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LSTM Deep Learning Based Stock Price Prediction with Bollinger Band, RSI, MACD, and OHLC Features.

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Abstract: The prediction of stock prices is a challenging task due to the volatility of stock prices. This research article aims to identify the effectiveness of using different technical indicators and the LSTM neural network machine learning algorithm for predicting trends and stock prices. This study used historical stock price data from the National Stock Exchange of India (NSE) for the period from January 1, 2020, to July 10, 2023, and used the Yahoo Finance API, which provides Open, High, Low, and Close (OHLC) values. By using these values, we calculated different technical indicators such as the Relative Strength Index (RSI), Bollinger Bands, and Moving Average Convergence Divergence (MACD) and used these indicators as features. In this study, the next day's closing price of stocks and trend are predicted using the Long Short-Term Memory (LSTM) algorithm. The performance of this model is evaluated using different metrics such as R-squared (R2 score), mean absolute percentage error (MAPE), and root mean squared error (RMSE). The trend identified is measured with the help of the confusion matrix. Sample stocks such as RELIANCE, ASIAN PAINTS, HINDUSTAN UNILEVER, KOTAK BANK, and INFOSYS were selected for study purposes. The results of this study demonstrate the ability of combining technical indicators and LSTM neural networks for stock price prediction and trend prediction.

Keywords: *Deep Learning, Machine Learning, LSTM, Stock Price Prediction, Relative Strength Index*

1. Introduction

Accurate stock price forecasting is difficult due to the complexity and volatility of the financial markets. However, improvements in data analysis methods and machine learning algorithms have created fresh opportunities for enhancing stock price forecast accuracy [1]. Technical analysis includes examining the historical price and volume of the selected stock. Analysts and traders prefer to identify different patterns and trends, such as uptrends and downtrends, which can help forecast future price movements. Another approach is fundamental analysis, which analyzes the potential of the selected stocks to determine whether they are good for investment or not. If the stock is fundamentally strong, then it is also good for technical analysis purposes [2]. Additionally, deep learning approaches, such as LSTM-RNN neural networks, have shown reliable results in time series forecasting tasks. LSTM can handle lengthy time-series sequences effectively [3], [4]. Some researchers introduced the hybrid approach for more accuracy which combines more than one algorithm for stock forecasting purpose [5]. LSTM is an improved version of RNN that overcomes the drawbacks of RNN, such as “vanishing gradient". Data mining techniques such as fuzzy c-means (FCM) are used to classify stocks for investment-related decisions. According to the classification, the input data are cleaned [6]. Several researchers have applied the support vector machine (SVM) algorithm to stock market prediction via trend identification methods such as uptrend and downtrend methods. SVM helps classify stocks according to trends [7], [8]. Among multiple machine learning algorithms, determining which algorithm is best for stock prediction is also an important task. Some researchers provide systematic surveys related to machine learning algorithms and leading and lagging stock market indicators that are helpful for stock price forecasting [9], [10]. Several researchers have used linear regression to identify the relationships between independent variables such as the trading volume of stocks and dependent variables such as stock closing prices [11], [12]. K-means clusters were used to analyze unsupervised data. By using K-means, the stock's specific data, such as earnings, fundamentals, and news related to the stock, is analyzed, and clusters are created. According to that cluster, trading-related decisions are made by creating different strategies [13], [14]. Some researchers considered news headlines along with multivariate time series data for stock trend prediction purposes. By using this approach, the model can learn the historic patterns, and if that pattern is repeated in the future, it can effectively predict the trends of selected stocks. There is a possibility of historic pattern repetition [15]. This study contributes to the growing sector of the stock market and artificial intelligence, with the ultimate goal of providing valuable outcomes for stock market participants and stakeholders. The proposed research

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combines technical analysis indicators and LSTM neural networks to develop a predictive model for stock price forecasting and trend identification. For this research, we have selected the RSI, MACD, and Bollinger bands as the technical indicators. This research article is divided into six sections. Section 1 introduces a brief idea related to stock price forecasting. Section 2 provides a literature review of the current work related to stock price prediction. A research gap is identified in this section. Section 3 introduces the methodology used in this research article. Section 4 reports the results and findings of the proposed LSTM model. Section 5 discusses the importance of technical indicators, the future research direction of the proposed system, and the limitations of the proposed system. Section 6 concludes the work proposed in this research article.

2. Literature Review

Shen and Shafiq (2020) proposed a comprehensive solution that combines dimensionality reduction, feature engineering, and a customized LSTM model for predicting short-term price trends of Chinese stocks. The results show that the proposed solution outperforms the other methods in terms of accuracy, precision, recall, and F1-score [16]. Mehtab et al. (2021) introduced a study in which the Nifty50 index value was considered for analysis. He used LSTM along with basic OLHC data. The findings show that the most accurate model is the LSTM-based univariate model, which predicts the open value of the NIFTY 50 time series for the coming week using data from one week ago as input [17]. Jin et al. (2019) added trader sentiment to the LSTM-RNN model. The trader's sentiment analysis, with the help of the LSTM-RNN algorithm, provides the next day's closing price of stock. The attention layer continuously monitors crucial information related to the stock [18]. In their research, Usmani and Shamsi (2023) added the weighted category of news related to finance. The selected news is combined with the LSTM model, and this combination of news and machine learning using LSTM is used for prediction purposes [19]. In their research, Mehtab and Sen (2021) chose a hybrid approach in which machine learning and deep learning were combined. The CNN algorithm is used to fine-tune the validation loss. The results showed that the CNN-based model is more useful for predicting stocks effectively [20]. Qiao et al. (2022) introduced a study in which Shanghai stock market trends, such as uptrends and downtrends, were identified. In this study, LSTM is combined with basic features such as open, high, low, and close values of stocks, which are ranked according to average income. With the help of LSTM, the results are more accurate in terms of the RMSE, MSE, and MAPE [21]. In 2023, Sreenu introduced a strategy in which the inflation rate and exchange rate volatility effects on the stock market are observed. The findings show that there are significant relationships between inflation rate and exchange rate volatility and stock market returns, especially during the COVID-19 pandemic [22]. In 2020, Moghar and Hamiche used the daily opening prices of two stocks (Google and Nike) from the New York Stock Exchange as the data for the model and compared the results of different numbers of epochs for training. The paper concludes that the LSTM model shows promising results and can trace the evolution of opening prices for both stocks [23]. In 2023, Shaban et al. proposed a new system for predicting stock market prices using deep learning. Two stages, data preprocessing and stock price prediction, are performed using a combination of LSTM and BiGRU models. The proposed system outperforms other existing methods in terms of accuracy, error rate, and correlation coefficient [24]. Srivastava et al. (2023) introduced research in which the direction of Nifty50 stocks in India was predicted. For the time series data, different algorithms such as LSTM, KNN, SVM, Random Forest, and gradient boosting are applied to get better accuracy in predictions. Additional data, like financial news tweets related to stocks, is also used to enhance efficiency. The result shows that the model reduces major investor losses [25].

2.1. Research Gap

Many researchers have focused on stock prices and simple OHLC features, along with machine learning algorithms such as RNN, LSTM, SVM, and linear regression algorithms. Some researchers have focused on the volume traded for the selected stocks. With these basic features, technical indicators can also play an important role in feature engineering. In this research, we have selected the RSI, Bollinger Band, and MACD indicators, which are popular for technical analysis of stocks, along with basic OHLC features and LSTM. By using this combination, we can predict the closing price and the trend (uptrend or downtrend) of a selected stock effectively.

3. Methodology

3.1. Long-Short-Term-Memory (LSTM) algorithm

Fig. 1. Shows the structure of LSTM cell state. (C_t) is the current state and (C_{t-1}) is the previous state of the LSTM.

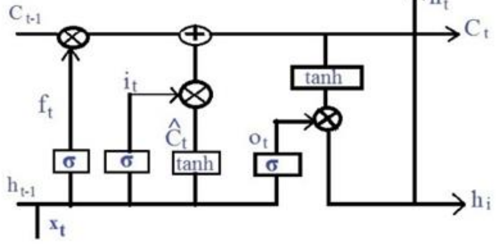


Fig. 1. LSTM Structure.

Forget gate (f_t) looks at (h_{t-1}) and(x_t). The activation function used is sigmoid (σ) for outputs between 0 and 1. The value 0 means completely forget and 1 means keep for the next state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) - - - - - - - - (1)$$

The input layer (i_t) decides the update of the value($\hat{C}_t$), and this new value is updated in the current state. We add a new input to replace the forgotten value. The *tanh* activation function is used for this purpose and is shown in equation (3).

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) - - - - - - - - - (2)$$

$$\hat{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) - - - - - - - (3)$$

Multiply the old state by(f_t), add ($i_t * \hat{C}_t$) and update the old state (C_{t-1}) into the new state (C_t) as shown in equation (4).

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t - - - - - - - - - - - - (4)$$

Finally, output (o_t) is calculated as follows

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) - - - - - - - - - (5)$$

$$h_t = o_t * \tanh(C_t) - - - - - - - - - - - - - - (6)$$

Equations (1), (2), and (5) simultaneously indicate the forget gate, input gate, and output gate respectively [26].

3.2. System Architecture

The proposed system architecture is shown in Fig. 2. The system architecture involves the following steps:

1. Data Collection from the NSE: Historical stock price data for a specific company (e.g., ASIANPAINT) is obtained from NSE, India by using the Yahoo Finance API [27].

2. Data Preprocessing: MinMaxScaler was used to scale the dataset's features. After that, input sequences for the LSTM model are created.

3. Feature Engineering: Different technical indicators, such as Bollinger Bands, MACD, and RSI, are calculated using the Pandas-TA library. These indicators capture different parameters of price and volume patterns.

4. Model Development: The Keras library is used to create the LSTM neural network model. The model takes the input sequences of technical indicators as input and predicts the next day's closing price with a trend such as an uptrend or downtrend.

5. Model Training and Evaluation: The LSTM model is trained using a portion of the dataset (80%) and evaluated using metrics such as the Confusion Matrix, MAPE, R2 score, and RMSE. The performance of the LSTM model is analyzed, and the predictions are compared with the actual stock prices to check the accuracy and reliability of the model.

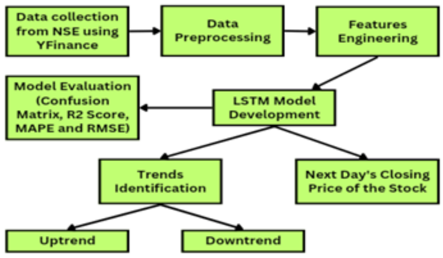


Fig. 2. System Architecture.

3.3. Algorithm elaboration:

1. Import the necessary libraries:

Pandas, Numpy, and Matplotlib for data manipulation and visualization, Yfinance for downloading stock price data, Pandas_ta for calculating technical indicators, MinMaxScaler for feature scaling, Keras, and TensorFlow for building and training the LSTM model.

2. Download historical stock price data:

We used the YFinance library to download the historical data for the desired stock. The ticker symbol and the start and end dates of the data are specified.

3. Calculate technical indicators:

The pandas_ta library was used to calculate technical indicators such as the RSI, MACD, and Bollinger Bands. The calculated indicators are added as additional columns to the dataset which are considered as additional features.

4. Preprocess the data:

Drop any rows with missing values from the dataset. Reset the index of the dataframe. Remove unnecessary columns from the dataset.

5. Prepare the input and target variables:

The feature columns were scaled using MinMaxScaler. The number of past candles (backcandles) to consider for input is defined i.e. 30. Empty lists are created to store the input (X) and target (Y) variables. The feature columns are iterated, and input sequences of length 30 (backcandles) are created. The axis of the input array is moved to match the LSTM input shape. The target variable is reshaped to match the input shape.

6. The data are split into training and testing sets:

We have specified the split limit (e.g.80% for training, 20% for testing). The input (X) and target (Y) variables into training and testing sets.

7. Building the LSTM model:

Fig. 1 shows the structure of LSTM. For building the model, define the input layer with the shape (backcandles, num_features). After that, an LSTM layer with a specified number of units is added, e.g., 150. Finally, a dense layer with a single unit is added for output. The model is compiled using an optimizer (e.g., Adam) and the mean squared error loss function.

8. Train the LSTM model:

The model was fit to the training data. The batch size and 30 number of epochs are specified. The training data were shuffled, and a validation split of 0.1 was used to monitor the model's performance.

9. Make predictions:

The trained model is used to make predictions based on the testing data. Conversely, the predicted and actual values are scaled to their original ranges, and the trends are identified such as uptrend or downtrend.

10. Evaluate the model's performance:

Metrics such as the MAPE, R2 Score, and RMSE were calculated between the predicted and actual values. The predicted and actual values were plotted for visual analysis. The trend identification accuracy is measured with the help of the confusion matrix.

4. Results And Findings

The experimental results demonstrate that the proposed approach, which combines technical indicators with OHLC, volume, and LSTM neural networks, can effectively predict the next day's closing stock prices and trends. The model achieved low MAPE, RMSE, and improved R2 scores for all the selected stocks, indicating good performance of the model and efficient predictions of the next day's closing price and trends. Table 1 shows performance metrics for the training dataset, which is 80% of the total dataset.

Table 1. Performance Metrics for Training Dataset.

Name of Stock	R-squared	MAPE	RMSE
ASIANPAINTS	0.986	2.505	69.387
RELIANCE	0.975	2.333	57.663
HINDUNILVR	0.944	3.513	48.354
INFOSYS	0.992	1.669	30.255
KOTAK BANK	0.961	3.42	48.407
MIN	**0.944**	**1.669**	**30.255**
MAX	**0.992**	**3.513**	**69.387**
AVERAGE	**0.972**	**2.688**	**50.813**

Table 2 lists the performance metrics on the testing dataset, which accounts for 20% of the total dataset. The testing dataset is completely new to the model because the model is trained using the training dataset, so we have chosen the data from Table 2. The R2 score further confirms the model's ability to capture the variance in stock prices. The average R2 score value from Table 2 is 0.878. An R2 score value for the selected stocks of 0.85<R2<1 indicates the strong predictive power of our model. Equation (7) represents the formula used to calculate the R2 score.

$$R^2 = 1 - \frac{sum\ squared\ regression\ (SSR)}{total\ sum\ of\ squares\ (SST)} - - - - - (7)$$

The average MAPE of the testing dataset is 2.206 from Table 2. The lower value of MAPE indicates the better performance of the proposed model. Equation (8) represents the formula for calculating the MAPE.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| - -where, A_t = Actual, F_t = Predicted, n = \ No. of\ iteration - -(8)$$

The RMSE metric shows the model's prediction errors, which are relatively small for all selected stocks, indicating good overall performance. The average RMSE value of the testing dataset is 42.791. Equation (9) represents the formula for calculating the RMSE.

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(Predicted_i - Actual_i)^2}{n}} - -Where, n = Total\ number\ of\ observations. - - (9)$$

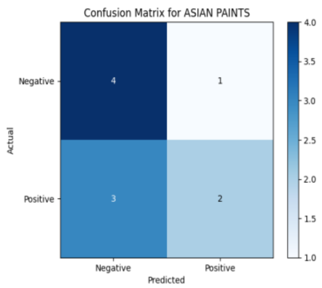
Table 2. Performance Metrics for Testing Dataset.

Name of Stock	R-Squared	MAPE	RMSE
ASIANPAINTS	0.933	1.912	49.265
RELIANCE	0.862	1.803	45.082
HINDUNILVR	0.852	2.599	47.523
INFOSYS	0.909	2.058	36.805
KOTAK BANK	0.835	2.657	35.282
MIN	**0.835**	**1.803**	**35.282**
MAX	**0.933**	**2.657**	**49.265**
AVERAGE	**0.878**	**2.206**	**42.791**

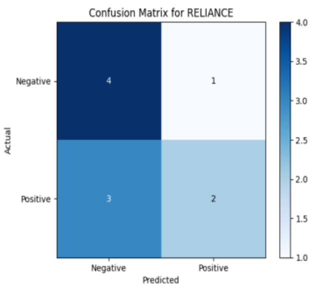
The graph of the "Asian Paint" sample stock, in which the predicted and tested values are plotted, is shown in Fig. 3. This indicates that the model can predict stock prices efficiently. The plotted chart shows 20% of the total dataset, which was reserved for testing purposes.

Fig. 3. Prediction of testing data for ASIAN PAINTS stock

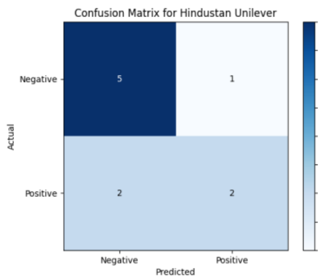
Our proposed model can predict the next day's trend in the stock. There are two types of trends: uptrends (Positive) and downtrends (Negative). Fig. 4 represents the confusion matrix of the selected stocks for the period from June 19th, 2023, to July 4th, 2023. A total of 10 trading-day readings related to stock trends were taken using the model. A confusion matrix is a matrix used in classification to assess the performance of a machine learning model, where each column represents the predicted class and each row represents the actual class. In our model, there are two classes: positive (P) and negative (N). A positive (P) represents an uptrend in the stock, and a negative (N) represents a downtrend in the stock.



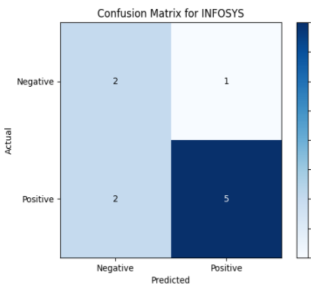
a) ASIAN PAINT



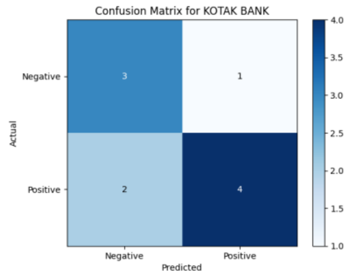
b) RELIANCE



c) HINDUSTAN UNILEVER



d) INFOSYS



e) KOTAK BANK

Fig. 4. Confusion Matrix of stocks selected for study purposes a) ASIAN PAINTS b) RELIANCE c) HINDUSTAN UNILEVER d) INFOSYS e) KOTAK BANK

Table 3. Accuracy, Precision, Recall, Specificity, and F1 Score of Selected Stocks.

Name of Stock	Accuracy	Precision	Recall	Specificity	F1 Score
ASIAN PAINTS	0.60	0.67	0.40	0.80	0.50
RELIANCE	0.60	0.67	0.40	0.80	0.50
HINDUSTAN UNILEVER	0.70	0.67	0.50	0.83	0.57
INFOSYS	0.70	0.83	0.71	0.67	0.77
KOTAK BANK	0.70	0.80	0.67	0.75	0.73

Table 3 lists the accuracy, precision, recall, specificity, and F1 score, which are calculated by using the confusion matrix. Table 3 shows that the accuracy of the RELIANCE and ASIAN PAINTS stocks is 60%, whereas that of the HINDUSTAN UNILEVER, INFOSYS, and KOTAK BANK stocks is 70%. KOTAK BANK and INFOSYS showed good precision, i.e., 0.80 and 0.83, respectively, and F1 scores, i.e., 0.73 and 0.77, respectively, which indicated that the model predictions for positive instances were accurate. The high specificity of the HINDUSTAN UNILEVER (0.83), ASIAN PAINTS (0.80), and RELIANCE (0.80) stocks indicates that the model's predictions for negative instances are accurate and that the number of false positives is reduced.

5. Discussion

The findings of this research paper highlight the potential of utilizing technical indicators and LSTM neural networks for stock price prediction.

5.1. Importance of Technical Indicators:

The inclusion of technical indicators, such as Bollinger Bands (Fig. 5), MACD, and RSI (Fig. 6), enhances the model's ability to capture market trends and patterns.

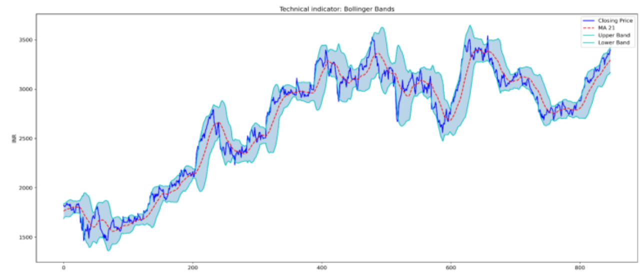


Fig. 5. Bollinger Bands for Asian Paints Stock.

With its ability to learn and model sequential data, the LSTM neural network effectively predicts the next day's closing price and trends. The research also emphasizes the importance of data preprocessing, feature engineering, and model evaluation in developing accurate and reliable predictive models for stock price forecasting. The application of this research extends beyond stock price prediction to various other financial forecasting tasks such as forex, cryptocurrency, and commodities.

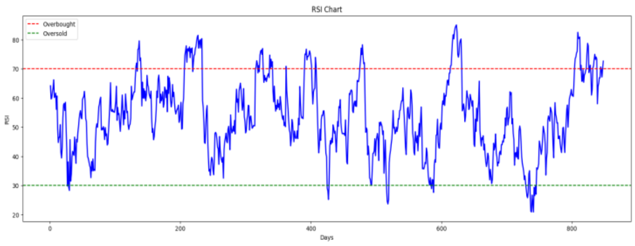


Fig. 6. RSI indicator of Asian Paints Stock

The combination of technical indicators and LSTM neural networks can be utilized in portfolio management, trading strategies, and risk assessment. Fig. 7 shows the validation and training loss of the model after 30 epochs, which indicates that the model is trained effectively.

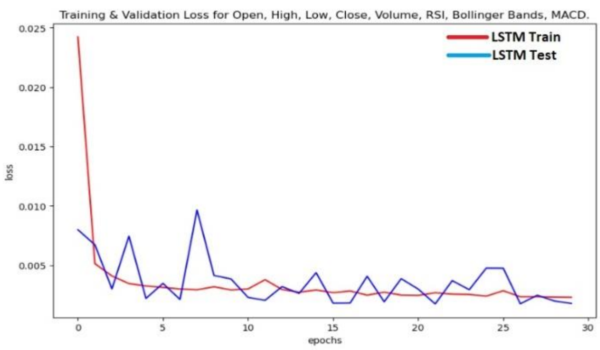


Fig. 7. Training and Validation Losses for OHLC, Bollinger Bands, RSI and MACD

5.2. Future Research Directions:

Further research can explore the incorporation of additional features and alternative deep learning architectures to enhance prediction accuracy. Alternative technical indicators can be used as features to improve the accuracy and performance of the model. Additionally, the research can be extended to multiple stocks or broader market indices such as forex, cryptocurrency, and commodities for comprehensive market analysis and forecasting.

5.3. Limitations of Proposed System:

LSTM-based stock price prediction models generally face overfitting issues. The model may perform well on training data but struggle with unseen data, indicating overfitting. Sudden and unexpected market changes might challenge the model's ability to adapt quickly. The performance of the model could be sensitive to hyperparameter choices, requiring fine-tuning for optimal results. While technical indicators and LSTM networks are powerful, their complexity might make them computationally expensive or challenging to interpret.

6. Conclusion

In conclusion, this research provides valuable insights into the application of technical indicators and LSTM neural networks for stock price and trend prediction. When the performance metric MAPE is reduced, and the R2-Score is between 0.85<R2<1, and the RMSE is reduced, indicating that the model works well in predicting the closing price of the selected stock for the next day. Trend identification is measured by using the confusion matrix. Sample stock readings show that the accuracy of INFOSYS, KOTAK BANK, and HINDUSTAN UNILEVER are remarkably good, i.e., 70%. Good Precision and F1 values in KOTAK BANK and INFOSYS indicate that the model's predictions for positive instances are accurate. The high Specificities of HINDUNILVR, ASIANPAINT, and RELIANCE indicate that the model's predictions for negative instances are accurate and the number of false positives is reduced. The results add to the body of knowledge in the field of financial market forecasting and offer useful recommendations for investors, traders, and financial organizations looking to enhance their stock market decision-making procedures.

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Author contributions

Mr. Rahul Maruti Dhokane: Data collection, conceptualization, methodology, software development, and original draft writing were conducted for this manuscript.

Dr. Sohit Agarwal: For this manuscript, software validation, visualization, investigation, and reviewing and editing were performed.

Conflicts of interest

The authors declare no conflicts of interest.

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