iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: IV Month of publication: April 2023

DOI: https://doi.org/10.22214/ijraset.2023.51011

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

Multivariate Index Relationship Exploration Using Advanced Machine Learning Techniques

Jay Patel[1], Siddhanth Jain[2], U. M. Prakash[3]
[1]*Department of Computer Science & Engineering, SRM institute of Science and Technology, Kattankulathur, Chennai, India, 603203*
[2]*Department of Computer Science & Engineering, SRM institute of Science and Technology, Kattankulathur, Chennai, India, 603203*
[3]*Department of Computing Technologies, SRM institute of Science and Technology, Kattankulathur, Chennai, India, 603203*

Abstract: Stock market forecasts have always attracted the attention of many analysts and researchers. Popular theory suggests that stock markets are inherently straightforward, and trying to predict them is a trivial matter. It is a difficult problem in itself. The market behaves like a voting machine in the short term, but in the long term it behaves like a pair of scales. Therefore, there is room to predict market movements over a longer period of time. Applying machine learning techniques and other algorithms to stock price analysis and forecasting is a promising area. This white paper begins with a brief overview of the stock market and a taxonomy of stock market forecasting methods. We then highlight some research findings on resource analysis and forecasting. We discuss technical, fundamental, short- term and long-term approaches to equity analysis. Finally, we present some challenges and research opportunities in this area.
Keywords: crash prediction, machine learning, python, correlation, drawdown

I. INTRODUCTION

Stock market forecasting and analysis is an attempt to determine the future value of an exchange-traded company's stock or other financial instrument. The stock market is an important part of the country's economy and plays an important role in the growth of the country's industry and trade which ultimately affects the country's economy. Both investors and industry are involved in the stock market and want to know whether stocks will rise or fall over a period of time. The stock market is the primary source for companies to raise funds to expand their operations. It is based on the concept of supply and demand. If demand for a company's shares is high, the company's share price will rise, and if demand for the company's shares is low, the company's share price will fall.

National Stock Exchange of India Limited (NSE) is India's leading stock exchange based in Mumbai. NSE was founded in 1992 as the first demutualized electronic exchange in the country. NSE is the first stock exchange in the country to offer a fully automated, modern, screen-based electronic trading system that offers easy trading opportunities to investors across the country.

NIFTY 50 Index is the National Stock Exchange of India's broad benchmark equity market index for the Indian equity market. It represents a weighted average of 50 Indian corporate stocks across 12 sectors and is one of two major stock indices used in India, the other being the BSE Sensex contains very large datasets that are difficult to extract information from and manually analyze work development as they involve many industries and companies. The application developed in this project not only helps predict the future movement of stocks in the market, but also automates data search, trend analysis, predictive analysis and stock insight generation at the click of a button. Stock market analysis and forecasting reveals market patterns and predicts when to buy stocks. Correctly predicting the future price of stocks can yield big profits.

.

II. LITERATURE SURVEY

1) Research on Stock Price Prediction Method Based on Convolutional Neural Networks, IEEE 2019 - Sayavong Lounnapha et al. The dataset is taught and tested in relation to the behavior of convolutional neural networks and the Thai stock market. The results show that models based on convolutional neural networks can effectively detect and imagine stock price trends. It provides an important indicator for stock price prediction. The accuracy of the forecast is high, which could also facilitate the financial sector.

2) Enhancing Profit by Predicting Stock Prices using Deep Neural Networks, IEEE 2019-Soheila Abrishami, et al., Economic time series forecasting is a very difficult task and has attracted the attention of many scientists. , is very important for investors. This white paper focuses on introducing a deep learning system that predicts stock values using a set of facts about a subset of stocks on the NASDAQ stock exchange. This model has been trained on the minimum data for a particular stock and in a few steps accurately estimates the final value of that stock. It consists of an autoencoder that removes noise and uses time-series data techniques to syndicate advanced features with original features. These new functions are fed into a stacked LSTM autoencoder to make multi-level predictions of final stock values. Additionally, this estimate is used by the profit maximization approach to provide guidance on the right time to buy or sell a particular stock. The results show that the proposed framework outperforms state-of-the-art time series forecasting methods in terms of analytical accuracy and effectiveness.
3) LSTM Method for Bitcoin Price Prediction: A Case Study Yahoo Finance Stock Market, IEEE 2019- Ferdiansyah et al., Bitcoin is a type of cryptocurrency and currently a type of stock market asset. There are some risks in the stock market And Bitcoin is a kind of virtual currency, and in recent years it has gone up and down violently, and it may plummet without knowing the impact on the stock market. Due to its volatility, automated tools are needed to predict Bitcoin on the stock market. This research study explores how LSTMs can be used to make modal predictive Bitcoin stock market predictions. Before confirming the results, the paper tries to measure the results using RMSE (Root Mean Square Error). RMSE is always greater than or equal to MAE. The RMSE metric evaluates how well the model computes continuous values. The method applied in this study to forecast Bitcoin on the Yahoo Finance stock market can predict results above US$12600 for days after the forecast.
4) Stock Prediction Using Machine Learning Techniques, IEEE 2019-Jeevan B et al., Everyone is talking about the stock market these days, and science and business people are interested. This paper mainly uses his RNN (Recurrent Neural Network) and his LSTM (Long Short Term Memory) on the National Stock Exchange, using many factors such as current market prices and anonymous events. It deals with an approach to predicting stock prices using This white paper also describes a recommendation system along with a model based on the RNN and LSTM methods used to select companies.
5) Stock Market Forecasting Using Machine Learning Techniques, IEEE 2020 – Naadun Sirimevan et al. Stock market prices play an important role in today's economy. Researchers have found that social media platforms such as Twitter and internet news tend to influence each individual's decision-making process. This study takes into account behavioral reflexes to web messages in order to reduce the gap and make predictions more accurate. Here, accurate predictions were made for 1 day, 1 week, and 2 weeks later.
6) Machine Learning Stock Market Forecasting, IEEE 2018 – Ishita Parmar, Ridam Arora, Lokesh Chouhan, Navanshu Agarwal, Shikhin Gupta, Sheirsh Saxena, Himanshu Dhiman. In this article, we examine a method [3] for predicting stock prices using regression and LSTM-based machine learning. The factors that are measured are opening price, closing price, low price, high price, and volume. This paper was an attempt to use machine learning techniques to improve accuracy and reliability in determining the future price of a company's stock. The LSTM algorithm produced positive results with higher accuracy in stock price prediction.
7) Stock Prediction Using Machine Learning Techniques, IEEE 2018 – Jeevan B, Naresh E, Vijaya kumar BP, Prashanth Kambli. This paper mainly used [5] long-short-term memory (LSTM) and recurrent neural network (RNN) to predict stock prices, using various factors such as current market prices, price-earnings ratios, and baselines. based on an approach to estimating stock prices for NSE data. and other anonymous events. Model efficiency is analyzed by comparing true and predicted data using RNN plots. Machine learning for predicting stock prices as the model can predict stock prices very close to the actual price. This model captures detailed features and uses different strategies to make predictions. The model trains all NSE data from the web, recognizes and groups inputs, and provides inputs according to user configuration. This RNN-based architecture is highly efficient in stock price forecasting by changing the configuration accordingly and using the backpropagation mechanism to avoid data mixing during data collection and grouping. It has been proven.
8) Stock Market Forecasting Using Machine Learning Techniques, IEEE 2016 - Mehak Usmani, Syed Hasan Adil, Kamran Raza, Syed Saad Azhar Ali. The main objective of this study is to predict the market performance of the Karachi Stock Exchange (KSE) at the end of the day using [6] machine learning algorithms. Predictive models are used to predict various attributes as inputs and predictive markets as positive and negative. Features used in the model include oil prices, gold and silver prices, interest rates, foreign exchange rates (FEX), news, and social media feeds. Machine learning algorithms including Single Layer Perceptron (SLP), Multilayer Perceptron (MLP), Radial Basis Function (RBF), and Support Vector Machine (SVM) are compared. The MLP algorithm, a multi-layer perceptron, performed best compared to other methods. The main feature that

helped predict the market was the oil price attribute. The final results of this study confirm that machine learning techniques can predict stock market trends. A multi-layer perceptron machine learning algorithm predicted 70% accurate market performance.

9) Development of Predictive Models for Stock Analysis, IEEE 2017 – R. Yamini Nivetha, Dr. C. Dhaya. A comparative study of three algorithms, namely multiple linear regression (MLR), support vector machine (SVM), and artificial neural network (ANN), is the main purpose of this work. Forecasts are determined by monthly and daily forecasts to forecast the market for the next day. Predict stock prices with sentiment analysis with the best prediction algorithms. A less sophisticated algorithm is the multiple linear regression algorithm that calculates the correlation between volume and price. After research, I found that deep learning algorithms are more developed than his MLR and SVM algorithms.
10) Stock Prediction Based on Information Entropy and Artificial Neural Networks, IEEE 2019 - Zang Yeze, Wang Yiying One of the most important elements of the financial system is the stock market. Funds are provided by affiliated investors to support activities and development. Together with information theory and artificial neural networks (ANNs) form a combination of machine learning frameworks. Informational entropy for nonlinear causality and inventory association is also creatively used in this method to facilitate ANN time series modeling. The feasibility of this machine learning framework is analyzed at Amazon, Apple, Google, and Facebook prices. In this paper, we review time series analysis techniques based on information theory and LSTMs for modeling stock price dynamics. Transfer entropy between related variables supporting LSTM time series forecasting is integrated into this modeling infrastructure, so the accuracy of hypothetical results is nearly guaranteed. Although the modeled and actual stock prices are highly correlated, they differ slightly in terms of mean absolute error (MAE) and mean squared error (RMSE), which are examined using the results.

III. METHODOLOGY

The first step in this process is collecting financial data and identifying crashes. We've been looking for daily price information from major stock markets with low correlation. Low cross-correlation is important for effective cross- validation and model testing. To avoid overfitting, we avoided including two datasets with a cross-correlation greater than 0.5 in the collection. Overfitting occurs when a machine learning model tries to cover all data points or exceeds the required data points for a given dataset. Because of this, the model starts caching noise and inaccurate values in the dataset, all of which reduce the efficiency and accuracy of the model. To identify clashes in each dataset, we first calculate the markdown. A drawdown is a continuous drop in price over several consecutive days from the last high to the next low. Then use Emily Jacobson's methodology. In this methodology, a crash in any market he defines as a drawdown at the 99.5% quantile. A quantile defines a specific portion of a data set. H. The quantile determines whether the values in the distribution are above or below certain limits.

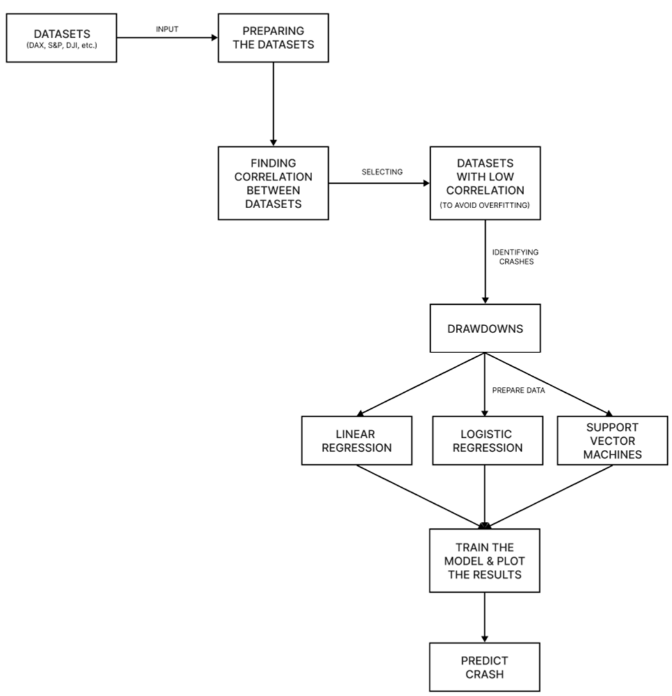


Fig - 1: Block diagram of our project

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

For our project, we collected data from Yahoo Finance. Our dataset consists of historical data for the following major indices: (India), DAX (Europe), SMI (Switzerland), MXX (Mexico), BVSP (Brazil). Select a dataset to investigate further and later use to develop algorithms to predict crashes. The datasets used should not exhibit strong cross-correlations to avoid overfitting to specific patterns or biased test sets.

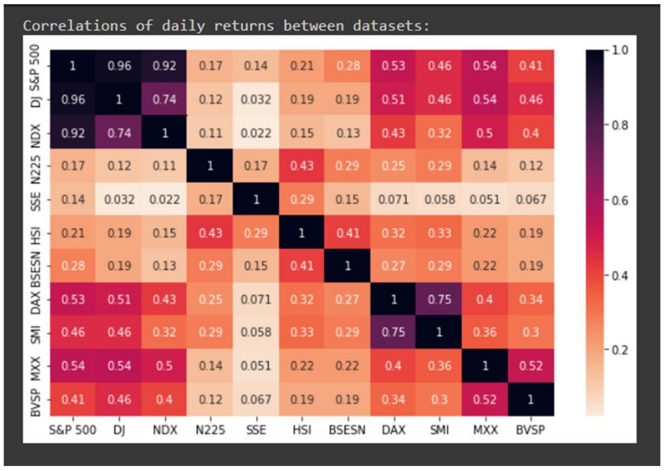


Fig - 2: Correlation between datasets

The correlation matrix shows that the three US indices (S&P, DJ, NDX), DAX and SMI, and MXX and BVSP are highly correlated. To avoid overfitting when training a predictive model, we need to avoid correlations above 0.5 for any two datasets. Therefore, SJ, NDX, DAX, and MXX are excluded for further analysis.

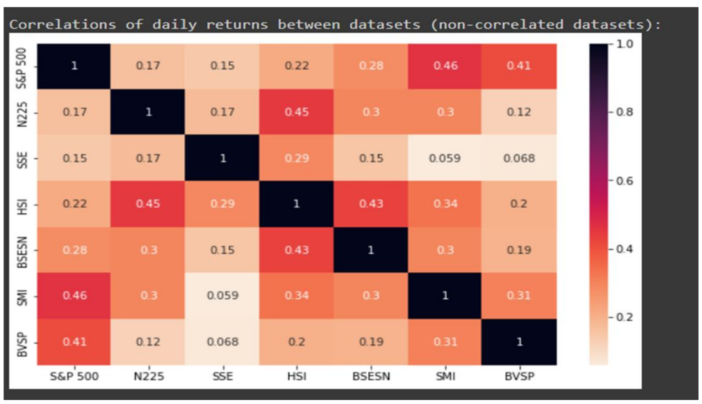


Fig - 3: Datasets with correlation <0.5

The correlation matrices of the remaining data sets show no correlation between any two data sets above 0.5. Now, I will plot the distribution of prices, daily returns and drawdowns.

Fig - 4: Price Vs Time Graph of S&P

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

Fig - 5: Price Vs Time Graph of N225

Fig - 6: Price Vs Time Graph of SSE

Fig - 7: Price Vs Time Graph of HSI

Fig - 8 Price Vs Time Graph of BSESN

Fig - 9: Price Vs Time Graph of SMI

Fig - 10: Price Vs Time Graph of BVSP

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

The time series plots give an impression of the performance of the different markets over the past 50-20 years.
Now I'll plot the Daily Return Graph for the above mentioned Index.

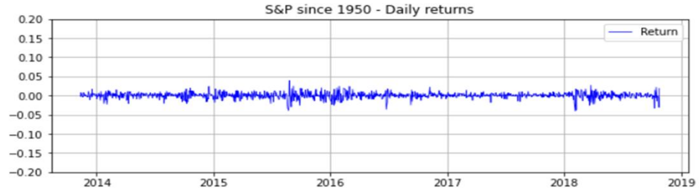


Fig - 11: Daily Return Vs Time Graph of S&P

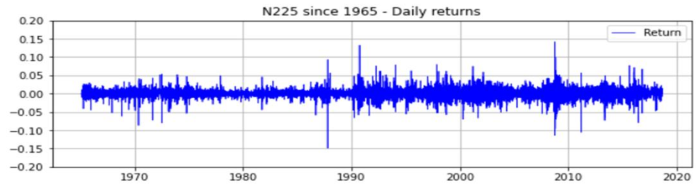


Fig - 12: Daily Return Vs Time Graph of N225

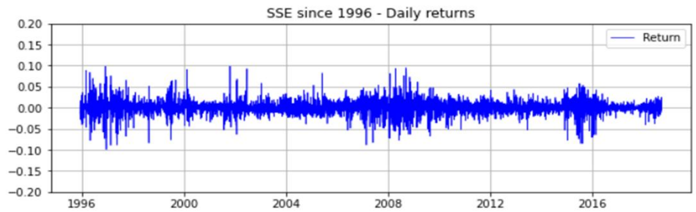


Fig - 13: Daily Return Vs Time Graph of SSE

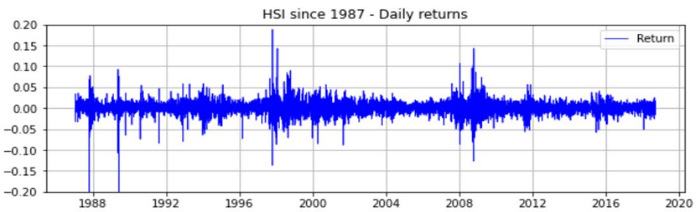


Fig - 14: Daily Return Vs Time Graph of HIS

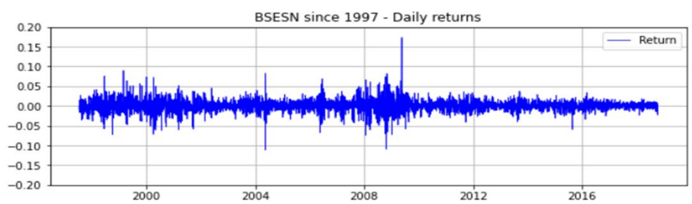


Fig - 15: Daily Return Vs Time Graph of BSESN

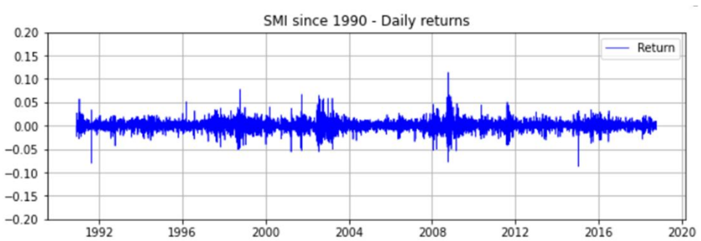


Fig - 16: Daily Return Vs Time Graph of SMI

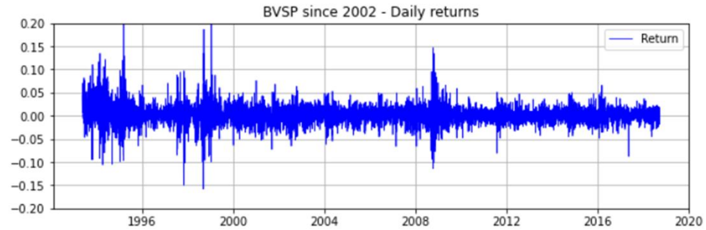


Fig - 17: Daily Return Vs Time Graph of BSVP

The amplitude of daily returns over time for all datasets give an impression of the volatility in the different markets with the Brazilian market showing the largest daily gains/losses.

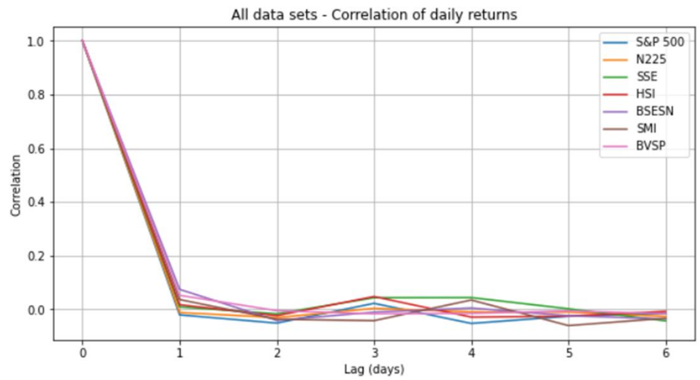


Fig - 18: Correlation of daily return of all Datasets

The autocorrelation of daily returns approaches zero when the lag exceeds one day, indicating that daily returns are not strong predictors of next-day price movements.

Now we will identify crashes. crashes as the 99.5% empirical quantile of the drawdowns (as suggested by Jacobsson, E., Stockholm University, in 'How to predict crashes in financial markets with the Log-Periodic Power Law', 2009).

SSE since 1996 - all crashes (99.5% drawdown quantile):

Date	drawdown	crash_st	crash_end	duration	rank
1996-12-11	-0.272568	1996-12-11	1996-12-17	4	1
2008-06-02	-0.170638	2008-06-02	2008-06-13	9	3
2008-09-25	-0.129240	2008-09-25	2008-10-10	11	6
2008-10-20	-0.126978	2008-10-20	2008-10-27	5	7
2015-06-24	-0.135842	2015-06-24	2015-06-29	3	5
2015-06-30	-0.138012	2015-06-30	2015-07-03	3	4
2015-08-19	-0.228465	2015-08-19	2015-08-26	5	2

Fig - 19: All crashes in SSE since 1966

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

N225 since 1965 - all crashes (99.5% drawdown quantile):

Date	drawdown	crash_st	crash_end	duration	rank
1970-04-24	-0.127345	1970-04-24	1970-04-30	4	11
1971-08-13	-0.197097	1971-08-13	1971-08-19	4	3
1973-11-30	-0.131144	1973-11-30	1973-12-13	9	10
1974-09-25	-0.169037	1974-09-25	1974-10-09	10	6
1987-10-14	-0.177748	1987-10-14	1987-10-20	4	5
1990-03-26	-0.120552	1990-03-26	1990-04-02	5	13
1990-08-15	-0.155609	1990-08-15	1990-08-23	6	7
1990-09-21	-0.149550	1990-09-21	1990-10-01	6	8
1997-01-06	-0.110169	1997-01-06	1997-01-10	4	16
2000-12-13	-0.115071	2000-12-13	2000-12-21	6	14
2008-10-01	-0.271970	2008-10-01	2008-10-10	7	1
2008-10-15	-0.114064	2008-10-15	2008-10-16	1	15
2008-10-21	-0.230313	2008-10-21	2008-10-27	4	2
2011-03-09	-0.187388	2011-03-09	2011-03-15	4	4
2015-08-17	-0.136446	2015-08-17	2015-08-25	6	9
2016-02-08	-0.120657	2016-02-08	2016-02-12	4	12

Fig - 20: All crashes in N225 since 1965

HSI since 1987 - all crashes (99.5% drawdown quantile):

Date	drawdown	crash_st	crash_end	duration	rank
1987-10-14	-0.416907	1987-10-14	1987-10-26	8	1
1989-05-29	-0.264112	1989-05-29	1989-06-05	5	3
1992-11-27	-0.168457	1992-11-27	1992-12-03	4	7
1997-10-17	-0.233417	1997-10-17	1997-10-23	4	5
1997-10-24	-0.187037	1997-10-24	1997-10-28	2	6
1997-12-30	-0.244914	1997-12-30	1998-01-12	9	4
2008-09-08	-0.152052	2008-09-08	2008-09-18	8	9
2008-10-02	-0.152620	2008-10-02	2008-10-08	4	8
2008-10-20	-0.281092	2008-10-20	2008-10-27	5	2
2011-08-01	-0.147051	2011-08-01	2011-08-09	6	10

Fig - 21: All crashes in HSI since 1987

S&P since 1950 - all crashes (99.5% drawdown quantile):

Date	drawdown	crash_st	crash_end	duration	rank
1962-05-15	-0.136724	1962-05-15	1962-05-28	9	3
1974-08-07	-0.097762	1974-08-07	1974-08-19	8	17
1974-09-20	-0.112062	1974-09-20	1974-10-03	9	9
1974-11-11	-0.096474	1974-11-11	1974-11-20	7	18
1980-11-28	-0.093652	1980-11-28	1980-12-11	9	20
1987-10-13	-0.285133	1987-10-13	1987-10-19	4	1
1987-10-21	-0.118856	1987-10-21	1987-10-26	3	7
1997-10-21	-0.098007	1997-10-21	1997-10-27	4	16
1998-08-25	-0.124052	1998-08-25	1998-08-31	4	5
2000-04-07	-0.105378	2000-04-07	2000-04-14	5	13
2001-09-10	-0.116005	2001-09-10	2001-09-21	9	8
2002-07-17	-0.119575	2002-07-17	2002-07-23	4	6
2008-09-30	-0.229037	2008-09-30	2008-10-10	8	2
2008-10-13	-0.095191	2008-10-13	2008-10-15	2	19
2008-11-04	-0.100293	2008-11-04	2008-11-06	2	14
2008-11-18	-0.124174	2008-11-18	2008-11-20	2	4
2009-02-12	-0.109987	2009-02-12	2009-02-23	7	12
2009-02-24	-0.099348	2009-02-24	2009-03-03	5	15
2011-08-03	-0.111779	2011-08-03	2011-08-08	3	10
2015-08-17	-0.111694	2015-08-17	2015-08-25	6	11

Fig - 22: All crashes in S&P since 1950

BSESN since 1997 - all crashes (99.5% drawdown quantile):

Date	drawdown	crash_st	crash_end	duration	rank
2000-04-11	-0.185957	2000-04-11	2000-04-24	9	5
2001-09-04	-0.170386	2001-09-04	2001-09-17	9	6
2008-01-11	-0.196736	2008-01-11	2008-01-22	7	3
2008-10-01	-0.193619	2008-10-01	2008-10-10	7	4
2008-10-21	-0.203478	2008-10-21	2008-10-27	4	1
2008-11-10	-0.197904	2008-11-10	2008-11-20	8	2

Fig - 23: All crashes in BSESN since 1997

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

SMI since 1990 - all crashes (99.5% drawdown quantile):

Date	drawdown	crash_st	crash_end	duration	rank
1998-09-28	-0.166382	1998-09-28	1998-10-05	5	3
2001-09-17	-0.119478	2001-09-17	2001-09-21	4	7
2002-07-17	-0.130555	2002-07-17	2002-07-24	5	5
2003-03-03	-0.122230	2003-03-03	2003-03-12	7	6
2008-01-14	-0.110609	2008-01-14	2008-01-21	5	9
2008-10-03	-0.222768	2008-10-03	2008-10-10	5	1
2008-10-20	-0.115113	2008-10-20	2008-10-27	5	8
2011-07-21	-0.177769	2011-07-21	2011-08-08	12	2
2015-01-13	-0.149264	2015-01-13	2015-01-16	3	4

Fig - 24: All crashes in SMI since 1990

BVSP since 2002 - all crashes (99.5% drawdown quantile):

Date	drawdown	crash_st	crash_end	duration	rank
1995-02-03	-0.273958	1995-02-03	1995-02-16	9	5
1995-02-24	-0.346266	1995-02-24	1995-03-09	9	1
1997-10-21	-0.245774	1997-10-21	1997-10-27	4	7
1998-08-18	-0.234409	1998-08-18	1998-08-27	7	8
1998-09-01	-0.311696	1998-09-01	1998-09-10	7	2
1999-01-06	-0.310190	1999-01-06	1999-01-14	6	3
2008-10-01	-0.284925	2008-10-01	2008-10-10	7	4
2008-10-20	-0.253695	2008-10-20	2008-10-27	5	6

Fig - 25: All crashes in BSVP since 2002

Now we've prepared our dataset and we'll train out Models after finding the best parameter for each of the Models.
After training each model, we will test the model for each of the indices we are considering and then finally we can predict any index we want.
Datasets that we are using for training of Linear Regression are as follows:
S&P500 (USA), Nikkei225 (Japan), SSE (Shanghai/China), HSI (Hong Kong), BSESN (India), SMI (Switzerland), BVSP (Brazil).
Datasets that we are using for training of Logistic Regression are as follows:
S&P500 (USA), Nikkei225 (Japan), SSE (Shanghai/China), HSI (Hong Kong), BSESN (India), SMI (Switzerland), BVSP (Brazil).
Datasets that we are using for training of Support Vector Machine are as follows:
S&P500 (USA), Nikkei225 (Japan), SSE (Shanghai/China), HSI (Hong Kong), BSESN (India), SMI (Switzerland), BVSP (Brazil)

```
Logistic Regression prediction of a crash within 1 months: 0.23
Logistic Regression prediction of a crash within 3 months: 0.97
Logistic Regression prediction of a crash within 6 months: 0.99
```

Fig - 26: Prediction of SVM for S&P

```
Linear Regression prediction of a crash within 1 months: 0.48
Linear Regression prediction of a crash within 3 months: 0.65
Linear Regression prediction of a crash within 6 months: 0.68
```

Fig - 27: Prediction of SVM for S&P

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IV Apr 2023- Available at www.ijraset.com

```
SVM: linear Classification prediction of a crash within 1 months: 0.24
SVM: linear Classification prediction of a crash within 3 months: 0.79
SVM: linear Classification prediction of a crash within 6 months: 0.83
```

Fig - 28: Prediction of SVM for S&P

IV. CONCLUSION

We found that returns are based on duration and drawdown and are not dependent on the index's daily returns.

To identify the decline in each dataset, we first calculated the price decline. A drawdown is a continuous drop in price for several days in a row from the last high to the next low.

Simple price patterns defined by long-term price movements and volatility changes seem to occur regularly before crashes. The best models were able to learn these patterns and predict crashes much better than comparable random models. For example, the best regression model for 3-month crash prediction achieved an accuracy of 0.15 and a recall of 0.59 on the test set, whereas an equivalent random model with no predictive power achieved an accuracy of 0.04 and a recall of 0.16. Achieved. The results for 1-month and 6-month crash predictions are similar, with the highest F-beta scores for 6-month prediction and the worst for 1-month prediction. Whether these results are sufficient to optimize investment strategies is debatable.

Looking at the test data during the crashes and the price index chart of the crash predictor indicator, some crashes were detected very well, while others occurred with little or no warning from the crash predictor.

REFERENCES

[1] Chiu, DY, & Chen, P.J. (2009). Dynamically explore the internal mechanisms of the stock market through fuzzy-based support vector machines with high-dimensional input spaces and genetic algorithms. Expert Systems with Applications, 36(2), 1240-1248.

[2] Chong, E., Han, C., & Park, F.C. (2017). Deep Learning Networks for Analysis of Stock Market and Forecasting: Methodology, Data Plots, and Case Studies. Expert Systems with Applications, 83, 187-205.

[3] Dai, W., Wu, J.Y., and Lu, C.J. (2012). A combination of non-linear independent component analysis and neural networks for predicting Asian stock market indices. Expert Systems with Applications, 39(4),-4452.

[4] Das, S.P., & Padhy, S. (2012). Supporting vector machines for predicting Indian stock market futures prices. International Journal of Computer Applications, 41(3).

[5] Dash R. & Dash P.K. (2016). A hybrid stock trading framework that integrates technical analysis and machine learning techniques. Journal of Finance and Data Science, 2(1), 42-57.

[6] Enke, D. & Thawornwong, S. (2005). Predict stock market returns using data mining and neural networks. Expert Systems with Applications, 29(4), 927-940.

[7] Goodhue, D.L., & Thompson, R. L (1995). Adaptability of task technology and individual performance MIS Quarterly, 213-236.

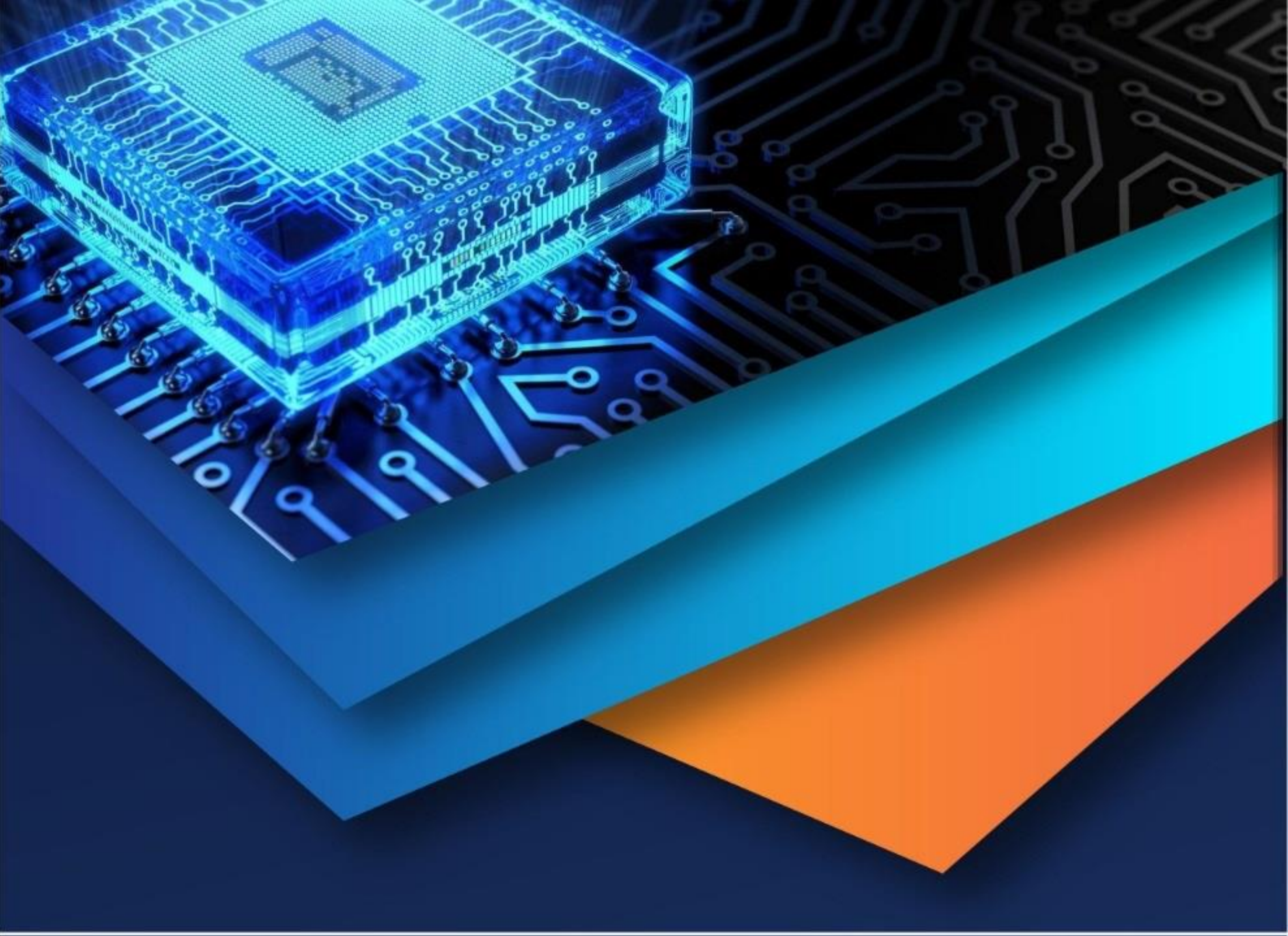
[8] Guresen, E., Kayakutlu, G., & Daim, TU (2011). Use of artificial neural network models in prediction of the stock market. Expert Systems with Applications, 38(8), 10389-10397.

[9] Kim, K.J. & Lee, W.B. (2004). Stock market forecasting using artificial neural networks with optimal feature transformations. Neural Computing and Applications, 13(3), 255-260.

[10] Jasic, T. & Wood, D. (2004). Profitability of Daily Stock Market Indices Based on Neural Network Predictions: A Case Study of the S&P 500, DAX, TOPIX, and FTSE from 1965 to 1999. Applied Finance, 14(4), 285-297.

[11] Kim, H.J. & Shin, K. S (2007). A hybrid approach on study of neural networks and genetic algorithms to identify temporal patterns in stock markets. Applied Soft Computing, 7(2), 569-576.

[12] Kim, K. J. & Han, I. (2000). A Genetic Algorithm Approaches Feature Discretization in Artificial Neural Networks for Stock Index Prediction Expert Systems with Applications, 19(2), 125-132.



10.22214/IJRASET

INDEX COPERNICUS
45.98

ISRA JIF
IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR: 7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)