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Introspecting predictability of market fear in Indian context during COVID-19 pandemic: An integrated approach of applied predictive modelling and explainable AI

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ABSTRACT

Financial markets across the globe have seen rapid volatility and uncertainty owing to scary and disruptive impacts of COVID-19 pandemic. Mayhem wrecked by frequent lockdowns, curfews, emergencies, etc. has stoked the high quantum of chaotic movement in equity markets and resulted in perplexed investor behaviour. It, therefore, is of paramount practical relevance to measure predictability of market fear at such a crucial juncture of time. Market fear can effectively be measured in terms of implied and historic volatility of equity markets. The present study chooses India VIX and 20-day rolling standard deviation of NIFTY returns to account for implied and historic volatility respectively during the ongoing COVID-19 timeline. Pertinent macroeconomic constructs, technical indicators and Google search volume index on meaningful keywords have been chosen as raw explanatory features for inspecting predictability. Boruta feature selection methodology has been used in a supervised manner to select significant features. State-Of-The-Art machine and deep learning algorithms namely Gradient Boosting (GB), Extra Tree Regression (ERT), Deep Neural Network (DNN), Long Short Term Memory Network (LSTM) are then used on processed feature set to scrupulously evaluate the quantum of predictability of said assets. The integrated predictive frameworks have been subjected to a battery of numerical and statistical checks to draw inferences. Additionally, Explainable AI frameworks have been used to analyse the nature of influence of respective features. Findings indeed suggest that despite exhibiting high degree of volatile traits, both India VIX and historic volatility can be predicted utilizing the proposed architectures effectively and serve practical actionable insights.

1. Introduction

The outbreak of COVID-19 (Berber, Sumbria & Canakoglu, 2021) has created a sense of growing fear and intense uncertainty among common people that have eventually been reflected in equity markets across the world. The World Health Organization (WHO) has declared the infection as pandemic after its skyrocket jump in spreading new infections and adverse impacts on livelihood (Ali, Baloch, Ahmed, Ali, & Iqbal, 2020). Since then, the first and second waves of the pandemic have resulted in lockdowns, disruptions in supply chain, and closure of business in different sectors across the world. Stock markets of developed and emerging economies have received severe impacts of COVID-19 pandemic (Duan, Liu & Wang, 2021; Ozkan, 2021). Yousfi, Zaid, Cheikh, Lahouel & Bouzgarrou (2021) studied the difference in behavioural pattern of stock market response to 1st and 2nd wave of pandemic distinctly. Market fear induced profound spill-overs among different finan-

cial assets (Feng, Sun, Liu, & Li, 2021). Study of Liu, Wei, Wang, & Liu (2021) hinted at risk contagion realized by volatility information among the equity markets during the pandemic timeline. Therefore, it indeed is of utmost importance to investigate the pattern of market fear as accounted by the inherent volatility for various strategic implications and decision making.

Market fear is a critical macroeconomic construct which demands in-depth and thorough monitoring due to its strong nexus with critical financial assets even in normal circumstances (Bouri, Gupta, Housseini and Lau, 2018; Just & Echaust, 2020). It can be represented by various means as reported in literature (Sarwar, 2012; Zhu, Liu, Wang, Wei, & Wei, 2019). The underlying work advances manifests linked to economic indicators to measure the extent of market fear. Implied volatility index (VIX) is a proxy to account for futures volatility of option pricing (Bekaert & Hoerova, 2014). VIX is marked as a major asset to capture market fear in leading developed and developing economies. India VIX (IV) has been chosen as an instrument of the same in Indian context. On

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the other hand, it is a common practice to estimate realized volatility of financial assets and plethora of heterogeneous commodities to evaluate the quantum of historic volatility (HV) and chaotic traits in the trading atmosphere. We have incorporated HV of NIFTY index, major stock exchange of India, as another indicator to gauge the inherent fear component. The present research aims to carry out predictive modelling of both IV and HV separately to establish a framework in order to anticipate fear in future.

It should be noted that throughout the literature interplay and connections of VIX and HV with different assets have been critically delved into (Kang et al., 2020; Shahzad et al., 2019; Sarwar et al., 2021; Yang & Shao, 2020). Their respective influence on predicting important variables linked to financial and economic health has been studied minutely as well (Wang, 2019; Wang et al., 2021). However, dedicated exercise to develop a holistic framework to actually demystify micro dynamics of IV or HV is comparatively indeed scarce. Specifically in Indian context, there exists a clear paucity of research in modelling and predicting future figures of IV and HV in the new normal time horizon. Designing a robust framework capable of decoding the complex dynamics would be of paramount significance as the same directly benefits investors and government regulators working at different hierarchies of capital markets. Efficient policy formation and regulation can be performed if precise estimates of future figures of the considered variables can be achieved. To address the aforesaid research void, the present study attempts to construct a predictive architecture to obtain accurate forecasts of both variables on daily time intervals.

The major contribution of the current research lies in the process of decoding the inherent dynamics of market fear in India during the pandemic situation through the lens of advanced predictive analytics. The work critically identifies a set of explanatory features based on relevant past literature. It is very crucial to systematically identify them beforehand as they directly govern the performance of any predictive model. The present research incorporates three broad categories of explanatory variables namely, macroeconomic indicators, technical indicators and sentiment indices during the pandemic. Macroeconomic indicators include daily observations of national and global stock indices, sectoral indices, and essential commodities. The technical indicators are basically simple mathematical functions on historical information of the target itself. Both macroeconomic and technical indicators have been reported to be highly useful in modelling complex financial time series (Ghosh, Jana & Sanyal, 2019). Incorporation of sentiments pertinent to the unprecedented event adds a new dimension to the research. The rationale behind selection of social media sentiments is drawn from literature wherein work dedicated to development of new index based on internet search volumes to measure the market fear of COVID-19 pandemic (Su et al., 2021; Yu, Xiao and Liu, 2021) have been reported. Ridhwan & Hargreaves (2021) critically decoded the public sentiment based on information retrieved from the social media platform during the pandemic. Sentiments reflected in social media tend to substantially govern different assets at various capacities (Ahn, Son and Chung, 2021; Neogi, Garg, Mishra & Dwivedi, 2021; Stone & Can, 2021; Tandon, Revankar, Palivela & Parihar, 2021). Liu et al. (2021) argued fear sentiment owing to COVID-19 pandemic augmented the possibility of market crash. In general media coverage, sentiments, etc. have been observed to possess some explanatory capacity in governing the volatility of financial markets Guidolin & Pedio (2021). The present work resorts to Google Search Volume Index (GSVI) (Swamy, Dharani & Takeda, 2019; Afkhami, Ghoddsi & Rafizadeh, 2021) on different keywords to extract the cognate sentiment effectively. It nevertheless, is pretty apparent that predicting asset movement during Pre COVID-19 time horizon is relatively easier whereas drawing prediction during the pandemic regime is extremely challenging and arduous. The novelty and systematic set up of predictive structure decide the eventual outcome. Thus mere inclusion of potential features in machine or deep learning architectures directly may not be ideal. The present research relies upon Boruta feature selection algorithm to evaluate the explanatory capability of individual

features and filter out features associated with statistically insignificant capability. Presence of insignificant features may result in overfitting problems as well. Afterwards, the filtered feature set is plugged into four machine and deep learning algorithms for performing predictive analytics of IV and HV. In this research, Extreme Gradient Boosting (XGB) and Extremely Randomized Trees (ERT) techniques have been chosen ensemble machine learning techniques to check predictability whilst standard deep neural network (DNN), and Long Short-Term Memory Network (LSTM) have been chosen as deep learning counterparts. All predictive tools have been subjected to a battery of rigorous performance checks to ascertain the quality of forecasts. Additionally, statistical comparative tests have been conducted to draw further insights. Barring the scrupulous predictive exercise, black box type working principles of the presented applied predictive structures have been attempted to be interpreted as well using 'Shapash' Python library which adopts Explainable Artificial Intelligence (AI) paradigm. The said exercise is useful to comprehend the role of predictors in governing IV and HV.

The remaining segment of the paper is arranged as follows. Section 2 reports the summary of review of previous literature to describe the ongoing trends and gaps to rationalize the current work. Complete elucidation of the research methodology in terms of individual components and research flow are enunciated in Section 3. Data descriptions in detail including the fundamental statistics, definitions and other relevant features of compiled datasets are then presented in Section 4. Section 5 illustrates the results of predictive exercise and caters proper analyses of the same. The contribution towards cognate literature and practical implications are discussed explicitly in Section 6. Finally, the paper is concluded in Section 7, highlighting the major findings and presenting adequate remarks on scopes, limitations, and future research prospects.

2. Previous literature

In this section, we have critically summarized the outcome of an exhaustive survey of relevant literature to illustrate implications of modelling volatility, rationale of selecting predictors, and highlight the trend of cognate predictive modelling work. We have confined the review to literature on market fear manifested by VIX and HV only.

2.1. Implications of volatility

Kang et al. (2020) investigated the contagion interaction of stocks, commodities, bonds and VIX markets exhaustively. Findings indicated that the stock markets were largely affected by the shocks. Research of Shahzad, Aloui & Jammazi. (2020) implied existence of strong bond among US sectoral CDS, stock, and VIX indices. Presence of asymmetric association was unveiled. Laborda & Olmo (2021) Study of Wang et al. (2020) demonstrated VIX alongside economic political uncertainty (EPU) turned out to be a critical predictor variable for forecasting future figures of equity markets during the pandemic. Sarwar et al. (2020) thoroughly investigated the interplay of volatility contagion in terms of second moments of VIX of US and European markets. VIX shocks emerged to be key enablers of risk transmission which intensified during Brexit and GFC periods. US VIX on the other hand has emerged to be a prominent explainer of Chinese stock market volatility as per the findings of Xiao, Wen, Zhao & Wang. (2021). Research of Kang et al. demonstrated that the impact of historic volatility of global equity markets to commodity prices varies across time and geography. Wen et al. (2021) empirically investigated the volatility spill-over dynamics of Chinese stock and commodity markets. Study revealed that during the COVID-19 pandemic, shocks arising from historic volatility of stock markets intensely affected commodity markets. Thus, it is apparent that market fear manifested through IV and HV do share a strong connection with financial assets. Therefore, choosing macroeconomic indicators as explanatory features to estimate future figures of IV and HV. It is also amply evident that precise modelling volatility can serve meaningful

insights which can be leveraged accordingly for effective controlling of other assets, risk mitigation, and portfolio realignment.

2.2. Predictors of volatility

As discussed, barring macroeconomic indicators, technical indicators and GSVI data have been used as explanatory constructs as well. Financial time series literature is replete with technical analysis based forecasting models to estimate future figures of different financial and time series data (Ayala, Garcia-Torres, Noguera, Gomez-Vela & Divina, 2021; Dai, Zhu & Kang, 2021; Peng, Albuquerque, Kimura, Portela & Saavedra, 2021). Series exhibiting autoregressive or long memory dependence tend to be significantly explained by technical indicators. As the current work attempts to predict market fear through forecasting time series observations, it is justified to deploy technical indicators as predictors. Degree of efficiency of financial assets determines the degree of dependence on external events and news. Agarwal et al. (2019) conducted an exhaustive review on the impact of information floating on the internet to stock market movements. Predictive capacity of relevant sentiment in driving equity markets has been documented by Maqsood et al. (2020). Volatility and market fears too have been acknowledged to be influenced by the same. Literature reports development of a new index based on internet search volumes to measure the market fear of COVID-19 pandemic (Su et al., 2021). Li, Jiang, Li & Wang. (2021) explained fear sentiment owing to COVID-19 pandemic augmented possibility of market crash. Work of John & Li (2021) explained efficacy of Google search data to capture sentiment pertinent to COVID-19 pandemic. Lehrer, Xie & Zhang. (2021) critically measured the explanatory prowess of social media sentiment manifesting consumer confidence on volatility of economic indicators using the heterogeneous auto regression (HAR) model. Results suggested social media sentiment improved forecasting accuracy in the short run. Hence, the growing prominence of social sentiment in predictive analysis of complicated forecasting tasks is apparent which motivated us to undertake GSVI on COVID-19 linked keywords in Indian context as independent variables.

2.3. Predictive modelling of volatility

Forecasting volatility is an extremely arduous task which has garnered growing attention amongst the researchers (Chatziantoniou, Degiannakis, Delis & Filis, 2020; Hasanov, Shaiban & Al-Freedi, 2020; Cheng, Swanson & Yan, 2021). Model based estimation of volatility through conventional and advanced econometric modelling, autoregressive conditional heteroscedasticity (ARCH), Generalized ARCH (GARCH), etc. has seen substantial traction in literature (Kim and Fan, 2021; Ghosh, Sanyal & Jana, 2021; Aras, 2021; Werge & Wintemberger, 2021). These work nevertheless, predominantly aim to test hypothesis, draw inferences, checking leverage effects, etc. For trading or investing purposes, forecasting based models are preferred. Luo, Klein, Ji & Hou (2019) leveraged integrated HAR models with hidden Markov regime-switching structures to account for jumps, leverage, and speculation effects to perform realized volatility modelling of five agricultural commodity futures namely, Corn, Cotton, Indica Rice, Palm Oil, and Soybeans. Efficiency of said approaches was established through rigorous performance assessment. Work of Liu (2019) carried out a comparative predictive analysis of LSTM and support vector machine for volatility forecasting. Predictive outcome suggested in terms of accuracy there was no significant difference between the models. Hu, Ni & Wen. (2020) developed a hybrid framework of LSTM and Artificial Neural Network coupled with GARCH for predictive modelling of Copper price volatility wherein the output of GARCH framework was feed into the formers in conjugation with other features for drawing forecasts. The model emerged to be extremely efficient in terms of prediction quality. Vidal & Kristjanpoller (2020) developed a hybrid framework of LSTM and Convolutional Neural Network (CNN) for predicting

realized volatility of Gold price. The famous pre-trained VCG16 network was used as CNN architecture. Predictive performance indicated that the framework outperformed standalone LSTM and classic GARCH model statistically. Yanget al. (2020) carried out rigorous predictive analytics of high frequency financial market volatility of Chinese market through combining Support Vector Machine and HAR model. Outcome of the exercise duly justified the efficiency of the presented framework. Zhang, Wang & Wang (2020) presented a novel framework of LSTM coupled with a stochastic time strength function for predicting energy futures index volatility at different time intervals. The empirical findings rationalized the usage of the framework. Li et al. (2021) advanced a granular deep learning model combining variational mode decomposition (VMD) and bidirectional LSTM for forecasting historical Crude Oil returns and volatility based on sentiment reflected in oil related news. It was found that the proposed neoteric approach outperformed several benchmark models. Weng, Zhang & Yang. (2021) proposed an integrated forecasting model of genetic algorithm regularization online extreme learning machine with a forgetting factor for estimating volatility of crude oil futures on the basis of opinion and news linked to COVID-19 pandemic.

Comprehensive review of previous literature assists in identifying the key explanatory features for predictive analytics of market fear in India. It is amply apparent that despite the implications of VIX and historic volatility in economic development, modelling the governing pattern of the same in Indian context has been overseen largely. Proper modelling can trigger close monitoring of other allied assets as well. It is extremely critical to conduct the said exercise during the pandemic environment for estimating the futuristic trends precisely in new normal to gauge the nexus of IV and HV with other assets beforehand. Thus, undertaking the research to demystify the behavioural dynamics of market fear measured through IV and HV is well justified considering the existing research gaps. Successful development of robust predictive architectures would therefore be a significant contribution. Predictive modelling literature has been found to be predominantly bank on advanced machine and deep learning based computational frameworks for forecasting assignments which rationalize the methodologies decided for the present work.

3. Research methodology

This section elaborates the different research components utilized in present work to achieve desired research goals, data sources, and performance metrics used for evaluating and validating the eventual findings. Detailed procedural steps of feature selection algorithm, Boruta is outlined at first as the same is invoked initially to build the predictive structure. Subsequently, fundamentals of machine and deep learning frameworks have been summarized.

3.1. Boruta algorithm

It is a random forest (RF) based ensemble machine learning inspired feature selection paradigm (Kursa, Jankowski & Rudnicki, 2010, Kursa & Rudnicki, 2010). RF typically employs several unbiased classification/regression trees as base learners which are grown using bootstrapped training samples for performing predictions. Relevance of independent features is realized based on reduction of prediction precision caused by artificially changing the values of explanatory features. Boruta is an extended version of RF which simply adds a high level of randomness in its methodological framework for evaluating features. Detailed description of it can be found in the work of Kursa et al. (2010). Outcome of Boruta can be explained through visualizations to distinguish between the significant and insignificant features. Implementation of the framework has been carried out using 'Boruta' package of R.

3.2. Extreme gradient boosting (XGB)

It is a scalable and time effective implementation of ensemble gradient boosting algorithm for predictive modelling (Friedman, 2001). It follows the same logical operational sequences of Boosting technique for accomplishing predictive modeling tasks. XGB uses decision trees as base learners for arriving at the final outcome. In this framework individual training samples are assigned weightage based on the error rate after completion of the learning process by a base learner. Updated weights subsequently enable the rest of the base learners to put more emphasis on training samples associated with high error rate. The fundamental steps of the predictive modeling process have been enunciated as follows.

- Step 1: Given a set (D) containing N training samples ($\langle x_1, y_1 \rangle, \langle x_2, y_2 \rangle, \dots, \langle x_N, y_N \rangle$) initial weights of individual samples are assigned to $1/d$ (d denotes cardinality of the set).
- Step 2: Individual base learner (i) are employed carry out following steps in sequential way.
 - Step 2.1: A new training set, D_i is generated by drawing bootstrapped samples.
 - Step 2.2: The said set D_i is used to train the model M_k .
 - Step 2.3: Estimate the resultant error of M_k (Error(M_k)).
 - Step 2.4: If the magnitude of error is higher than 0.5 repeat steps 2.1-2.3 else perform 2.5
 - Step 2.5: Modify the respective weights assigned to training samples D_i .
 - Step 2.6: The weight values are normalized.
- Step 3: Determine accuracy of individual base learners.
- Step 4: Weighted sum of predictions derived by base learners becomes the final output.

The model has been implemented in Python programming language using the 'XGBoost' library whilst process parameter tuning has been accomplished using the 'GridSearch' utility based 10-fold cross validation approach of Python.

3.3. Extremely randomized trees (ERT)

Proposed by Geurts, Ernst & Wehenkel. (2006), ERT is an ensemble predictive modelling framework wherein the thresholds for branching operations in base learners are selected randomly apart from picking random subset of features for executing the said operations. It is a collection of unpruned decision trees for predictive modelling. Based on the nature of the decision trees, regression or classification task. Present work incorporates classical regression trees for implementing ERT. Predictions of individual trees are aggregated by arithmetic average to yield the final prediction. The advantage of ERT method ensemble learning lies in the integrated process of explicit randomization of threshold and attribute selection coupled with ensemble averaging which would drastically reduce bias variance in comparison to other weaker randomization processes of other methods. Unlike the majority of ensemble techniques, ERT relies upon the entire calibration sample instead of bootstrapped one for completion of learning. Performance of ERT depends upon three process parameters, number of unpruned decision trees, number of attributes to be selected randomly, and minimum sample size for splitting operations. We have simulated ERT using the 'sklearn' library of Python and process parameters have been auto tuned using the 'GridSearch' utility based 10-fold cross validation approach of Python.

3.4. Deep neural network (DNN)

The ongoing surge in development and subsequent success of deep learning paradigms in performing complex pattern recognition tasks

have seen growing traction towards construction of predictive architectures incorporating multiple hidden layers in traditional ANN models. Frameworks composed of conventional ANN with more than one hidden layer are termed as DNN (Liu, Wang, Liu, Zeng & Liu, 2017; Qureshi, Khan, Zameer & Usman, 2017). Stacking of multiple hidden layers serves as a provision for generating better decision boundaries through a myriad of feature transformations and interactions. It has been found to be extremely effective in drastically augmenting the quality of predictions. Individual hidden layers of the DNN model consist of a number of neurons which are connected to neurons of adjacent layers. They receive output from the previous layer and result in output to be served as input to the subsequent layer through applying different activation functions.

In the hidden layer, neurons weigh the output of the previous layer and transmit them to the next layer. Mathematically, the basic operations of DNN can be surmised through following equations.

$$x_{k,i} = \sum_{j=1}^{N_{k-1}} [(w_{k-1,j,i} z_{k-1,j}) + b_{k,i}] \tag{5}$$

$$z_{k,i} = \frac{1}{1 + e^{-x_{k,i}}} \tag{6}$$

$$Y = \sum_{i=1}^{N_3} w_{3,1,i} Z_{3,i} \tag{7}$$

where, $x_{k,i}$ is the i th neuron of k -th hidden layer, N_k denotes the number of neurons in k -th layer, b represents the bias unit, w represents the weigh connecting two layers, z is the resultant value after applying transformation function, and Y is the final outcome. Depending upon the nature of the problem, DNN can be utilized for classification and regression task. In the underlying work, DNN has been chosen as one of the predictive modeler for estimating the exchange rate in recursive manner by predicting the figures of expected volatility of the same at the first stage.

The simulation DNN model has been carried out using the 'Keras' interface in the Python programming environment. Three hidden layers comprising 50 hidden nodes each, have been used. 'Rectified Linear' activation functions are used in the hidden layer while 'Linear' activation function is used at the output layer. A dropout layer of 20% after each hidden layer is added to avoid overfitting. For learning the parameters, 'Adam' optimization algorithm is selected with 1000 iterations.

3.5. Long and short-term memory neural network (LSTM)

Brainchild of Hochreiter & Schmidhuber (1997), LSTM possesses the capability of overcoming the 'vanishing gradient' problem while delving into critical nonlinear pattern (Graves & Schmidhuber 2005, Graves, Liwicki, Fernandez, Bertolami & Bunke et al. 2009, Fischer & Krauss 2018). LSTM is an extended version of standard recurrent neural network (RNN) model which has been observed to yield robust performance in performing complicated predictive modelling tasks (Harikrishnan & Urolagin, 2021; Urolagin, Sharma & Datta, 2021). In addition to the capability of standard DNN models, LSTM can preserve both adjacent and long-term temporal information for mining the evolutionary pattern of time series observations through introducing several logical operations in deep learning frameworks. The LSTM model comprises memory cells to preserve information and three types of controlling gates to maintain the flow. Memory cells are responsible for restoring short to long range information which are controlled through the constituent gates. The Input gates govern the quantum of present information to be used as input for obtaining present state. Forget gates monitor the extent of stored records of memory cells to be held or to be updated with newer information. Finally, the output gate sets the forward propagation of information by filtering operations to produce the final output representing the predictions. Likewise DNN, LSTM can be used for both classification and regression tasks. The input (i_t) and cell state (C_t) figures of respective memory units are estimated by following equations

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{8}$$

$$C_t = \tanh(W_C x_t + U_C h_{t-1} + b_C) \tag{9}$$

where W , U , b represent the layer wise weight matrices and bias units whilst σ and \tanh are sigmoid and nonlinear hyperbolic tangent function.

Output of forget gate is computed as:

$$f(t) = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{10}$$

The updated memory cell state is generated using the following.

$$\tilde{C}_t = i_t \times C_t + f_t \times C_{t-1} \tag{11}$$

Outcome of output gates can be calculated as

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o C_t + b_o) \tag{12}$$

Final output is calculated as:

$$h_t = o_t \times \tanh(C_t) \tag{13}$$

The back-propagation through time (BPTT) algorithm has been used for learning process in LSTM model. In our study, 3 LSTM blocks comprising 50 units each have been considered. ‘Sigmoid’ functions are chosen as activation functions while ‘ADAM’ optimizer is used in BPTT framework. The LSTM algorithm has been implemented using Python Programming language in ‘Tensorflow’ platform.

3.6. Explainable AI

The current work also carefully attempts to explain the role of underlying features through systematic interpretation of the black box type predictive modelling. It should be noted that all four underlying models, XGB, ERT, DNN, and LSTM have emerged to be highly effective in analysing the predictability of exchange rates in different regimes. Despite the success of yielding accurate forecasts, the models offer very little interpretation on feature influence over the target construct. On the other hand, it often becomes necessary to critically evaluate the contribution of explanatory features in driving the target for managerial and strategic implications. Conventional statistical models viz. regression analysis can provide the said interpretation at the cost of prediction accuracy and satisfaction of several constraints. The constituent variables in this study have barely been found to exhibit normal distribution and compromising quality of prediction does not arise as well. Thus to gauge the influence structure based on nonlinear modelling strictly, we have resorted to Explainable AI framework implementation via ‘Shapash’ library of Python. At the backend of the library, two Explainable AI algorithms namely, Local Interpretable Model-Agnostic Explanations (LIME) (Ribeiro, Singh & Guestrin, 2016) and Shapley additive explanation (SHAP) (Lundberg and Lee, 2017) for model interpretation. LIME builds sparse linear models on perturbations of data points predicted by a global model to demystify how the black box model works in the local vicinity and surmises the influence of individual features. On the other hand, SHAP leverages the conventional game-theory driven Shapley values for identifying critical features and ranking them accordingly. Shapley values are computed based on the average marginal contributions of respective explanatory features considering all possible coalitions. ‘Shapash’ provides a plethora of modelling algorithms including RF, Catboost, XGboost, LightGBM, SVM, etc. Thus, deploying the library explicitly provides deeper insights pertinent to relevance of explanatory features at local and global level.

3.7. Data sources

Daily observations of IV during March 1, 2020 to May 31, 2021 from ‘Metastock’ data repository have been compiled. The ‘Metastock’ package is a commercial data hub for wide range financial trading data. The timespan critically embodies the 1st and 2nd wave of COVID-19 pandemic in Indian context. The HV series is computed applying 20-day rolling standard deviation on daily returns of NIFTY index collated

from the same data source. The study uses 9 macroeconomic variables, 11 technical indicators, and 8 GSVI constructs as explanatory features. Data of macroeconomic variables have been compiled from ‘Metastock’; technical indicators are computed based on the actual figures of targets, and GSVI sentiment indicators have been extracted using Python library.

3.8. Performance metrics

To assess the quality of obtained predictions by respective models, four performance indices have been deployed in this work. Definitions of these indices are enunciated below.

3.8.1. Nash-sutcliffe efficiency (NSE)

It measures the relative strength of residual variance emerging from the underlying predictive model compared to the original variance of the dataset and is calculated as:

$$NSE = 1 - \frac{\sum_{i=1}^N \{\hat{Y}_i - Y_i\}^2}{\sum_{i=1}^N \{Y_i - \bar{Y}_i\}^2} \tag{14}$$

The values of NSE range from $-\infty$ to 1 where high values imply supreme precision of forecasts.

3.8.2. Index of agreement (IA)

It is estimated as:

$$IA = 1 - \frac{\sum_{i=1}^N (\hat{Y}_i - Y_i)^2}{\sum_{i=1}^N \left\{ \left| \hat{Y}_i - \bar{Y}_i \right| + \left| Y_i - \bar{Y}_i \right| \right\}^2} \tag{15}$$

IA attempts to check the strength of error parts to judge the quality of forecasts. IA values should be close to 1 for superior forecasts.

3.8.3. Theil inequality index (TI)

It is a useful indicator to measure predictive accuracy for financial time series forecasting (Ghosh et al., 2019). TI values are calculated using Eq. (13).

$$TI = \frac{\left[\frac{1}{N} \sum_{i=1}^N (\hat{Y}_i - Y_i)^2 \right]^{1/2}}{\left[\frac{1}{N} \sum_{i=1}^N (\hat{Y}_i)^2 \right]^{1/2} + \left[\frac{1}{N} \sum_{i=1}^N (Y_i)^2 \right]^{1/2}} \tag{16}$$

Unlike the other two metrics, lower TI figures indicate better predictive accuracy.

3.8.4. Directional predictive accuracy (DA)

It is computed as:-

$$DA = \frac{1}{N} \sum_{i=1}^N D_i, \quad D_i = \begin{cases} 1, & (Y_{i+1} - Y_i)(\hat{Y}_{i+1} - Y_i) \geq 0 \\ 0, & \text{Otherwise} \end{cases} \tag{17}$$

Directional predictive performance is extremely critical to check since it can examine the ability of prediction models in yielding accurate future trends in short and long-time scales. DA figures close to 1 suggests better directional accuracy, while figures close to 0 imply poor results.

3.8.5. Comparative performance evaluation

It is occasionally necessary and interesting too to carry out comparative predictive performance to figure out the statistically superior model in terms of quality of predictions. To achieve the goal, Model Confidence Set (MCS) based statistical superior predictive ability assessment (Hansen, Lunde & Nason, 2011) has been invoked. In this paper, we have used MCS to rank the predictive performance of XGB, ERT, DNN, and LSTM for drawing forecasts of IV and HV separately.

Table 1
Fundamental properties of IV and HV.

Regimes	IV	HV
Sample	278	278
Minimum	16.89	0.0058
Maximum	64.41	0.0284
Mean	25.05	0.0114
Median	22.50	0.0107
SD	7.65	0.0036
Skewness	2.29	1.47
Kurtosis	5.74	3.34
ADF Test	-3.0622***	-2.6174***
JB Test	658.4***	225.41***
Frosini Test	1.89***	0.84***
Terasvirta's NN Test	8.79**	8.49**
Hurst Exponent	0.81***	0.79***

** Significant at 5% Level of Significance,

*** Significant at 1% Level of Significance,

SD: Standard Deviation, ADF Test: Augmented Dickey-Fuller Test, JB Test: Jarque-Bera Test

4. Data descriptions

Basic statistical properties of underlying dataset have been analysed in this section which provides key insights that justify the design and usage of the research framework. Table 1 reports fundamental statistical properties of IV and HV.

Both IV and HV have appeared to be stationary as manifested by the significant test statistics of ADF test. Outcome of JB and Frosini tests suggest underlying variables are strictly nonparametric in nature as the test statistics have emerged to be highly significant. Proceeding with the analysis, we next inspect the extent of nonlinear traits in temporal dynamics of market fear indicators. Output of the Terasvirta's NN test imply existence of nonlinear traits entrenched in evolutionary patterns of concerned time series variables. Therefore, deployment of state-of-the-art predictive modelling and Explainable AI components capable of modelling nonlinear patterns in nonparametric setup is duly justified. Magnitude of estimated Hurst exponent for both components has emerged to be substantially greater than 0.5 which simply indicates the underlying indicators are not random and can be predicted (Jana, Ghosh & Sanyal, 2020). Presence of long memory dependence is implied which also vindicates the decision of employing technical indicators as independent features.

The rationale behind selection of said macroeconomic variables for explaining movements of IV and HV has been discussed in the previous section. The sectoral indices, AUTO, METAL, and PHARMA have been chosen on the basis of consistent demand for vehicles and medicines during the pandemic in Indian market. On the other hand, the BANK index reflects the performance of the financial sector across India. It is also important to check the impact of shocks received by relatively smaller sectors which is why MIDCAP and SMALLCAP are chosen. DJIA is a proxy of influence of the global market whilst CRUDEOIL is an extremely critical asset to monitor owing to its impact in upstream industrial activities.

The selection of technical indicators for forecasting volatility has been rare in literature despite their widespread use in predicting other financial assets. As the present research attempts to decode market fear by recognizing the hidden pattern of time series observations, we have deployed technical indicators as explanatory features. The definition of incorporated technical indicators are presented in following Table 3.

Lastly, GSVI sentiment indicators are used to capture the role sentiments related to COVID-19 pandemic in Indian context on driving IV and HV. The keywords used to form respective GSVI are outlined in Table 2. The choice of these keywords lie in careful extraction of negative and positive sentiments floating on the internet. The first four keywords resemble negative feelings associated with the new virus strain, fatality,

restrictions, curbs etc. whereas the remaining four keywords resemble positive feelings linked to vaccination, government initiatives, leisure, declaration of packages or funds, etc.

Figs. 1–6 depict the box and whisker plots of independent feature setups for respective predictive exercises.

The aforesaid figures clearly hint at presence of wide variety in distribution of three categories of explanatory features for predictive exercises of IV and HV respectively. Apparently, the existence of few outliers actually account for extreme events which are quite common in the new normal time regime and can effectively explain the unexpected behaviour of targets.

The following Figs. 7–12 visually exhibit the degree of linear association between the target and 4 input features of respective categories of independent variables, measured through Pearson's Product Moment Correlation amongst the dataset.

The above figures reflecting degree of linear association between the target and respective independent manifests imply presence of substantial interaction on most of the occasions. The independent constructs, nevertheless, have been found to be affected by multicollinearity effects on certain occasions. The remaining explanatory features also exhibit similar behavioural traits. Thus, the prevailing nonlinear and nonparametric structure of IV and HV in addition to multicollinearity has propelled us to rely upon complete nonparametric frameworks capable of modelling nonlinear patterns. On the other hand, bare presence of linear association does not imply linear causal interrelationship. As both IV and HV have prevailed to be nonlinear as per the Terasvirta's NN test, outlined in the Table 1, existence of nonlinear bond between target and explanatory feature is highly likely. Presence of multi-collinear movements in conjunction with nonparametric and nonlinear behavioural pattern rules out possibility of deploying conventional statistical models to accomplish endeavours. On the other hand, machine and deep learning algorithms are well known and tailor made for delving nonlinear pattern irrespective of distribution assumptions (Nasir, Khan & Varlamis, 2021; Tripathi, Goswami, Trivedi & Sharma, 2021). Therefore, applying machine and deep learning for predicting market fear manifested through IV and HV is duly rationalized.

5. Results and analysis

This section elucidates the outcome of the entire predictive modelling tasks in detail with critical analysis of findings for drawing inferences. As stated earlier, chosen explanatory features have been carefully evaluated to inspect their predictive capabilities through Boruta feature selection method for forwarding the significant ones into the machine and deep learning methods to draw forecasts. The detailed outcome of the feature engineering process is explained initially.

5.1. Outcome of feature selection

All 28 features for predicting IV and HV have been considered for evaluation. Number of iterations of the Boruta algorithm has been fixed to 500. Beyond 500 iterations no changes in the results were observed. Output of the said feature selection procedure have been visually represented in Figs. 13 and 14. Shadow features are marked in Blue box plots, features with significant explanatory prowess are marked using Green box plots, statistically insignificant features are pointed through Red box plots, and the Yellow box plots signify the tentative features.

GSVI sentiment indicators on keywords 'DEATH' has been identified as insignificant feature while 'GOVERNMENT', 'NETFLIX', and 'FUND' based GSVI have emerged to be tentative as per the Boruta method for feature evaluation for IV prediction. The remaining 24 features have been identified to be significant features with statistically more explanatory power than the Shadow ones. LAG1 has been marked as the most prominent feature with highest predictive power. As overfitting is typically very common in applied predictive analysis tasks, we have filtered out the tentative features as well from the final set of selected fea-

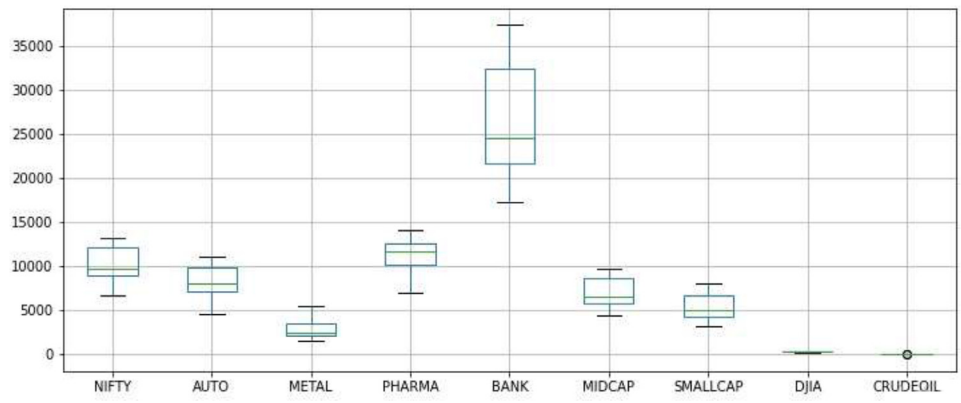


Fig. 1. Box and whisker plot of macroeconomic variables for IV prediction.

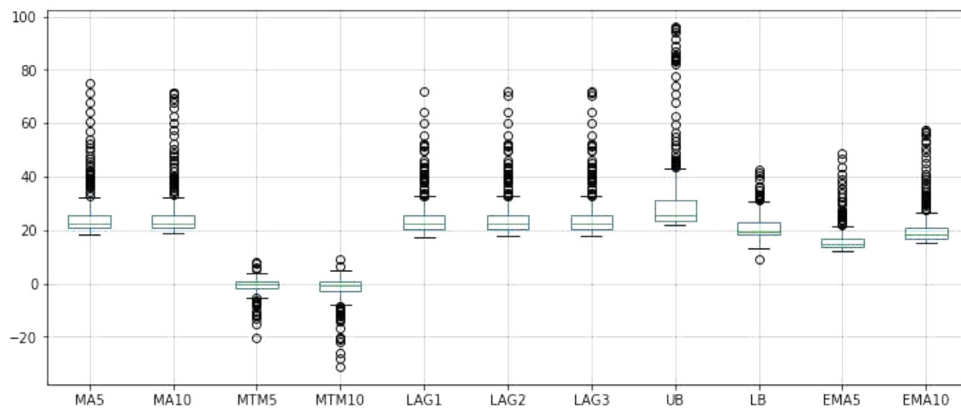


Fig. 2. Box and whisker plot of technical indicators for IV prediction.

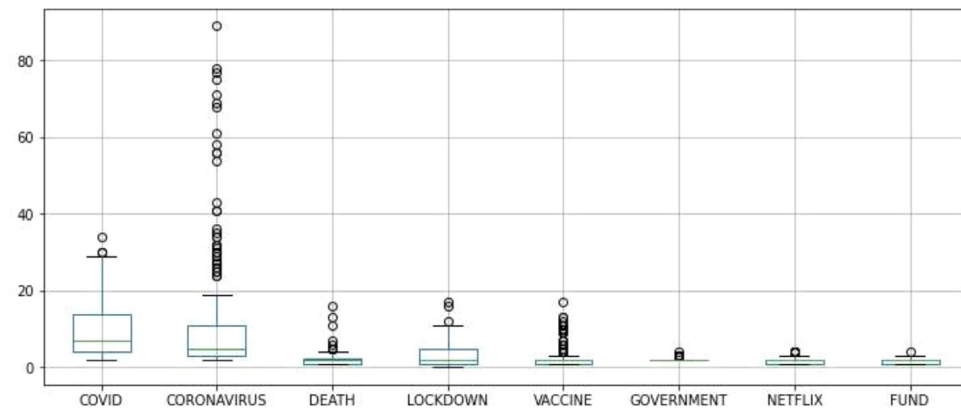


Fig. 3. Box and whisker plot of GSVI sentiment indicators for IV prediction.

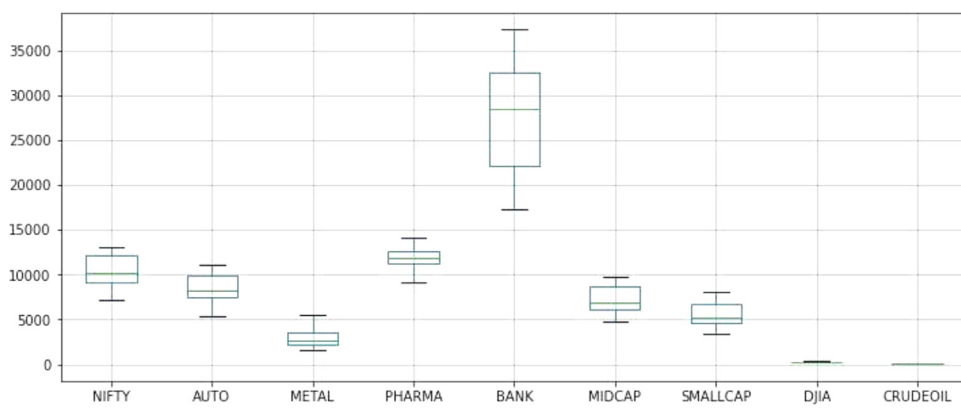


Fig. 4. Box and whisker plot of macroeconomic variables for HV prediction.

Table 2
Explanatory variable details

Macroeconomic Variables	Technical Indicators	GSVI Sentiment Indicators
Closing Prices of NIFTY, Auto Sector (AUTO), Metal Sector (METAL), Pharmaceutical Sector (PHARMA), NIFTY Bank Index (BANK), Mid Cap Sector (MIDCAP), Small Cap Sector (SMALLCAP), DJIA, WTI Crude Oil Futures (CRUDEOIL).	5-Day Moving Average (MA5), 10-Day Moving Average (MA10), 5-Day Momentum (MTM5), 10-Day Momentum (MTM10), One-day Lag (LAG1), Two-Day Lag (LAG2), Three-Day Lag (LAG3), Upper Bollinger Band (UB), Lower Bollinger Band (LB), 5-Day Exponential Moving Average, 10-Day Exponential Moving Average (EMA10)	'COVID', 'CORONAVIRUS', 'DEATH', 'LOCKDOWN', 'VACCINE', 'GOVERNMENT', 'NETFLIX', 'FUND'.

Table 3
Definition of technical indicators.

Technical Indicators	GSVI Sentiment Indicators
MA5	$MA5 = \frac{\sum_{i=t-4}^t P_i}{5}$, P_i represents actual observation at i^{th} day
MA10	$MA10 = \frac{\sum_{i=t-9}^t P_i}{10}$
MTM5	$MTM5 = P_i - P_{i-5}$
MTM510	$MTM10 = P_i - P_{i-10}$
LAG1	$LAG1 = P_{i-1}$ where P_{i-1} denotes observation at previous day
LAG2	$LAG2 = P_{i-2}$
LAG3	$LAG3 = P_{i-3}$
UB	$UB = MA20 + (20 \times \sigma_{20})$ where σ_{20} denotes standard deviation of observations previous 20 days
LB	$LB = MA20 - (20 \times \sigma_{20})$
EMA5	$EMA5 = \frac{2}{5+1} \times P_3 + \frac{5-1}{5+1} \times EMA4$, where $EMA1 = P_1$
EMA10	$EMA10 = \frac{2}{10+1} \times P_9 + \frac{10-1}{10+1} \times EMA9$

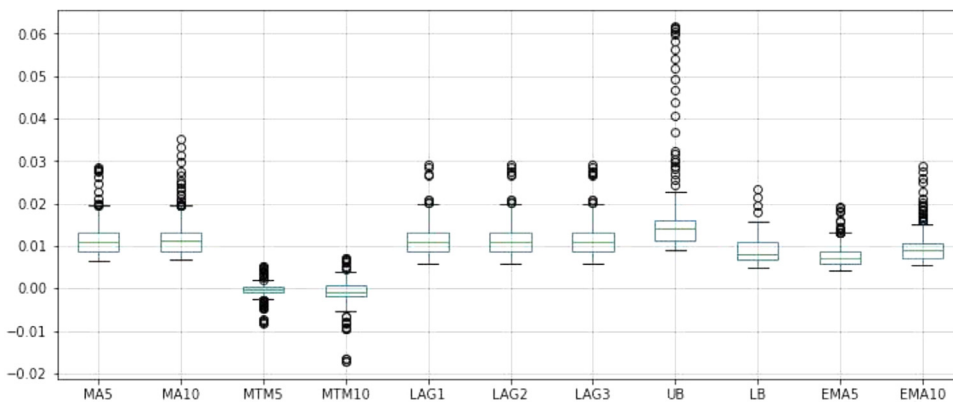


Fig. 5. Box and whisker plot of technical indicators for HV prediction.

tures which comprises significant attributes only. Similar phenomenon has prevailed for HV as well with clear distinction. The same four keywords, 'DEATH', 'GOVERNMENT', 'NETFLIX', and 'FUND' based GSVI indicators have emerged to be statistically insignificant. Remaining 24 features appear to possess significant predictive ability in comparison to the Shadow features. No features have turned out to be tentative whilst likewise IV, LAG1 has emerged to be the most influential feature for HV too. Thus the final feature set for HV prediction is similar to the feature set for predicting IV. On the basis final feature sets for both variable learning operations of utilized machine and deep learning algorithms have been performed.

5.2. Outcome of predictive analytics

To conduct predictive exercise, the entire data segment needs to be partitioned into training and test segments in an effective manner. Random partitioning is not well suited for determining predictability of time series data. To accomplish the task, the present study resorts to forward-looking segmentation (Ghosh et al., 2019) of the entire samples of IV and HV into training (85%) and test (15%) sets. Approximately, the data spanning from March, 2020 to March, 2021 are used to form training samples whilst data of April to May, 2021 construct the test segment.

Table 4
Predictive performance for modelling IV.

	XGB	ERT	DNN	LSTM
Training Dataset				
IA	0.9911	0.9908	0.9905	0.9902
TI	0.0173	0.0177	0.0175	0.0179
DA	0.9837	0.9837	0.9837	0.9796
NSE	0.9891	0.9886	0.9887	0.9881
Test Dataset				
IA	0.9835	0.9829	0.9833	0.9819
TI	0.0194	0.0198	0.0196	0.0203
DA	0.9767	0.9767	0.9767	0.9767
NSE	0.9806	0.9792	0.9798	0.9785

The said partitioning effectively introspects the quantum of predictability of market fear specifically to the time horizon heavily affected by 2nd wave of COVID-19 in India. Therefore, efficacy of the frameworks would be tested on a highly volatile and uncertain time period. Tables 4 and 5 summarize the predictive performance of utilized models measured through the performance indicators discussed in the previous section on both training and test samples for respective variables.

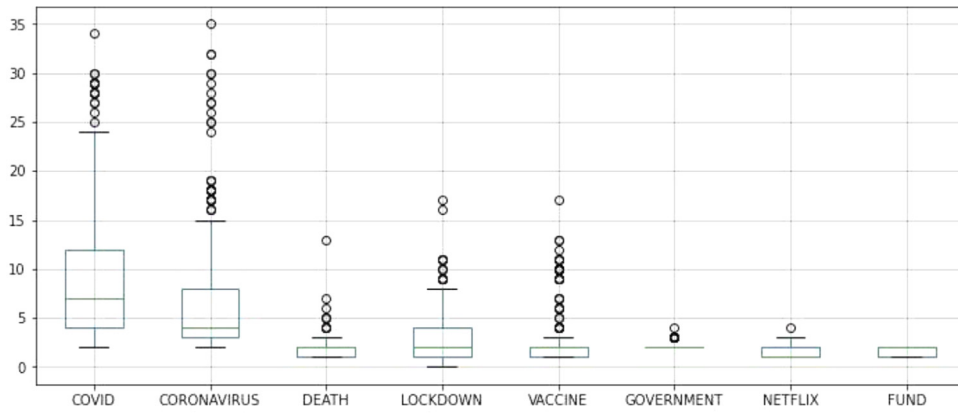


Fig. 6. Box and whisker plot of GSVI sentiment indicators for HV prediction.

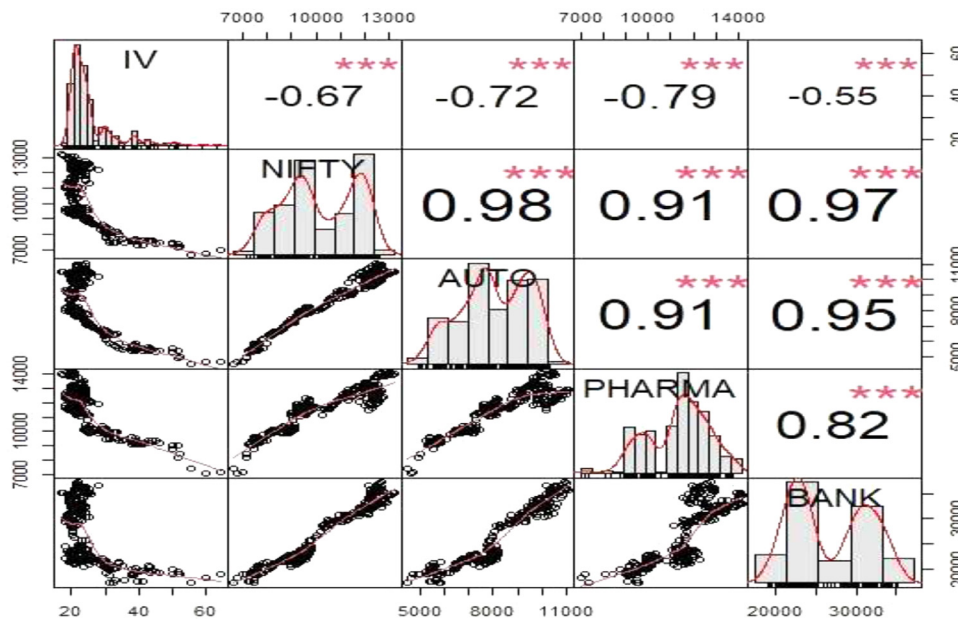


Fig. 7. Correlation between IV and macroeconomic variables.

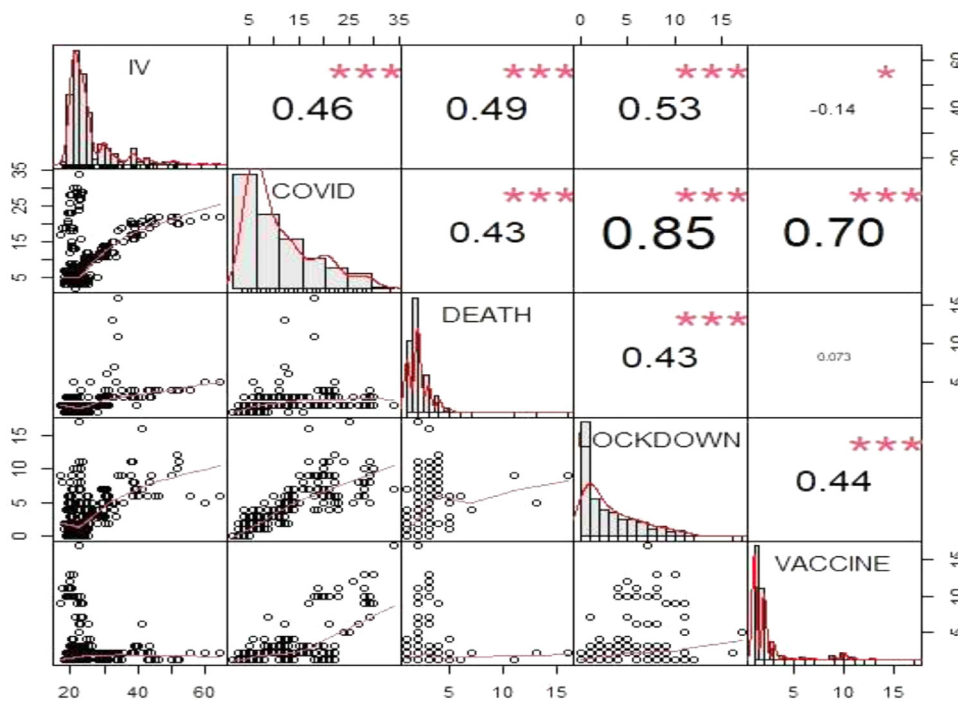


Fig. 8. Correlation between IV and technical indicators.

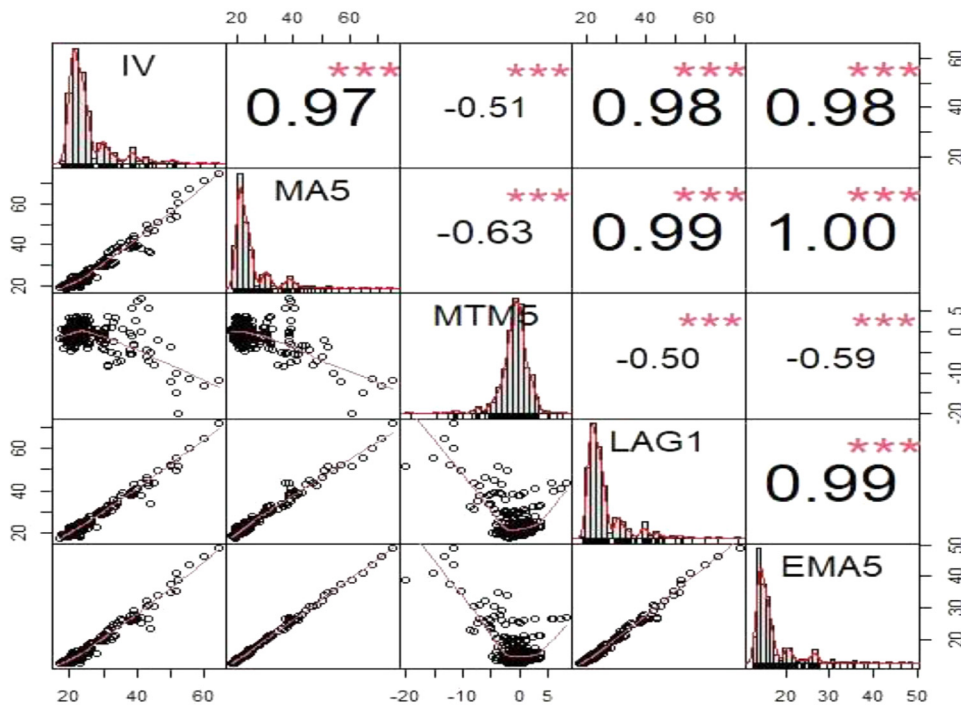


Figure 9. Correlation between IV and GSVI sentiment indicators.

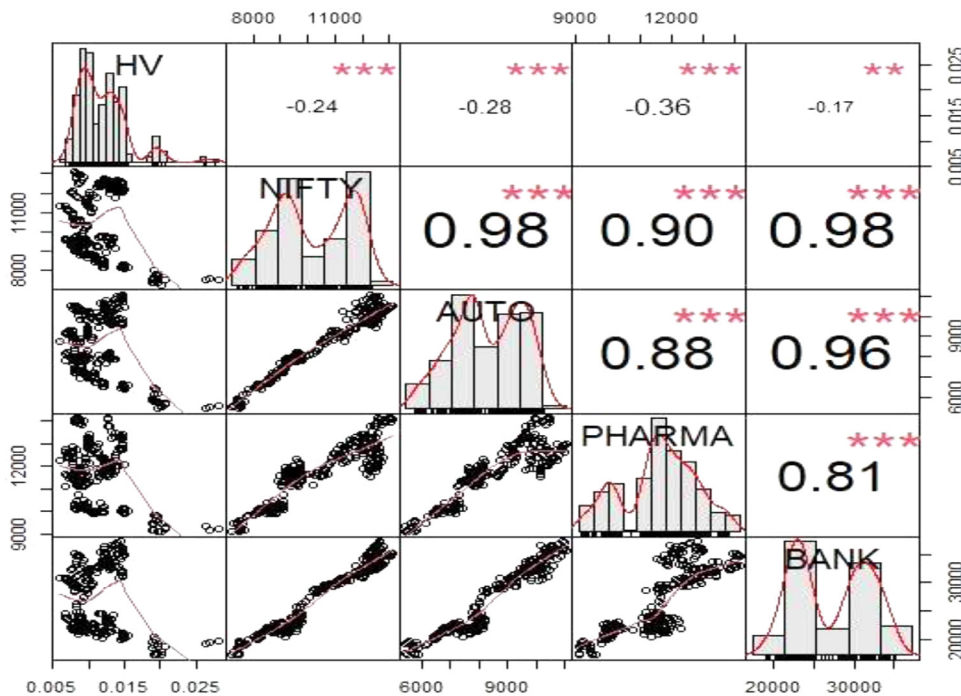


Figure 10. Correlation between HV and macroeconomic variables.

It can be seen that figures of IA and NSE for the time series variable have appeared to be pretty high on training and test segments across all four predictive models. On the other hand, values of TI have emerged to be substantially low also on all occasions. Values of DA have turned out to be highly appreciable as well as manifested on training and test data segments which is very encouraging for traders to predict trends with utmost effectiveness. Hence, it can be concluded that XGB, ERT, DNN, and RF have been extremely successful in precise estimation of future movements of IV. Visually, it seems XGB has a marginal edge over the remaining three models in terms of the performance indicators. Statistical significance of the claim has been drawn using MCS evaluation,

reported later. It can be inferred that market fear accounted for by IV is indeed predictable using the entire integrated research model.

Outcome of predictive exercise for HV also suggests similar findings to that of IV. IA and NSE values have appeared to be on the higher side while magnitude of TI values lies on the lower side on training and test samples. Figure of DA has been found to be more than satisfactory as well which implies apart from achieving precise estimates of absolute figures of HV, the trend of the same can be forecasted with superlative degree of precision too. It is interesting to note that in comparison to IV, figures of estimated performance indicators characterizing HV forecasting have seen a decrease. For example, the value of IA for the XGB

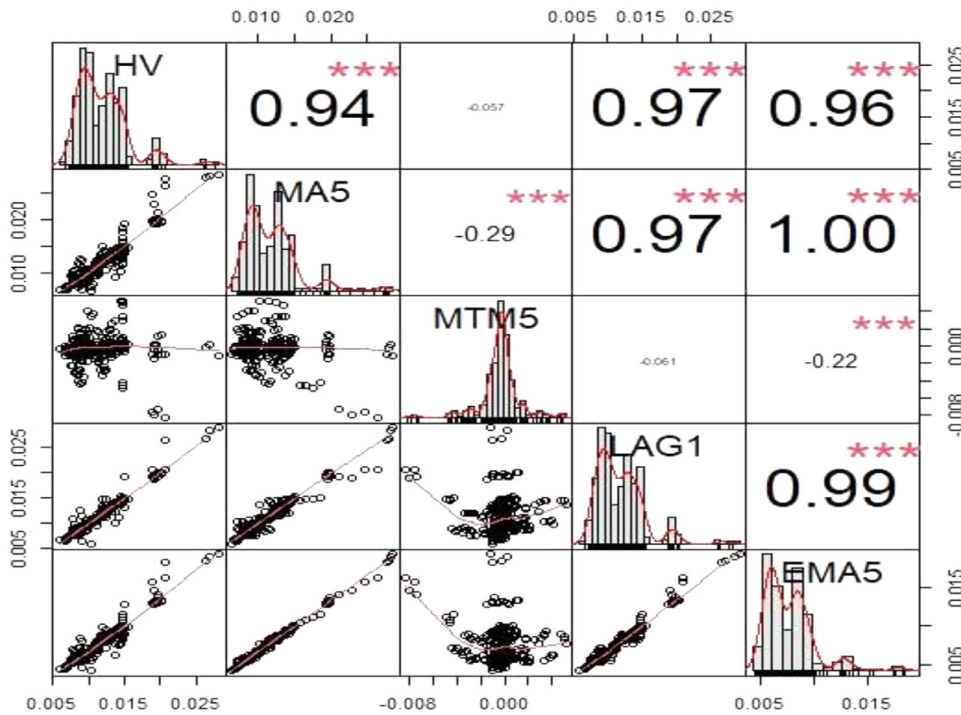


Fig. 11. Correlation between HV and technical indicators.

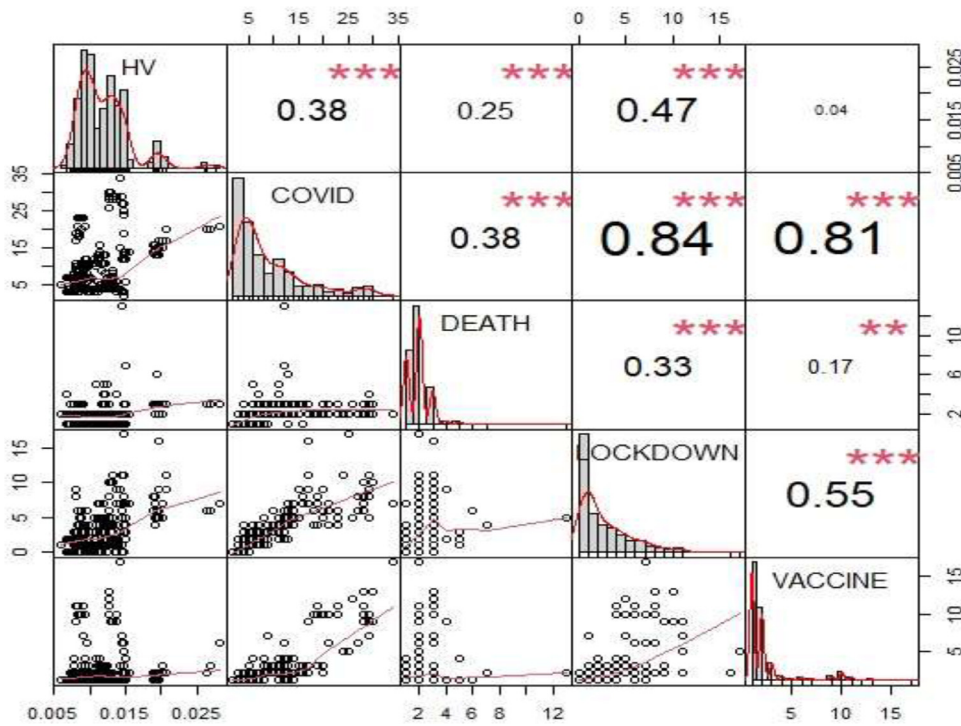


Fig. 12. Correlation between HV and GSVI sentiment indicators.

model has experienced a decline of 0.1% almost. A closer inspection of performance of other models would result in similar intuition. Therefore, IV can be marked to be more predictable than HV. The practical implications of said outcome can be multifaceted. A deeper separate investigation is required to figure out the potential reasons for such behaviour. Additionally, to introspect whether feature selection through Boruta has significantly augmented the quality of predictions or not, we have also repeated the same predictive exercise with all features. Table 6 reports the performance on test segments.

Figures of performance metrics clearly indicate that inclusion of all features actually degrade the predictive performance marginally. Hence, the utility of feature screening through Boruta algorithm is duly justified.

Inference can be drawn that deployment of integrated research model encompassing selection of raw features and feature evaluation through Boruta in conjunction with four predictive modelling techniques has significantly decoded the market fear in Indian context during the pandemic time horizon and thereby accomplishing the desired

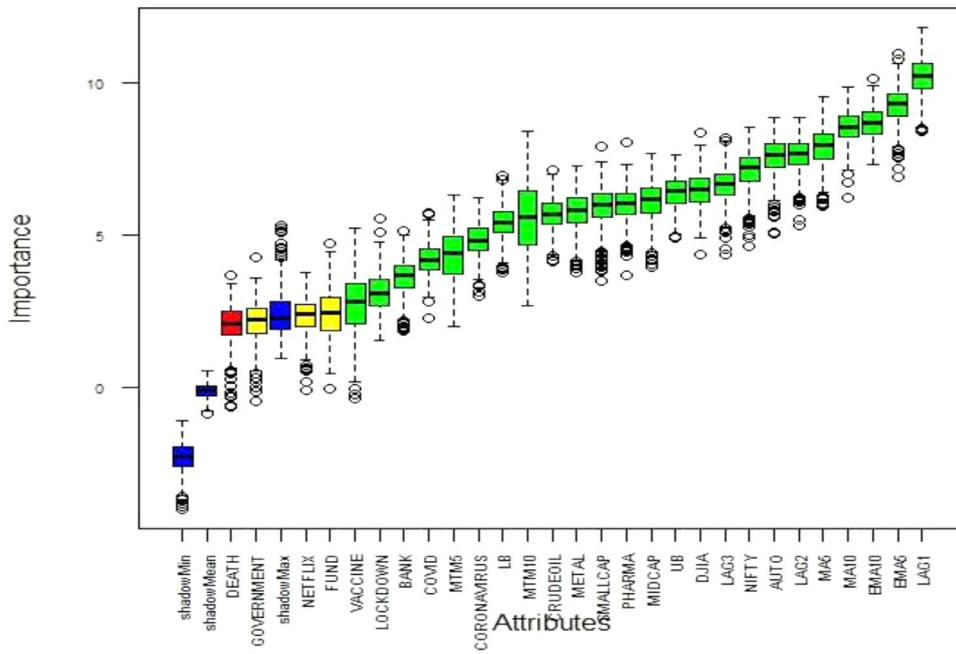


Fig. 13. Outcome of Boruta algorithm for feature selection of IV.

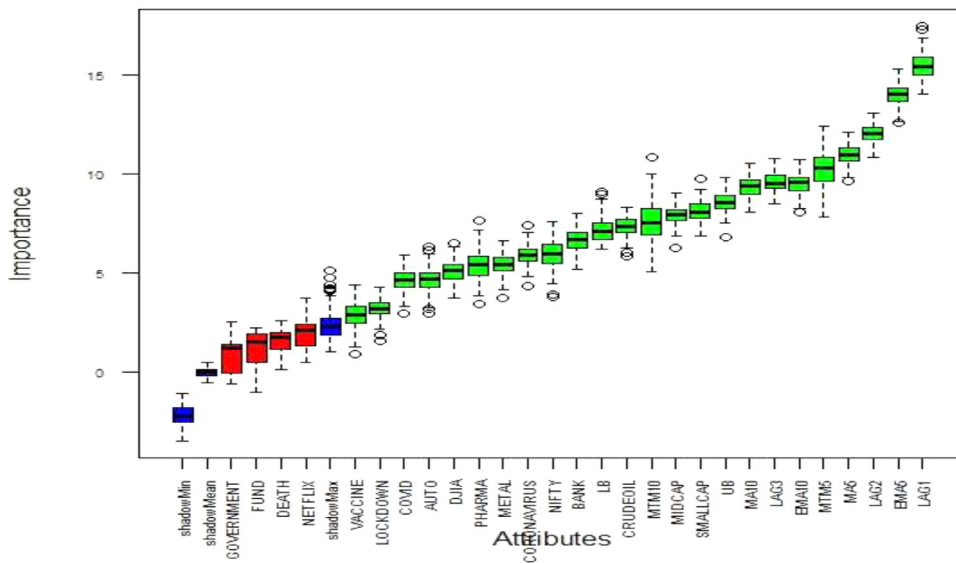


Fig. 14. Outcome of Boruta algorithm for feature selection of HV.

Table 5
Predictive performance for modelling HV.

	XGB	ERT	DNN	LSTM
Training Dataset				
IA	0.9816	0.9813	0.9828	0.9807
TI	0.0188	0.0184	0.0174	0.0201
DA	0.9767	0.9767	0.9767	0.9767
NSE	0.9802	0.9787	0.9790	0.9782
Test Dataset				
IA	0.9720	0.9709	0.9711	0.9715
TI	0.0284	0.0297	0.0301	0.0293
DA	0.9750	0.9500	0.9750	0.9750
NSE	0.9671	0.9658	0.9663	0.9665

Table 6
Predictive performance without feature screening on test segment.

	XGB	ERT	DNN	LSTM
IV				
IA	0.9705	0.9731	0.9722	0.9725
TI	0.0293	0.0291	0.0288	0.0304
DA	0.9780	0.9780	0.9780	0.9780
NSE	0.9693	0.9698	0.9689	0.9693
HV				
IA	0.9635	0.9628	0.9633	0.9639
TI	0.0326	0.0345	0.0354	0.0339
DA	0.9750	0.9500	0.9750	0.9750
NSE	0.9611	0.9589	0.9616	0.9608

research objectives. The study can definitely be considered to be a meaningful contribution to existing pertinent literature.

Although all four machine and deep learning models have appeared to draw forecasts of supreme precision, it is relevant to identify the

Table 7
Outcome of MCS evaluation.

Series	XGB	ERT	DNN	LSTM
IV	1	2	3	4
HV	1	2	3	4

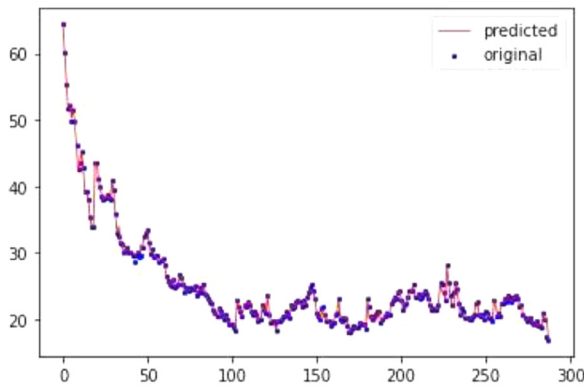


Fig. 15. Actual and predicted figures by XGB for IV.

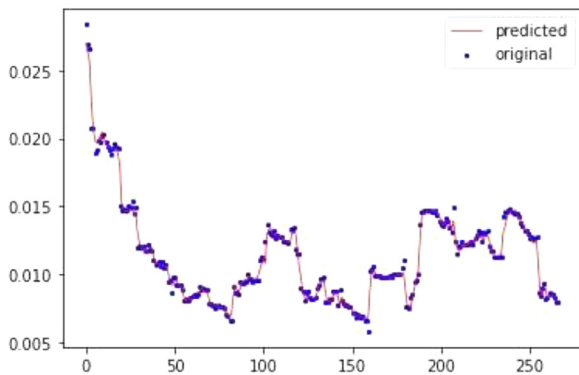


Fig. 16. Actual and predicted figures by XGB for HV.

statistically superior model. Investors and traders may be benefited by the finding. As discussed MCS based SPA is executed to identify the best model from the set of all competing models with specified level of significance. It can effectively discriminate between superior and inferior models through effective deployment of appropriate loss functions. Table 7 outlines the outcome of MCS evaluation.

It is clear that as appeared before XGB framework has emerged to be the most superior model in estimating accurate predictions of future figures of IV and HV. ERT resembles the 2nd position whilst DNN and LSTM secure 3rd and 4th positions respectively on both occasions. Hence, machine learning models have appeared to be statistically marginally superior to deep learning counterparts. It, nevertheless, should be noted that DNN and LSTM are equally impressive in carrying out predictive analysis. Perhaps explicit deployment of essential independent features has resulted in the demonstrated efficiency of machine learning algorithms.

The following Figs. 15 and 16 betray the actual and predicted figures obtained by XGB on entire samples of IV and HV.

Additionally, an attempt has been to evaluate the efficacy of applied predictive structures on surrogate time series to rationalize the deployment and to measure the robustness. In this work, we have utilized the 'seriesEntropy' package of 'R' statistical software to generate a set of surrogate series using the Sieve Bootstrap (Buhlmann, 1997) procedure. The simulation is performed by resampling the residuals from fitting an auto regressive (AR) model. Applying the 'surrogate.AR' function, five series have been generated from the original series of IV and HV. Such

Table 8
Predictive Performance on surrogate time series of IV.

	XGB	ERT	DNN	LSTM
Sample 1				
IA	0.9683	0.9655	0.9669	0.9667
TI	0.0322	0.0335	0.0328	0.0334
DA	0.9302	0.9302	0.9302	0.9302
NSE	0.9619	0.9568	0.9601	0.9578
Sample 2				
IA	0.9659	0.9651	0.9648	0.9643
TI	0.0336	0.0347	0.0352	0.0355
DA	0.9302	0.9302	0.9302	0.9302
NSE	0.9582	0.9572	0.9571	0.9564
Sample 3				
IA	0.9667	0.9661	0.9662	0.9657
TI	0.0326	0.0330	0.0328	0.0328
DA	0.9302	0.9302	0.9302	0.9302
NSE	0.9593	0.9591	0.9590	0.9589
Sample 4				
IA	0.9637	0.9635	0.9629	0.9631
TI	0.0362	0.0369	0.0378	0.0377
DA	0.9302	0.9302	0.9070	0.9070
NSE	0.9546	0.9541	0.9539	0.9538
Sample 5				
IA	0.9689	0.9681	0.9685	0.9684
TI	0.0319	0.0331	0.0322	0.0324
DA	0.9535	0.9535	0.9535	0.9535
NSE	0.9625	0.9618	0.9620	0.9619

Table 9
Predictive performance on surrogate time series of HV.

	XGB	ERT	DNN	LSTM
Sample 1				
IA	0.9472	0.9466	0.9468	0.9469
TI	0.0475	0.0487	0.0482	0.0484
DA	0.9250	0.9250	0.9250	0.9250
NSE	0.9401	0.9392	0.9398	0.9395
Sample 2				
IA	0.9497	0.9495	0.9484	0.9487
TI	0.0453	0.0454	0.0461	0.0459
DA	0.9250	0.9250	0.9250	0.9250
NSE	0.9413	0.9410	0.9404	0.9407
Sample 3				
IA	0.9453	0.9446	0.9441	0.9437
TI	0.0492	0.0495	0.0498	0.0499
DA	0.9250	0.9250	0.9250	0.9250
NSE	0.9369	0.9366	0.9364	0.9368
Sample 4				
IA	0.9486	0.9480	0.9482	0.9477
TI	0.0460	0.0464	0.0463	0.0469
DA	0.9250	0.9250	0.9250	0.9250
NSE	0.9409	0.9401	0.9406	0.9402
Sample 5				
IA	0.9423	0.9419	0.9412	0.9417
TI	0.0517	0.0526	0.0530	0.0529
DA	0.9000	0.9000	0.9000	0.9000
NSE	0.9348	0.9341	0.9338	0.9339

approaches of generating surrogate series have been found to result in more volatile series than the original ones (Jana, Ghosh and Das, 2021). The outcome of predictive exercises on five sets of surrogate series for both IV and HV have been carried out on the same set of explanatory features identified by Boruta algorithm and on same forward looking training (85%) and test (15) data partitions. Tables 8 and 9 outline the findings of predictive analytics on test data segments of both variables.

The estimated values of four performance indicators clearly suggest that quality obtained forecasts lie in the satisfactory zone. In fact, the precision of forecasts for IV and HV can easily be classified to be pretty

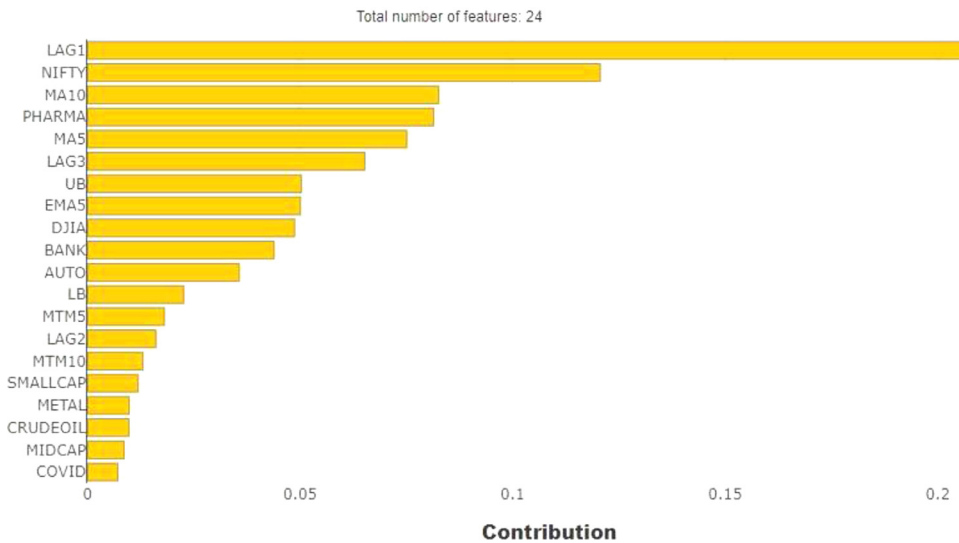


Fig. 17. Contribution of underlying features in predicting IV.

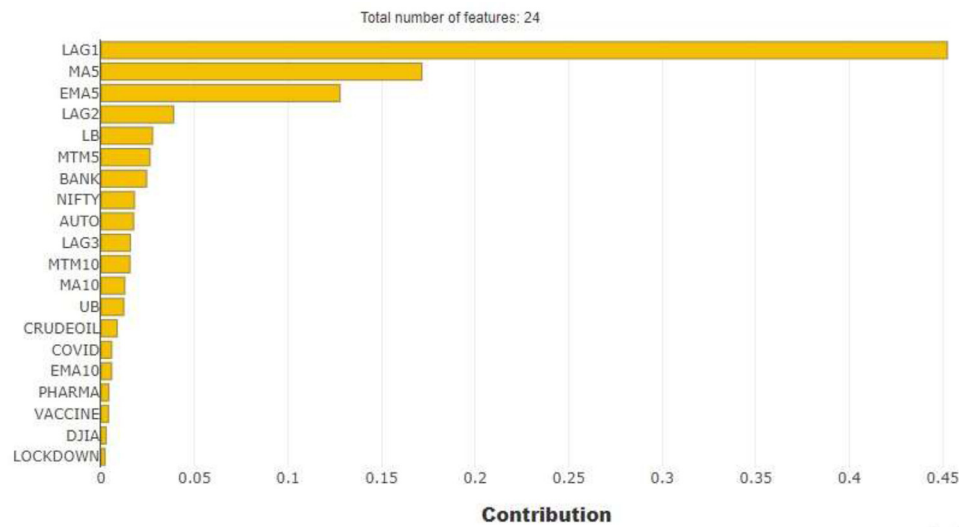


Fig. 18. Contribution of underlying features in predicting HV.

effective for actual deployment of existing frameworks for practical purposes. Likewise on original datasets, surrogate series of IV appears to be relatively more predictable than surrogate series of HV. The predictive performance on surrogate series is not as solid as that of the original series which is obvious due to properties of former series. The entire validation process of presented frameworks survives the test of forecasting assignment of more random and volatile series. Hence, it is evident that the research structure is capable -enough to capture the dynamics of market fears even at extreme circumstances. The frameworks, thus, can definitely be relied upon for tasks viz. risk mitigation, portfolio realignment, hedging, etc.

5.3. Model explanation

The predictive architectures have emerged to be highly successful considering the inherent uncertainty of the time horizon and complex behavioural pattern of the underlying variables. The machine and deep learning frameworks, nevertheless, offer very little insights on the influence of different features utilized for modelling purposes owing to black box nature of operations. The library, ‘Shapash’ has been effectively leveraged for model interpretation based on the available utilities. Figs. 17 and 18 display the respective contribution of top 20 features in forecasting IV and HV.

It can be seen that LAG1 has resembled to be the topmost important feature for both IV and HV. Feature evaluation through Boruta also catered to similar results. Close look at top 5 influential features for predictive modelling reveals macroeconomic variables play a significant role in predicting IV in conjugation with technical indicators as NIFTY and PHARMA resemble 2nd and 4th spot respectively. Thus, it can be inferred that market fear manifested by volatility of option prices heavily depends on the market sentiment and one of the leading performing sectors during the pandemic. Influence of GSVI sentiment indicators on IV is relatively low. The said finding contradicts with sizable literature (Broadstock & Zhang, 2019; Liang, Tang, Li & Wei, 2020; Koratamaddi, Wadhwani, Gupta & Sanjeevi, 2021) emphasizing on the profound influence of social sentiments on the financial market. Perhaps in Indian context, markets exhibit a comparatively weak form of efficiency to be resilient against such sentiments. On the flipside, dynamics of HV is largely decoded by the incorporated technical indicators. Influence of macroeconomic constructs is marginally less when compared with HV. Therefore, it can be concluded that the degree of nexus of HV with other assets is relatively weaker. Likewise IV, HV is not heavily driven by GSVI sentiment indicators. Hence, decoupling HV based fear components can be achieved through close monitoring of technical indicators.

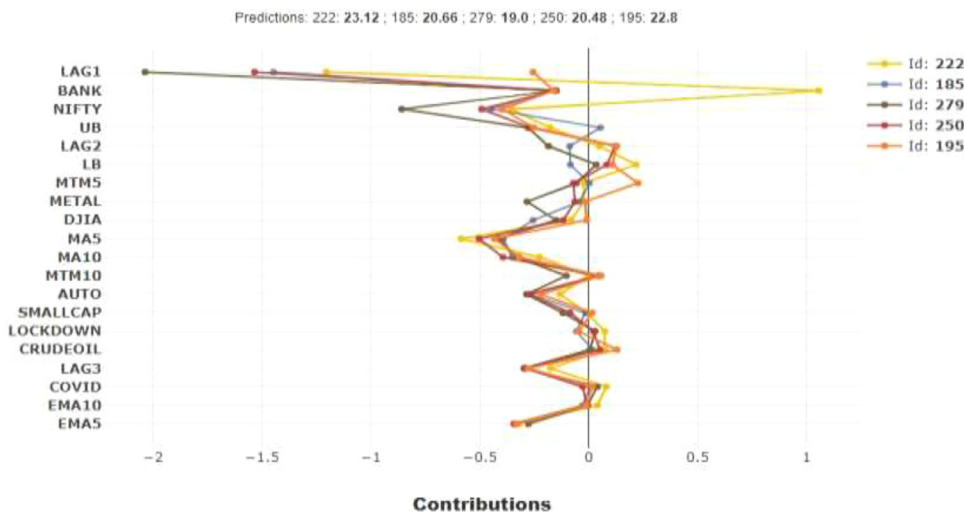


Fig. 19. Local level contribution of features in modelling IV.

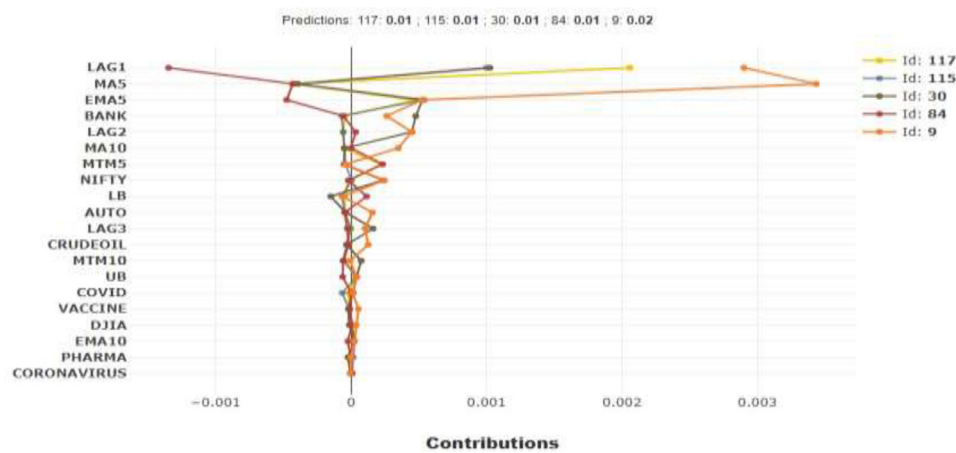


Fig. 20. Local level contribution of features in modelling HV.

The above results reflect the global perspectives. However, it is equally important to introspect at the local level as well. To get necessary purview of the same, ‘Shapash’ library has been used to plot contributions on randomly selected data instances. Findings are portrayed in Figs. 19 and 20.

It can be observed that several features impart negative contribution to IV and HV on certain data samples. The magnitude of influence varies as well. Thus, too much dependence on LAG1 in explaining future figures of IV and HV is not encouraged. To critically comprehend and predict future states of market fear the entire framework encompassing the 24 explanatory features should ideally be relied upon. The diagrams become enormously easy to interpret when confined to a single data instance. Figs. 21 and 22 betray the contribution plot on a randomly selected data instance. The procedure of estimating the direction of contribution is similar to that of the LIME framework.

The exercise is pretty helpful in analysing the direction and extent of impact of underlying features on a particular date of interest or a small time window.

6. Discussions

Rigorous assessment of predictive performance in tandem to comparative analysis and checking predictability in extreme conditions duly rationalized the efficacy of integrated research framework in accomplishing the research endeavours. It, nevertheless, is necessary to critically evaluate the positioning of the current research to existing strands of literature and to translate the key findings into practical relevance. In

this section, the overall contribution to literature and major practical implications have been demonstrated in brevity.

6.1. Contribution to literature

The scrupulous assessment of predictive modelling suggests historical and implied volatility of Indian market do not exhibit complete efficiency. Market fear can, therefore, be anticipated beforehand. It simply implies presence of strong market governance which successfully averts high quantum of random fluctuation despite prevailing uncertainty of the pandemic and restores confidence of common investors. As overall market fear has transpired to be predictable. It is apparent that Indian financial market sentiment reflected by NIFTY or BSE would also exhibit the same trait. The aforesaid findings conform to the strand of literature wherein the predictable patterns of market fear have been emphasized (Li et al., 2021; Weng et al., 2021). Research of Narayan, Phan & Liu (2021) indicated that pandemic eventually had a positive impact on stock returns of G7 countries. Precise estimation of fear counterparts in Indian market demonstrates the resilience and inefficiency structure during pandemic as well. It, nevertheless, should be noted that the present research does not directly contradict with the segment of literature linked to uncertain and unpredictable traits of market fear. Basically, the underlying research has been successful in advancing a robust architecture capable of unearthing the complex hidden pattern of apparently chaotic looking volatility counterparts. Sentiment reflected through different GSVI have transpired to play an important role in driving both IV and HV to a reasonable extent as manifested

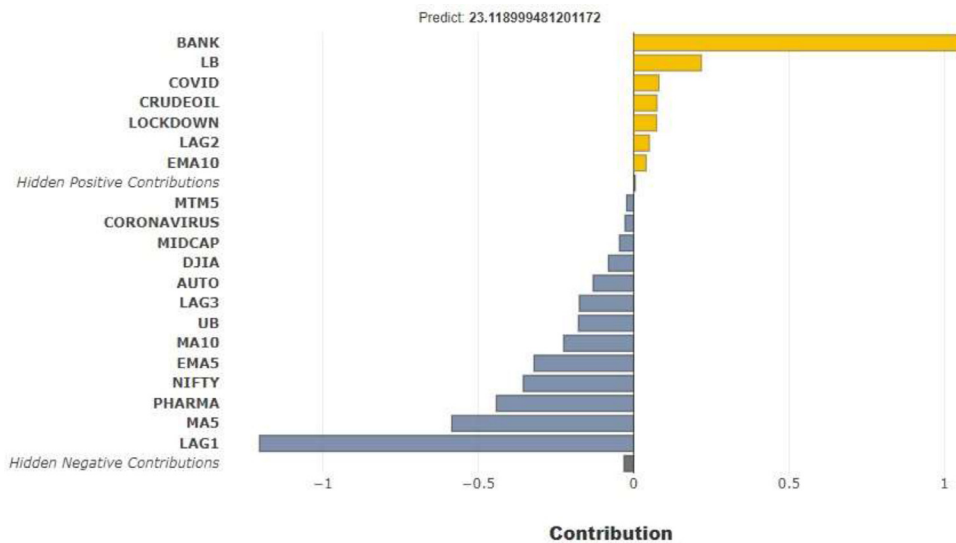


Fig. 21. Direction of contribution of iv modelling on a selected instance.

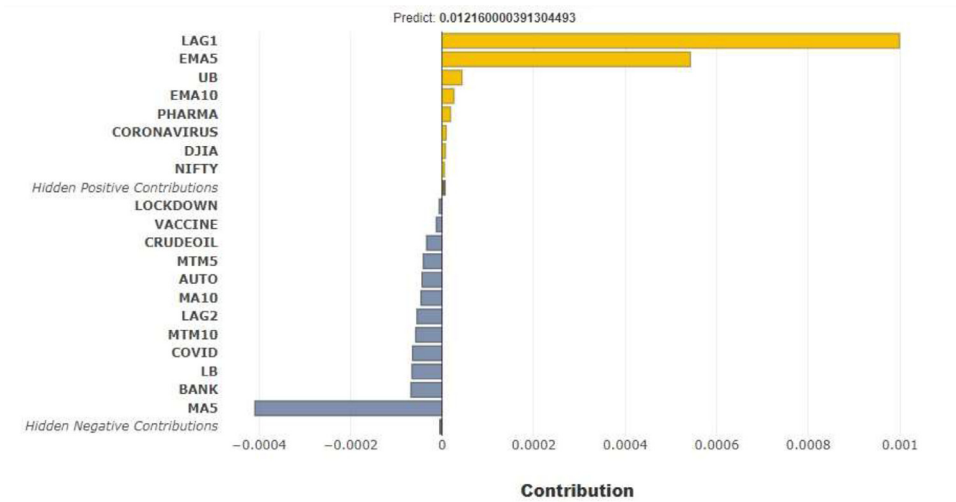


Fig. 22. Direction of contribution of HV modelling on a selected instance.

by model explanation exercise. The aforesaid findings infer that social sentiment share a close nexus with financial market in Indian context. Literature has been reported on leveraging of social media sentiment for better control and management of education and corporate sectors (Chakraborty & Kar, 2021; Yadav, Kar & Kashiramka, 2021). In nutshell, the current strives to establish the theory that inherent fear manifested in the form of implied and historical volatility in Indian equity market exhibited strong discoverable and predictable pattern following the methodological framework of Kar & Dwivedi (2021). Inspired by the work of Agarwal, Kumar & Goel (2019), present research contributes towards methodological front end as well considering the related literature. Dependence of financial markets on social media sentiment can therefore be captured efficiently with data driven AI based information system which can indeed be utilized for various practical purposes as illustrated below.

6.2. Practical implications

The implications of the present research are manifold and of practical relevance. Success in precise estimation of market fear can effectively be leveraged by different market players for in trading and investment. Short term investment can be profitable and less risky. Resilience of Indian market against the uncertainty arising from the first and second wave of COVID-19 pandemic strongly implies inefficient structure

of market dynamics. Predictable nature of implied volatility would encourage market player to enter and explore options markets. As Bank has emerged to be significant explanatory feature that largely explains the variability of considered assets, dependence of overall market on financial sectors of India is also imminent. Thus, overall banking system has played pivotal role in restoring normalcy in market when possibility of market crash has been highly anticipated. Technical indicators have been found to be critical too which can be utilized effectively for profitable trading. Overall, the presented predictive structure can be used for risk mitigation and portfolio realignment through estimating future figures accurately.

7. Conclusions

The endeavour of the present work is to comprehend the inherent pattern of the market fear in Indian context during mayhem of unprecedented events of COVID-19 pandemic embodying the 1st and 2nd waves of infections. The research considers IV and HV as two major indicators of market fear and attempts to recognize the turbulent pattern of the same through systematic deployment of integrated research frameworks. Findings suggest both IV and HV despite showing high degree of nonlinearity and nonparametric traits, can be predicted with commendable level of accuracy in extremely challenging situations. It has been observed that IV, manifesting volatility of futures markets, has

emerged to be comparatively more predictable than the historic counterpart, HV. The findings serve insights of supreme practical relevance as the same can immensely assist policy makers in effective controlling of capital markets. It is also important to note that macroeconomic variables have been found to possess better control over IV than HV. Thus trading in the futures market looking at figures of salient explanatory features would be more profitable and less risky from the perspectives of investors. Unlike the significant footprint of social sentiment on financial markets as discussed in literature, GSVI sentiment scores have prevailed to possess very little impact on IV or HV in Indian context. Therefore, the inherent fear in Indian market can be inferred to be not highly sensitive to information floating on web portals. Macroeconomic and technical indicators largely explain the variation of underlying time series holistically but GSVI sentiment constructs play their part in local level prediction as well. So in nutshell, it can be said that the formulated frameworks presented in the study can be leveraged efficiently for decoding market fear in Indian financial markets with high degree of precision. Careful selection of explanatory features and rigorous feature filtering through Boruta algorithm equally contribute to the eventual success in generating quality predictions by all four models, XGB, ERT, DNN, and LSTM whilst Explainable AI has been enormously proficient in discovering the hidden pattern of influence of chosen independent features. The quantum of obtained accuracy classifies the frameworks for serious consideration as trading instruments. The frameworks can easily be extended to measure volatility in other influential assets.

Scope of the present study is confined to COVID-19 pandemic timeline explicitly. It would be interesting and of paramount importance to carry out a comparative study of predictability of market fear across different time regimes. In future it would be feasible to accomplish the task to distinguish the findings across Pre COVID-19, COVID-19, and Post COVID-19 time phases. Phase wise importance of respective features can be extracted through Explainable AI efficiently. Barring the modelling exercise of volatility of financial markets to interpret the dynamics of market fear, it would be an arduous task to perform predictive modelling of volatility essential commodities, foreign exchange rates, etc. The sample horizon can be extended to other developing and developed economies as well. Eqs. (5)–(12), Eqs. (14)–(17)

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