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Evaluating AI convergence and performance analysis for cross transfer entropy based learning among time-lagged data employing cognitive computing framework

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Abstract

Forecasting share market's imminent is a complex and challenging task, necessitating the examination of vast data and the evaluation of various political, social, and economic variables. Due to the intrinsic uncertainty and fluctuation of stock values, an investor consistently endeavors to identify ways for forecasting future trends to minimize losses and optimize profits. Modern developments in the areas of Machine Learning have enabled the application of diverse algorithms for stock price prediction. The paper delivers a inclusive study of different methods and tactics used in financial forecasting, encompassing fundamental evaluation. The research emphasizes the different techniques employed and evaluates their efficacy in forecasting stock market fluctuations. The present research intends to employ nine distinct methods: Regression, ARIMA, SVM, LSTM, CNN, RNN, LSTM – RNN, LSTM – CNN, and LSTM – PSO. The research presented here identifies algorithms that precisely represent real projections. These methodologies are implemented on NSE index data spanning from January 2008 to December 2018. This comprehensive analysis reveals

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that the deep learning algorithm surpasses all other algorithms in forecasting stock prices and time series, yielding findings with significant accuracy.

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Keywords: *Cognitive system, Mathematical computation, Artificial intelligence, AI-augmented framework, Intelligent decision making, Mathematical application and reasoning.*

1. Introduction

Predicting market index values are multifaceted as well as demanding endeavor which necessitates the examination of a number of economic, monetary, and geographical variables [1]. The stock market is a fluctuating and unstable system, shaped by multiple causes that might affect values of certain stocks and overall market performance. Notwithstanding the challenges associated with stock market forecasting, accurate predictions can greatly advantage investors, financial institutions, and politicians [2]. Our research encompasses the timeframe from 2008 to 2018, utilizing daily closing rates, initial cost. This research demonstrates deep analysis frameworks can generate dependable Predictions of NSE values. Forecasting the Indian stock market is essential for the nation's economic advancement and can provide substantial advantages for investors, politicians, and the overall populace. Several strategies and algorithms pertaining to machine learning have been examined and analyzed in [3-5]. Historically, numerous research studies have focused on various common machine learning algorithms to conduct predictive analytics. This research seeks to create machine learning models utilizing nine distinct algorithms and thereafter utilize them for forecasting stock market fluctuations. Subsequently, nine implemented frameworks will be compared against one another using various performance indicators. Machine learning algorithms are employed to construct models [6]. This study thoroughly examines all facets of these algorithms, beginning with their origins, detailing the technique employed, their application in the stock market. Confronted with rising inflation, decreasing bank financing rates, and aspirations for greater returns, wealthy investors are transitioning to the stock market. This highlights the increasing necessity of the financial markets [7-8]. OHLC graphs employ various statistical features to represent prediction numbers.

2. Stock Forecasting Algorithms Taxonomy

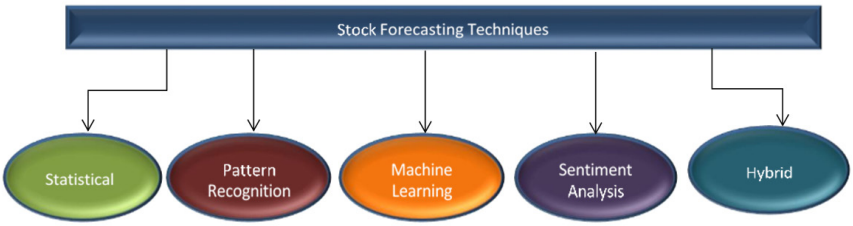


Figure 1

Market Prediction Techniques

Figure 1 shows recent advancements in share market forecasting developed different methodologies to predict stock performance [9]. The phrase 'Time Series,' frequently analyzed in stock market studies, refers to a systematic collection of data pertaining to daily sales, stock prices, investor counts, and similar metrics [10]. Statistical methodologies employed in stock market prediction, classified under univariate analysis due to their reliance on time series data, include the ARIMA framework, ARMA framework, STAR framework, and GARCH framework [11-12]. The ARIMA model can be employed to predict new data points using the current time series data. [13] A particular category of statistical methodologies utilizing many variables as inputs, including QDA, LDA, and regression methods, has been elucidated in. The second technology, Trend Recognition, closely resembles Artificial Learning; nonetheless, their applications significantly diverge in forecasting stock markets. Pattern recognition emphasizes on various observations in provided features [14-18]. Graphing is regarded as an effective method for technical assessment, since it juxtaposes market value and historical volume data with chart patterns to forecast future price fluctuations based on correlation levels [19-21].

3. Machine Learning Frameworks

The machine learning framework is shown in the below Figure 2.

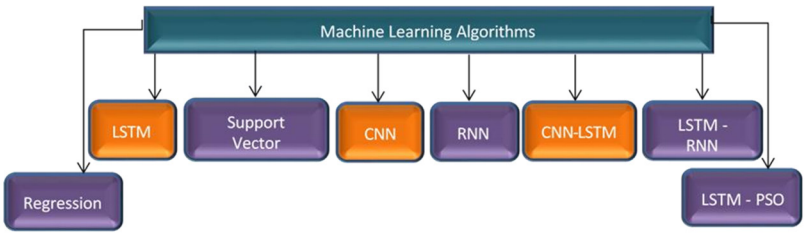


Figure 2
Machine Learning Algorithms

3.1 *Regression*

Linear regression is categorized as an example of supervised learning in artificial intelligence. This method predicts results that reside inside a defined range instead of classifying them. Scientists employed this technique for share market forecasting as well as concluded that its application in predicting daily stock prices. Investors cannot dependably allocate funds based on this algorithm's predictions.

3.2 *SVM Algorithm*

The SVM algorithm, a widely used supervised learning method, is designed for regression as well as categorization tasks. In SVM, the optimum hyperplane is defined as the one that encompasses the highest amount of value coordinates. In SVM technique, extreme vector elements referred as Support Vectors are selected to simplify creation of a hyperplane.

3.3 *LSTM Model*

In the event of an explosion, weights are probably to begin fluctuating, for the instance of vanishing, either the duration necessary to acquire knowledge across extended interval gaps exceeds acceptable limits, or, in the worst scenario, it fails entirely. LSTM method, a revolutionary form of RNN, fundamental form of this LSTM framework comprised solely cells, input gates, and outcome gates.

3.4 *ARIMA Model*

We have amassed ten years of National Stock Exchange index data from Yahoo Finance and employed opening price of the NSE as input for our prediction framework to project upcoming prices [22-24]. ARIMA is a

methodology employed for predicting future values according to data collected by modelling a framework [25].

3.5 *Recurrent Neural Network*

Since inputs and outputs in a conventional neural framework are completely separate from one another. Nonetheless, it is a beneficial proposal for several activities. A continue cycle, wherein result at every stage serves as foundation for subsequent phase, facilitates this endeavor [26].

3.6 *Convolutional Neural Network*

A CNN is engineered to replicate connectivity designs found in visual cortex. The neurons in a CNN framework are structured to identify and react to simultaneous conditions in the visual domain. Nonetheless, CNN frameworks solely focus on the specified response sequence.

3.7 *PSO Framework*

PSO is a biologically-inspired technique that effectively explores the solution space to identify optimal solutions. It distinguishes itself from other optimization methods by necessitating solely the goal function and being independent of the gradient or any differential representation of the objective.

4. Methodology

The technique of a research study is essential for achieving valid and precise results which is demonstrate in Figure 3. First stage entails gathering unprocessed data from many free bases. The next phase involves

Preparation of data, encompassing data scaling, uniformity, cleansing, and other processes technological methods to structure set of data. Final stage involves partitioning the dataset into training and testing portions. To prove the best model, we compared Regression model, SVM technique, ARIMA, CNN, RNN, LSTM, RNN-LSTM, PSO-LSTM and CNN-LSTM utilizing identical training and test datasets within the same operational setting. Finally, five distinct models for NSE datasets were assessed and analyzed utilizing performance indicators, specifically R^2 value, and RMSE, to evaluate and rank execution, enable evaluations and extract dependable conclusions concerning the frameworks.

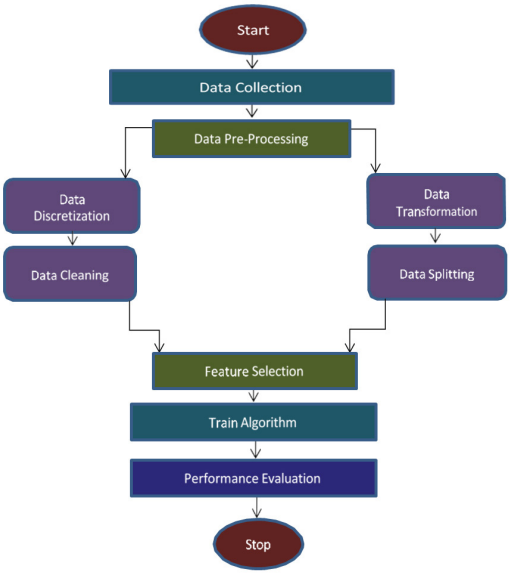


Figure 3

Deep Neural Network Architecture

5. Standard Deviation and Error Analysis

To evaluate the precision of a predictive model, error rate in stock market predictions is determined through an analysis of anticipated returns of an investment with the real returns. It computes mean of the squared discrepancies between forecasted and real earnings by squaring the errors and summing them across all time periods. Table 1 displays the computation parameters for nine models.

Table 1

Performance computation metrics of algorithms

Model	Error rate	Standard Deviation
Linear Regression	37.9624	216.3162
ARIMA Model	31.2597	213.4107
SVM	29.4100	202.3564
CNN	25.3967	181.9092
RNN	18.9624	170.3163

Contd...

LSTM	14.682	108.4572
RNN - LSTM	9.786	66.3498
PSO - LSTM	8.452	52.7431
CNN - LSTM	2.6580	28.1284

Table 2

Analysis of Nine algorithms assessment index

Algorithms	RMSE	R^2
Linear Regression	0.0148	0.8067
ARIMA Model	0.0120	0.8986
SVM	0.0108	0.9173
CNN	0.0102	0.9964
RNN	0.0099	0.9980
LSTM	0.0098	0.9982
RNN - LSTM	0.0054	0.9994
PSO - LSTM	0.0053	0.9996
CNN - LSTM	0.0051	0.9997

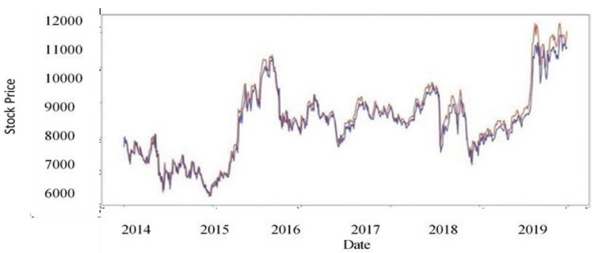


Figure 4

Comparison of Predicted data and Actual value for Regression

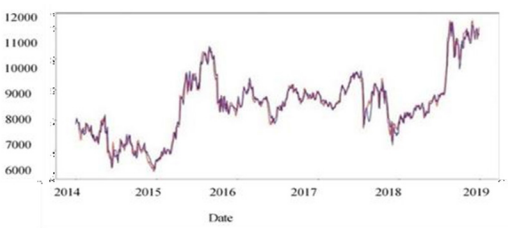


Figure 5

Comparison of Predicted value and Actual value for ARIMA

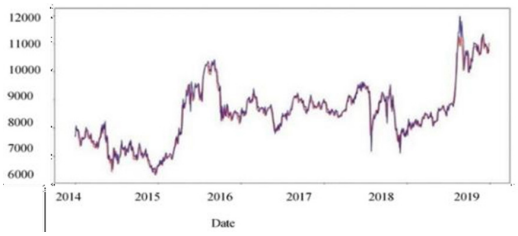


Figure 6

Comparison of Predicted data and Actual value for SVM

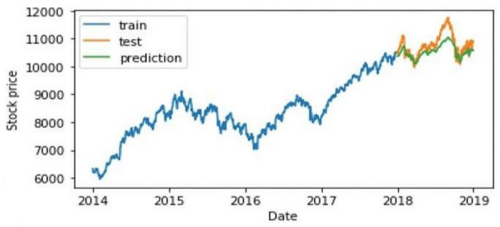


Figure 7

Comparison of Predicted data and the Real value for CNN

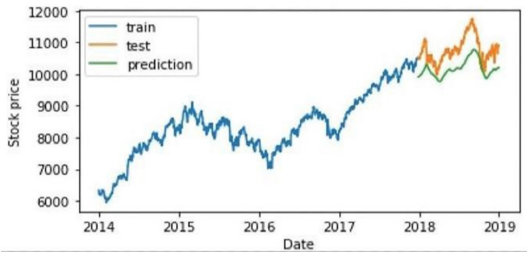


Figure 8

Comparison of Forecasted value and Actual data for RNN

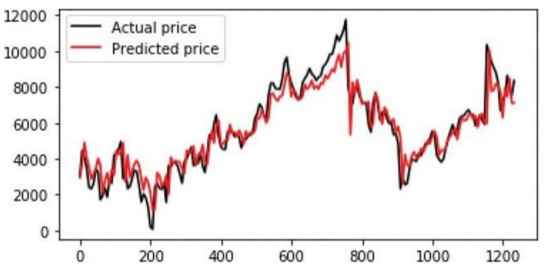


Figure 9

Comparison of Predicted data and Actual data for LSTM

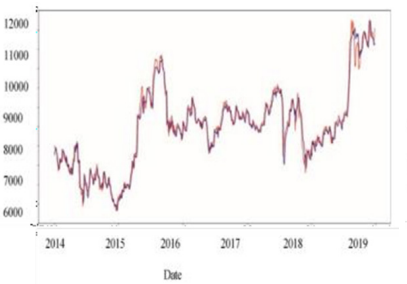


Figure 10

Comparison of Forecasted and the Actual value for RNN-LSTM

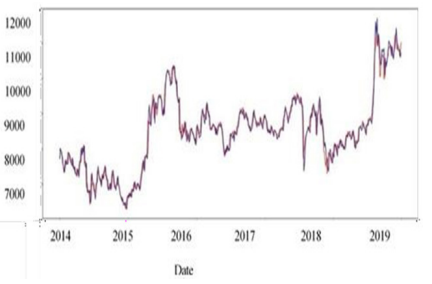


Figure 11

Comparison of Forecasted and the Actual value for PSO- LSTM

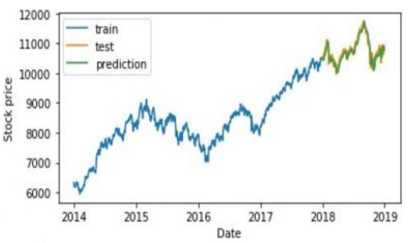


Figure 12

Comparison of Forecasted and the Actual value for CNN-LSTM

The performance evaluation metrics for nine frameworks on test data are presented in Table 1. All Nine machine learning algorithms shown strong performance in forecasting the movements of the NSE index. Comparison of predicted data and actual value for Regression, ARIMA, SVM, CNN, RNN, LSTM, RNN-LSTM, PSO-LSTM, CNN-LSTM demonstrated in Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, and Figure 12. Table 2 presents outcome for R^2 obtained for a specific framework which is evaluated using the NSE dataset. The table clearly indicates that CNN- LSTM algorithm produces the best results out of the nine algorithmic models, with an R^2 value of 0.9997, followed by PSO-LSTM at 0.9996, and so on. Figure 14 illustrates predicted performance of all nine algorithms, represented by R-squared values plotted against NSE dataset. Upon meticulous examination of the graph, it is evident that CNN-LSTM framework has produced most favorable outcomes, as highest positioned histogram (CNN- LSTM) is nearest to '1' in comparison to the other algorithms. The PSO – LSTM algorithm demonstrated second appropriate performance, whereas other

frameworks exhibited subpar and unreliable predictive capabilities. Table 2 and Figure 5 present the results in tabular form for RMSE obtained by testing a specific framework on the NSE. Table 2 clearly indicates that among nine algorithmic frameworks, CNN-LSTM framework demonstrates superior performance, exhibiting an RMSE of 0.0051. Figure 13 illustrates predicted performance of all nine algorithms, represented by RMSE in relation to NSE dataset.

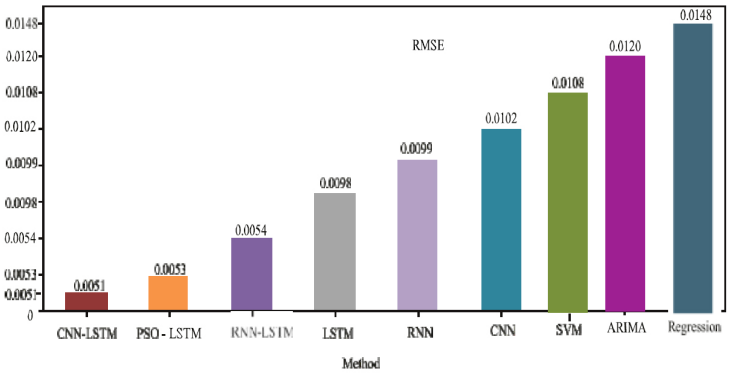


Figure 13

RMSE Analysis of Machine Learning Algorithms

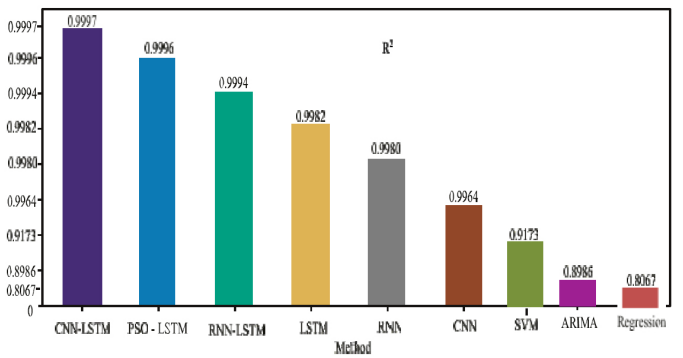


Figure 14

R^2 Analysis of Machine Learning Algorithms

6. Conclusion

Our research examined application of soft computing frameworks for forecasting stocks in India. To develop predictive models, we gathered and

pre-processed NSE data and employed nine distinct soft computing approaches: CNN, LSTM, RNN-LSTM, PSO-LSTM, CNN-LSTM, random, ARIMA, linear regression, support vector machine, and CNN. Financial analysts can significantly benefit from creating artificial intelligence models capable of processing and analyzing real-time data streams After this comprehensive examination, it can be concluded that deep learning algorithms much surpass basic machine learning algorithms in predicting time series data. The collected stock values spanned from 2008 to 2018. The CNN-LSTM algorithm yielded the most favorable outcomes in stock price predictions among the nine evaluated algorithms.

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