the recent COVID-19 pandemic, which caused a sudden downfall of the stock market. The results obtained from this study was decent enough as it produced an accuracy of 91%.*

I. INTRODUCTION

- The stock market is a platform where shares of companies are bought and sold. It consists of two main segments:
- Primary Market: This is where new stocks are issued through Initial Public Offerings (IPOs).
- Secondary Market: This is where investors trade existing securities that they already own.

Stock market data is highly volatile and follows a non-linear time series pattern. A time series refers to a collection of data points recorded at successive intervals to track the progress of a particular activity. Traditional linear models such as Autoregressive (AR), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) have been widely applied for stock market predictions. However, these models are limited in scope as they perform well only for a specific dataset and may not generalize effectively to different companies.

Stock market forecasting is challenging due to the market's unpredictable nature, making it riskier than many other sectors. This is where deep learning (DL) techniques play a crucial role in financial forecasting. Deep neural networks (DNNs), also referred to as Artificial Neural Networks (ANNs), leverage neural network architecture to make predictions. ANNs are highly efficient at recognizing patterns and generalizing from prior experiences, making them valuable tools for stock market prediction.

The success of ANNs in forecasting can be attributed to the following features:

They serve as excellent function approximators, allowing them to establish relationships between input and output even in complex datasets.

II. ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network (ANN) is a computational model that mimics the functioning of biological neurons. It is designed to recognize patterns in data and generalize from them. ANNs are widely regarded as powerful non-linear statisticaltools capable of modeling complex relationships between inputs and outputs.

One of the key advantages of ANNs is their ability to identify underlying patterns within data, which conventional methods often struggle to achieve. Typically, an ANN consists of three primary layers:

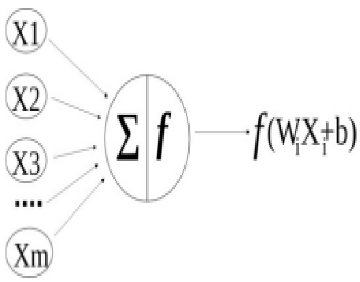
- **Input Layer**: Receives raw data and passes it to the next layer.
- **Hidden Layer**: Contains multiple neurons that process information using non-linear activation functions.

- **Output Layer**: Produces the final prediction or classification.

The hidden and output layers use non-linear activation functions, while the input layer simply transfers data. Each neuron in the input layer is connected to neurons in the hidden layer, which in turn are linked to the output layer, enabling the network to learn and make accurate predictions.

2.1. NEURONS

Traditional vehicle detection systems have primarily relied on infrared sensors, RFID technology, and acoustic recognition. These systems, while effective in some scenarios, suffer from limitations in accuracy, maintenance requirements,



The diagram illustrates an artificial neuron, a fundamental processing unit modeled after a biological neuron. It receives **m** inputs (xix each linked to the neuron through an associated weight (wiw) The neuron computes a weighted sum of the inputs using the equation:

A=∑xiwi+b

where A is the net sum, and b represents the threshold (bias). To generate an output, this sum is passed through an activation function F(A)F(A)F(A), expressed as:

Output=F(A)

The inputs and weights are real numbers, and in some cases, the bias bbb is treated as an imaginary input (x0=+1x_0 = +1x0=+1) with an associated weight w to simplify computations.

2.2. FEED FORWARD NETWORK

A **Feedforward Neural Network (FNN)**, also known as a **Multi-Layer Perceptron (MLP)**, is a fundamental type of neural network. In this architecture, each neuron in the input layer is connected to neurons in the subsequent hidden layer through a weighted matrix (wkiw_{ki}wki). The network is structured into three main layers: **input layer, hidden layer(s), and output layer**.

Artificial neurons are present in the hidden and output layers, where each neuron receives inputs from the preceding layer. Neurons within the same layer are not interconnected; instead, they are linked only to neurons in the next layer. The activation function for the **i**-th hidden neuron is mathematically represented as:

$$h_i = f(u_i) = f\left(\sum_{k=0}^{K} w_{ki} x_k\right)$$

hi : i th hidden neuron , f(ui) : link function which provides non-linearity between input and hidden layer , wki : weight in the (k, i) th entry in a (K X N) weight matrix , xK : Kth input value

III. DATASET 2

To evaluate whether the models can capture common patterns across different stock exchanges, we tested their predictive performance using stock data from the **New York Stock Exchange (NYSE)**. The data was sourced from **Yahoo Finance**, and we selected the two most actively traded stocks: **Bank of America (BAC)** and **Chesapeake Energy (CHK)**.

The dataset spans from **January 3, 2011, to December 30, 2016**, with stock prices denominated in **U.S. dollars**. For our analysis, we focused solely on the **daily closing prices** of these stocks.

Testing Procedure

To conduct the test, we extracted the daily closing prices of both companies for the specified period. Before feeding the data into the network, we applied **normalization** using Equation (1) to ensure uniformity across the dataset. This preprocessing step helped standardize the values, making them suitable for model training and comparison.

IV. RESULTS AND DISCUSSION

In this study, we analyzed stock market data from two exchanges: NSE (National Stock Exchange) and NYSE (New York Stock Exchange). To conduct the analysis, we employed four deep learning models: Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN).

For training, we utilized NSE data from Tata Motors, a company in the automobile sector. The trained models were then tested using stock data from both NSE and NYSE. The NSE dataset included stocks from the automobile, financial, and IT sectors, while the NYSE dataset covered the financial and petroleum sectors.

To compare linear and non-linear models, we also incorporated the AutoRegressive Integrated Moving Average (ARIMA) model, which is a linear forecasting method. Both ARIMA and neural networks were used to predict stock prices over a 400-day period. This approach allowed us to evaluate the predictive performance of traditional statistical process financial data and generate accurate forecasts. It consists of multiple stages, beginning with **data collection**, where historical stock prices are obtained from sources like Yahoo Finance. The next step is **data preprocessing**, which includes extracting relevant features such as daily closing prices and applying normalization techniques to standardize the data. The preprocessed data is then fed into a **feedforward neural network (FNN)** or a **deep learning model**, consisting of input, hidden, and output layers. The hidden layers use activation functions to capture complex relationships within the data. The model undergoes **training** using historical stock prices, adjusting weights through backpropagation to minimize prediction errors. Once trained, the model moves to the **testing phase**, where it evaluates unseen stock data to measure accuracy and performance. Finally, the system generates **predictions**, helping investors analyze market trends and make informed decisions. This architecture ensures a structured and efficient approach to financial forecasting using deep learning techniques.

V. CONCLUSION

In conclusion, stock market prediction is a complex task due to its highly volatile and non-linear nature. Traditional linear models, while effective for specific datasets, often fail to generalize across different companies. The application of Artificial Neural Networks (ANNs) and deep learning models has significantly improved forecasting accuracy by capturing intricate patterns in stock data. Through our analysis using NYSE data from Yahoo Finance, we demonstrated how deep learning models can identify trends across different stocks, specifically Bank of America (BAC) and Chesapeake Energy (CHK). By normalizing the daily closing prices before feeding them into the network, we ensured consistency in data processing. The study reinforces the effectiveness of ANN-based models in financial forecasting, highlighting their ability to learn and adapt to market fluctuations, making them a valuable tool for stock market analysis.

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