ISSN No:-2456-2165

Probabilistic LSTM Modeling for Stock Price Prediction with Monte Carlo dropout Long Short-Term Memory Network

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Abstract:- Investors and financial professionals in today's dynamic stock markets attach great significance to precise forecasts of stock returns. This emphasis is not only on accurate forecasting models but also their reliability. While conventional machine learning models can predict nonlinear datasets with high accuracy, they often overlook uncertainties in their predictions, leading to unreliable outcomes. This study employed the Bayesian LSTM (Long Short-Term Memory) model for stock price prediction and examined its performance with that of the conventional LSTM model. The findings revealed that the Bayesian LSTM model produces better results than the conventional LSTM model considering the R^2 (R-squared), MAPE (Mean Absolute Percentage Error), and RMSE (Root Mean Squared Error) values. The Bayesian LSTM model acknowledged the presence of inherent uncertainty in the underlying data and refrained from exhibiting excessive confidence in its predictions, having a confidence level of 48.67% in predicting the S&P 500 data for the study. This study provides a more reliable approach for stock price prediction to help investors and financial professionals make informed decisions.

***Keywords**:- Bayesian LSTM Model; Monte Carlo Dropout; Stock Price Prediction; LSTM Model; Machine Learning.*

I. INTRODUCTION

Investors and financial professionals today place high importance on accurate stock return forecasts in the ever-changing world of stock markets. This results from the stock prices' patterns being nonlinear and volatile [2]. One of the most crucial institutions in any economy is the stock market [8]. Therefore, it is essential to design a reliable model that can capture the nonlinear nature and produce credible accuracy. To forecast stock prices, researchers have explored a variety of statistical models [1], [12], [23], [19], but their accuracy cannot be compared to machine learning techniques [14], [21]. This is because machine learning can better capture nonlinear patterns and produce accurate results [13]. Machine learning techniques for stock prediction have recently attracted a lot of interest to improve their performance through various feature extraction methods [8]. Deep learning algorithms have emerged as attractive option among these methods since they are adaptable and produce a high accuracy level [28], [24], [11], [22], [8], [2]. However, most machine learning algorithms rely on point estimates, providing a single prediction without considering uncertainty. This can lead to a lack of transparency and potentially misleading results. Many researchers have attempted to develop an accurate stock price forecasting method from linear to nonlinear models and diverse machine learning algorithms. However, the concept of more resilient techniques continue to emerge. Utilizing the Auto-regressive Integrated Moving Average (ARIMA) model to forecast the prices of stocks on the New York Stock Exchange (NYSE) and National Stock Exchange (NSE), [1] discovered promising results for short-term forecasting. Advanced machine learning and deep learning strategies for stock price forecasting were proposed by [27]. Their results demonstrated that a deep learning LSTM network combined with high gradient boosting performs better than the traditional ARIMA approach. [26] employed various machine learning techniques and conventional statistical methodologies to forecast Karachi Stock Exchange (KSE) market performance. According to their findings, the multilayer perceptron (MLP) algorithm outperforms the benchmark methods. In a study by [17], different forecasting models were compared, and it was discovered that the convolutional neural network-Long Short-Term Memory (CNN-LSTM) approach achieved the highest prediction accuracy for stock prices. [7] addressed the challenge of stock price forecasting in dynamic situations by proposing an LSTM-based model, which achieved good accuracy with low error rates when trained on a sizable dataset. In a recent study by [4], the LSTM model was used to predict the next day closing price of the S&P 500 index. Their findings indicate that a single-layer LSTM model outperforms multilayer LSTM models, offering a better fit and higher prediction accuracy for the task. [20] also employed the transformer model to forecast the future stock prices on the Dhaka Stock Exchange (DSE), the prominent stock exchange in Bangladesh. The transformer algorithm exhibited strong performance with promising accuracy, surpassing the ARIMA model's forecasting capabilities from the study's findings.

Although these machine learning techniques are flexible and have great potential in handling nonlinear data, the problem of uncertainty still needs to be considered. While previous research has explored various machine learning and deep learning techniques [7], [27], [17], [20], we recognized the significance of this factor in enhancing prediction accuracy and minimizing biases. In this study, we propose a framework that treats LSTM weights as random variables and estimates posterior distributions by combining the strengths of LSTM and Bayesian models in capturing sequential dependencies and quantifying uncertainty, respectively. This will enable us to provide probabilistic forecasts in addition to point estimates, aiding in model transparency and interpretability and fostering trust in the forecasts of the LSTM to facilitate a more practical way of communicating results. Based on the literature, research gaps exist in predicting the prices of stocks, where this study would make significant contributions. These gaps include limited exploration of Bayesian approaches, the need for uncertainty estimation, handling dynamic situations with fluctuating values, and comparison with other contemporary models. By addressing these gaps, this paper would enhance the accuracy and interpretability of stock price predictions, provide probabilistic forecasts, and offer insights into the benefits of Bayesian inference in financial market forecasting. This study contributes to the existing literature by introducing uncertainty-aware machine learning algorithms to stock price predictions, delivering valuable insights for decision-making in financial markets, and guiding future research. The Bayesian LSTM model was compared with the regular LSTM model to measure the performance of both models in predicting stock prices. Other sections of the paper include Section II, which describes our research methodology for both the regular LSTM and the Bayesian LSTM models. Section III presents our findings and a discussion; Section V concludes the study.

II. MATERIALS AND METHODS

Our data set contains daily historical prices of Standard and Poor's 500 (S&P 500) from June 2017 to June 2022 which is publicly available on yahoo finance website. The data include Open, High, Low, Close, Adjusted Close, and volume as features. To scale the values to be in the range [0, 1], we utilized the minimum-maximum scaler represented mathematically as.

$$X_{Scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The data was split into training and testing sets: 80% for training and 20% for testing the performance of the models.

A. The Model Establishment.

Machine learning algorithms have become robust tools for stock price prediction recently. The Long Short-Term Memory (LSTM) model, to be specific, is well known for incorporating temporary dependencies and non-linear patterns in financial time series data [18]. However, traditional LSTM models lack uncertainty quantification in predictions. To overcome this limitation, the Bayesian LSTM model has emerged as an effective approach, incorporating Bayesian inference to provide rigorous uncertainty estimates [10]. Combining the strengths of LSTM and Bayesian inference, the Bayesian LSTM model presents a robust framework for accurate stock price prediction with quantified uncertainty. In this subsection, we establish the models of LSTM and Bayesian LSTM for stock price prediction, laying the groundwork for subsequent analysis and evaluation of their performance in forecasting financial markets.

B. The Long Short Term Memory Model (LSTM).

LSTM model is an extension of recurrent neural network (RNN) that excels in capturing and modeling long-range dependencies in sequential data, making it particularly suitable for time series analysis [24], [18]. Unlike traditional RNNs, LSTM networks combine specialized memory cells with input, output, and forget gates, which allows them to maintain relevant information over extended periods and selectively update or forget information as needed. Mathematically, an input $X = (x_1, x_2, \ldots, x_n)$, where each x_t, $t = 1, 2, 3, \ldots, n \in R^T$, n is the number of input dimensions and T represents the time lag. With an output $y = (y_1, y_2, \ldots, y_n)$, the forward training method of the LSTM model, as proposed by [16] can be formulated as follows:

$$I_t = \sigma(W_t \cdot [m_{t-1}, x_t] + b_t) \quad (1)$$

$$F_t = \sigma\left(W_f \cdot [m_{t-1}, x_t] + b_f\right) \quad (2)$$

$$C_t = F_t \cdot C_{t-1} + I_t \cdot \tanh(W_c \cdot [m_{t-1}, x_t] + b_c) \quad (3)$$

$$O_t = \sigma(W_0 \cdot [m_{t-1}, x_t] + b_0) \quad (4)$$

$$m_t = O_t \cdot \tanh(C_t) \quad (5)$$

Where I_t denotes the activation of the input gate, O_t denotes the output gate, and F_t denotes the forget gate. C_t also represents the activation vector for each cell, and m_t represents the memory block. The weight matrix and the bias vector are defined as W and b, respectively. The hyperbolic tangent function and the sigmoid function represented by tanh and σ respectively, are the two primary activation functions the LSTM model considers. The equations for these two activation functions are represented as follows:

$$\sigma(x) = \frac{e^x}{e^x + 1}$$

$$\tanh(x) = \frac{e^{2x} - 1}{e^{2x} + 1}$$

C. The Bayesian Deep Learning Model (Bayesian-LSTM).

The Bayesian LSTM model is an LSTM model which incorporates Bayesian inference techniques. It utilizes techniques such as Variational Inference, Gaussian Processes, and Monte Carlo Dropout to estimate uncertainty in predictions. In this paper, we used the Monte Carlo Dropout proposed by [9] for the uncertainty estimation. During the training process, the Monte Carlo Dropout randomly deactivates some LSTM units (neurons) by setting them to zero, effectively excluding them from the network. This procedure is iterated multiple times, generating distinct dropout masks for each iteration. By training the model using this dropout mechanism, the Bayesian LSTM can generate predictions resilient to the absence of specific neurons, thereby improving its generalization capability and preventing overfitting. By performing Monte Carlo simulations, the Bayesian LSTM generates a set of predictions, each associated with a distinct set of sampled weights. The mean prediction is the central estimate for the model's output and is calculated by finding the mean of all the forecasts generated during the simulations. It is expressed mathematically in Equation 8.

Given an input $X = (x_1, x_2, \dots, x_n)$, where each x_t, $t = 1, 2, 3, \dots, n \in R^T$, n is the number of input dimensions and T represents the time lag. With an output $y = (y_1, y_2, \dots, y_n)$, the Bayesian method aims to find the parameter w of the function $y = f^w(x)$ which produces the optimal results [3], [15], [10]. Viewing the LSTM as a probability model, we then consider w to be a random variable that follows the normal prior distribution. The posterior probability distribution denoted by $p(w|x, y)$ is based on the Bayesian principle. Calculating the posterior distribution $p(w|x, y)$ is challenging and quite impossible to obtain directly [6], [15]. To address this, [6] proposed an alternative variational distribution $q(w|\theta)$ parameterized by θ that can effectively approximate the actual posterior distribution derived from the available data. The prediction results for the Bayesian LSTM, as proposed by [6], are obtained by employing stochastic propagation and Monte Carlo integration for the output mean and can be expressed as.

$$p(y_t|x_t, x, y) = \int p(y_t|x_t, w) \cdot p(w|x, y)dw \quad (6)$$

$$p(y_t|x_t, x, y) \approx \int p(y_t|x_t, w) \cdot q(w|\theta)dw \quad (7)$$

$$p(y_t|x_t, x, y) \approx \frac{1}{N}\sum_{t=1}^{N} p(y_t|x_t, \hat{w}) \quad (8)$$

Where x_t and y_t represents the input data at time t and its corresponding output data at time t respectively. $\hat{w}$ is also sampled through dropout technology based on the Monte Carlo integration.

D. Evaluation Metrics.

The performance of LSTM model and the Bayesian-LSTM model in predicting stock prices are measured using evaluation metrics such as Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and Root Mean Squared Error (RMSE) in this study. These metrics provide quantitative measures of the models' accuracy and effectiveness in capturing the underlying patterns and trends in stock price data. By comparing the values of these metrics, we can evaluate and compare the predictive performance of the LSTM and Bayesian-LSTM models for stock price forecasting. Mathematically, they are represented in Equations 9-11. The closer the MAPE and RMSE to zero, the more accurate the model is, and the closer the R^2 to 1, the more precise the model is.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100 \quad (9)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (10)$$

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(y_t - \bar{y})^2} \quad (11)$$

Where, n represents the total number of observations or data points, y_t represents the actual value of the observation at time t, $\hat{y}_t$ represents the predicted value of the observation at time t, and $\bar{y}$ represents the mean of the actual values.

III. RESULTS AND DISCUSSION

A. Empirical Results.

This section presents the empirical findings derived from our study on probabilistic stock price prediction. Our analysis employed a Bayesian LSTM model to collect and analyze secondary data from the S&P 500. The result obtained from this study offers valuable insights into the importance of uncertainty quantification when predicting stock prices. In the Bayesian LSTM model, the number of LSTM units was set to 50 to determine the hidden state's dimensionality. The dense layer's units were set to 1, aligning with the prediction of a single target variable (Close price). We used the Adam optimizer to update the model weights during training, a popular choice for deep-learning models. To determine the number of samples taken from the Bayesian model to estimate uncertainty, we set the number of Monte Carlo samples to 100. These choices were made based on standard practices and experimentation.

The Price dynamics of the data for this study (S&P 500) are shown in Figure 1. Even though there are dynamics in the price movement, there is evidence of an increasing trend, as indicated by the Mann-Kendall test in Table 1.

Fig 1. The Close price Dynamics of S&P data

Table 1. Mann-Kendall Test.

FEATURE	TREND	S	Var (S)	Z	p-value
Open	increasing	654838	232743467.0	42.9	0.0
High	increasing	661344	232743467.0	43.3	0.0
Low	increasing	647001	232743467.0	42.4	0.0
Close	increasing	654293	232743467.0	42.9	0.0
Adjusted Close	increasing	654293	232743467.0	42.9	0.0
Volume	increasing	306398	232743467.0	20.1	0.0

Table 2 shows the Bayesian LSTM model and conventional LSTM models' performance metrics. From the table, the Bayesian LSTM model offers a better performance with a lower MAPE (0.0097), RMSE (47.82), and a higher R^2 (0.9594) compared to the LSTM model with MAPE (0.0154), RMSE (80.00) and R^2 (0.8865). These results indicate that the Bayesian LSTM model provides more accurate and reliable predictions, capturing a higher percentage of the variance in the target variable, which is also evident in the residual plot shown in Figure 4.

Table 2 Performance Metrics

MODEL	MAPE	R^2	RMSE
LSTM	0.0154	0.8865	80.00
BAYESIAN LSTM	0.0097	0.9594	47.82

The Actual and the predicted plot of the two models are shown in Figure 2, indicating the model's performance in predicting the S&P 500. In Figure 2, both models seem to capture the dynamic nature of the S&P 500 prices. However, the Bayesian LSTM model captured the nonlinear nature of the S&P 500 data for the study period's test set. With the Bayesian LSTM model demonstrating high prediction accuracy, the uncertainty inclusion provides valuable information, as depicted in Figure 3. The figure illustrates how the model acknowledges the presence of inherent uncertainty in the underlying data and avoids excessive confidence in its predictions. Additionally, Figure 5 displays the forecast's posterior probability distribution, which indicates that the model assigns higher probability to the prices that fall between \$ 4,200 and \$ 4,800. The broad tail on the left of the posterior probability distribution graph suggests a larger span of potential outcomes for lower stock prices. This indicates that accurately forecasting these lower values poses more difficulties for the model. This characteristic of the Bayesian LSTM model proves advantageous, especially in scenarios involving significant fluctuations or volatility in the data. It enables decision-makers to consider various potential outcomes, enhancing their ability to make informed choices.

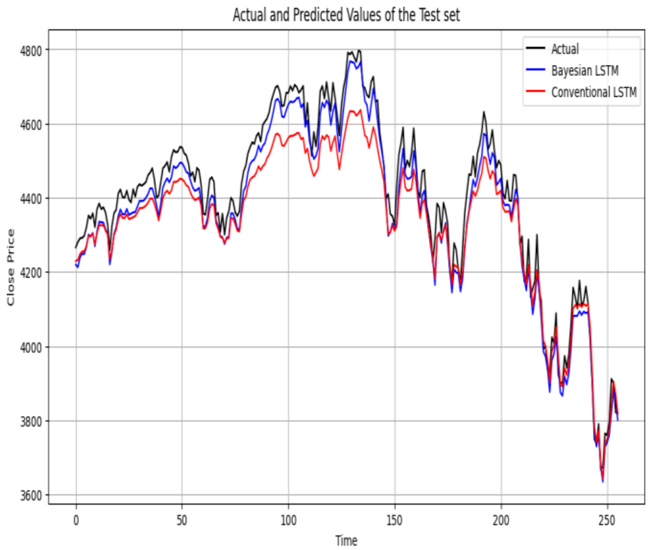

Fig 2. The two models' Actual and Predicted graphs for the test set

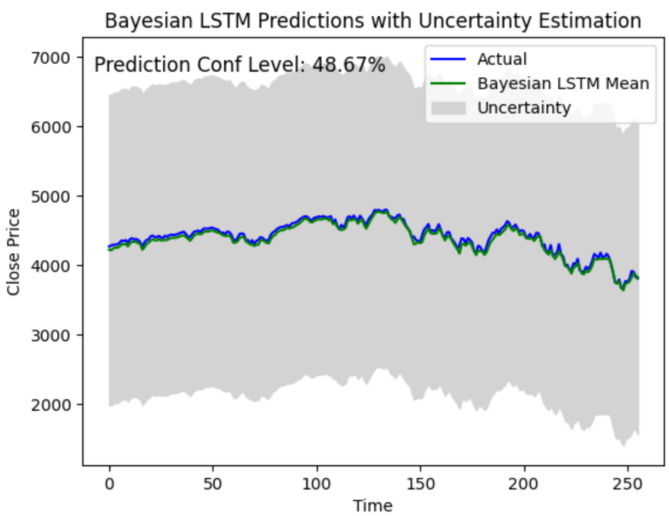

Fig 3. The Bayesian LSTM prediction with Uncertainty.

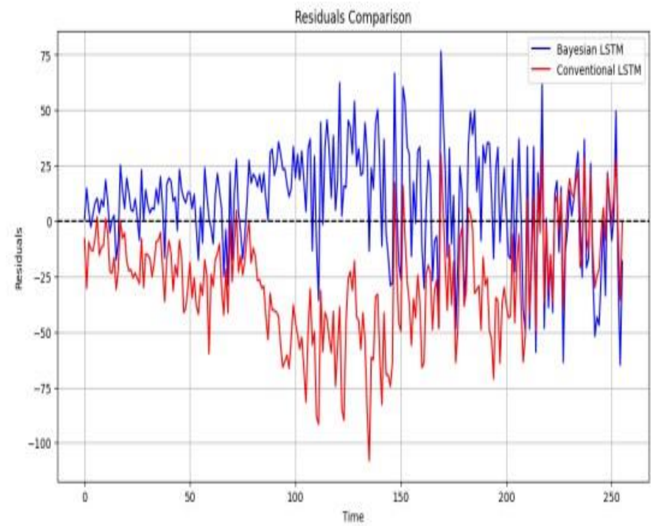

Fig 4. Residual plots of the two Models

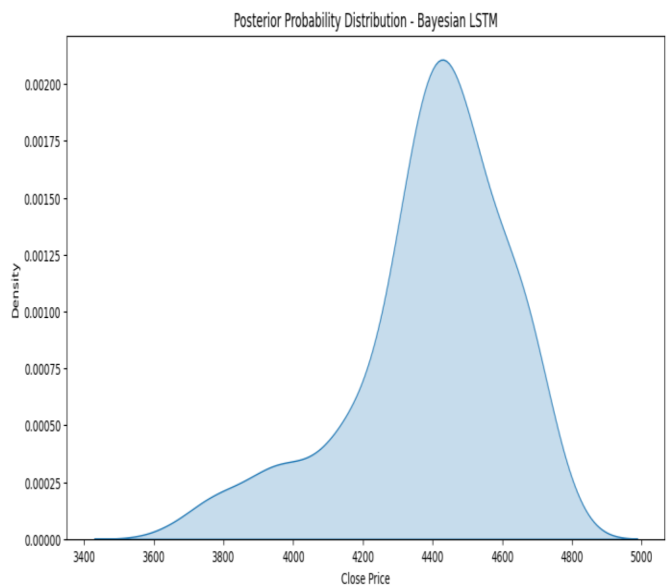

Fig 5. Posterior Probability distribution of the Prediction with uncertainty

B. Discussion.

The study's outcomes suggest that the proposed probabilistic LSTM model incorporating Monte Carlo dropout demonstrates promising performance in forecasting stock prices. By introducing uncertainty through dropout during training, the model becomes better suited to address the inherent unpredictability of financial markets. The model's capability to provide probabilistic predictions is particularly valuable for decision-makers, enabling them to grasp the range of potential outcomes and make well-informed choices. These findings align with existing literature such as [6], [5], [10], and [3] on the advantages of probabilistic modeling for prediction compared to traditional deterministic methods. The adoption of Monte Carlo dropout in LSTM networks has been effective in capturing uncertainty, consistent with other studies that

ISSN No:-2456-2165

have utilized dropout-based techniques for uncertainty estimation in deep learning models, such as [6].

The ability to generate confidence intervals and probability distributions for predictions helps investors and financial analysts to gain a comprehensive understanding of the risks associated with various investment decisions. While the results of this study are promising, it is crucial to acknowledge the limitations and potential challenges of the Bayesian LSTM model. The model's performance may rely on the quality and size of the training dataset, as well as the selection of hyperparameters. Additionally, future research should consider the uncertainties that arise from datasets (Aleatoric uncertainty) and uncertainties that arise from the models (Epistemic uncertainty) as they can provide valuable insight to help provide a more reliable prediction. By building on the existing literature and addressing the uncertainties associated with stock price prediction, this study contributes to the advancement of the field and opens new avenues for future research in financial forecasting and deep learning applications.

IV. CONCLUSION

Accurate predictive models are valuable; however, their dependability is paramount for investors and decision-makers. Although conventional machine learning models exhibit relatively high accuracy in predicting non-linear datasets, they often neglect uncertainties, resulting in unreliable outcomes. This study explored and compared the Bayesian LSTM model and conventional LSTM models' performance for stock price prediction. The results indicated the Bayesian LSTM is better than the conventional LSTM model using the MAPE (Mean Absolute Percentage Error) and R^2 values as evaluation metrics. The Bayesian LSTM model acknowledges the presence of inherent uncertainty in the underlying data and refrains from exhibiting excessive confidence in its predictions, it uses a confidence level of 48.67% for predicting the S&P 500 data in this study. Every model has room for improvement, and we will strive to enhance the accuracy of our forecast results in future endeavors.

DECLARATIONS

Funding

The authors received no specific funding for this work.

Declaration of Competing Interest

The authors have declared that no competing interests exist.

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