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Artificial neural network (ANN)-based estimation of the influence of COVID-19 pandemic on dynamic and emerging financial markets

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A R T I C L E I N F O

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A B S T R A C T

The COVID-19 pandemic is a serious global issue destroying financial markets awfully. The proper estimation effect of COVID-19 pandemic on dynamic emerging financial markets is a big challenge due to a complex multidimensional data. However, the present study proposes a Deep Neural Network (DNN)-based multivariate regression approach with backpropagation algorithm and structural learning-based Bayesian network with constraint-based algorithm to investigate the influence of COVID-19 pandemic on the currency and derivatives markets of an emerging economy. The output shows that the COVID-19 pandemic has negatively influenced the financial markets as indicated by sharply depreciating currency value around 10 % to 12 % and reducing short-position of futures derivatives around 3 % to 5 % for currency risk hedging. The robustness estimation shows that there have probabilistic distributed between Traded Futures Derivatives Contracts (TFDC), Currency Exchange Rate (CER), and Daily Covid Cases (DCC) and Daily Covid Deaths (DCD). Moreover, the output represents that the futures derivatives market conditionally depends on the currency market volatility given percentage of COVID-19 pandemic. This study may help to policymakers of financial markets in decision-making to control CER volatility that may promote currency market stability to enhance currency market activities and boost confidence of foreign investors in extreme financial crisis circumstances.

1. Introduction

After collapsed the Bretton-woods-economic system, the multi-currency system was deliberately launched to improve the global economic system by diminishing the problems in economic activities. Under this system, one particular currency swaps with another currency for international trade, transfer remittances, currency risk management, and other significant economic objectives. The financial risk is also associated with the new economic system, which is driven by the volatility of CER between two different currencies (Álvarez-Díez et al., 2016; Bernoth and Herwartz, 2021; Gadanecz et al., 2018; Hau, 2014; Sarno and Valente, 2005). The major factors of CER are the inflation rates, interest rates, balance of payments / current account deficit, government debt, terms of trade, remittances, political instability, recession, speculation, and financial crisis. But the global financial-nonfinancial crises keenly affect the CER (Antonakakis and Money, 2012; Choudhry et al., 2015; Dimitriou et al., 2017; Levy et al., 2022). However, the currency rate returns of developed, developing and underdeveloping countries were negatively forwarded during the great crises 2008 unless the United states dollar (USD), Japanese yen (JPY) and Chinese yuan renminbi (CNY) (Farhi and Werning, 2014; Monge-Naranjo, 2014).

As previous great crises, the COVID-19 pandemic is also a global financial crisis that destructively hitting the global economies (Dash et al., 2021; Hossain, 2021; Wuyts et al., 2020). Moreover, it is also severely devastating the derivatives and currency markets as well as commodity and stock exchange markets (Gunay, 2021). However, the CER has been highly volatilizing since the outbreak of COVID-19 pandemic (Beckmann and Czudaj, 2022; Benzid and Chebbi, 2020; Garg and Prabheesh, 2021; Güler and Tepecik, 2019). But the CER of

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emerging countries is comparatively more affected than developed countries by the COVID-19 pandemic (Aslam et al., 2020; Louhichi et al., 2021). The financial risk is driven by the volatility of CER between two different currencies (Kumar, 2014). A complex foreign currency derivatives instrumental approach is pretty useful for financial risk management (Kim et al., 2020; Rambo et al., 2011; Yu et al., 2020).[1] The futures and options are standardized foreign currency derivatives from all of them (Yu et al., 2020). So, the standardized foreign currency derivatives are excessively using than nonstandardized derivatives during current global crisis for financial risk hedging in dynamic emerging financial markets. We observed that the distribution of COVID-19 pandemic makes more complex situation in emerging and over-populated countries than developed countries due to lack of resources to manage the worse situation and inadequacies strategies for preventive measures, as shown in Fig. 2. Whereas, the India is a second-largest country with 1.38 billion population and the sixth-largest economy in the world with 2.66 trillion US dollar GDP in 2020 (World Bank Organization, 2020).

Moreover, the Bombay stock exchange (BSE) and National stock exchange (NSE) are both leading Indian over-the-counter (OTC) financial markets with 5565 and 1920 listed firms respectively.[2] As the OTC market, the Indian currency market is one of the largest and most highly dynamic emerging financial market in the world, where daily trading volume is 6.6 trillion (Investhub.agency, 2022).[3] But the higher level of financial risk is also involved in forex trading. However, the currency derivatives market takes more intentions to hedge the financial risk remarkably. The previous studies explored that the global financial crisis destructively affects emerging financial markets. Moreover, the COVID-19 pandemic has negatively influenced the Indian currency market (Mishra et al., 2020; Njindan Iyke, 2020; Xu and Lien, 2022). Triennial Central Bank Survey reported that the absolute turnover of currency risk hedging with foreign derivatives was 1527 billion USD in 1998 and 3981 billion USD in 2010 (Kumar, 2014). Therefore, we cannot neglect the significance of the derivatives market, especially at a time of currency market uncertainty, because the currency market instability spillover on the derivatives market. To our best knowledge, the previous studies have poorly ignored the COVID-19 pandemic effect on the Indian derivatives market. However, the present study simultaneously estimates the impact of COVID-19 pandemic on the Indian currency and derivatives markets to fulfill the research lacuna. Moreover, the numerous scholars reported that the Traditional Econometric Models (TEMs), Conventional Machine Learning Models (MLMs) and Shallow Neural Networks (SNNs) approaches cannot properly investigate the complex multidimensional and high volatile nonlinear financial market data (HongXing et al., 2022; Wookjae Heo et al., 2020). With this motivation, the present study employs a novel ANN-based approach (DNN-based multivariate regression with a backpropagation algorithm) to estimate the influence of the COVID-19 pandemic on both financial markets. In addition, this study further employs a structural learning-based Bayesian network approach with a constraint-based algorithm to forecast the association between Indian currency market, derivatives market and COVID-19 pandemic. Moreover, to our best knowledge, this is the first study to examine the conditional effect of Indian currency market volatility on the derivatives market given the percentage of the COVID-19 pandemic by employing a structural learning-based Bayesian network approach.

The remaining sections will be organized as follows: most similar literature regarding entire variables to explore the association between the COVID-19 pandemic, currency market and derivatives market and recent developments in financial system modelling in perspective of TEM, conventional MLMs and ANNs for the assessment of the COVID-19 pandemic effect is presented in Section 2. Section 3 keenly describes the composition of empirical datasets, mathematical interpretation of proposed models, and its implementations for financial predictions. Section 4 represents the financial prediction performance of the proposed models to find an appropriate model for further financial predictions to estimate the influence of the COVID-19 pandemic on both financial markets. It also comprises the discussion and contribution of the study. Section 5 summarizes the conclusion, implications and further developments of the study.

2. Literature review

The foreign currency risk is a serious concern in financial risk management that is associated with CER volatility. Although there are several reasons for higher CER volatility, the financial crisis is one of them. So, the COVID-19 pandemic is a global financial crisis that has confounded the financial markets (Long et al., 2022). The currency market has been comparatively 8th times over affected by the COVID-19 pandemic than previous global financial crises (Gunay, 2021). The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1)-mean model estimated that the JPY has depreciated by 58.8 % leads 71 % average market returns at a preliminary stage of the current global financial crisis (Narayan et al., 2020). A Wavelet Neural Network model assesses the impact of the COVID-19 pandemic on the volatility of currency and cryptocurrency markets. There is a strong coherence between CER (EUR, GBP, CNY against USD) and the COVID-19 pandemic as well as developments in the Bloomberg Galaxy Crypto Index (Umar and Gubareva, 2020). Moreover, a Wavelet Coherency Approach determined that the CER and COVID-19 pandemic are strongly associated (Thaker and Sakaran, 2021). By using a conventional approach (Fixed-effect), the present study determined that the COVID19 pandemic and CER of 37 currencies against USD are positively associated with each other (Sethi et al., 2021). Furthermore, the Bagging Ridge regression with Bi-directional long short-term memory neural network estimates the COVID-19 pandemic effect on 21 various currency markets (Abedin et al., 2021). The output shows that the currency markets have been severely affected by the COVID-19 pandemic, which is represented by the density of CER volatility during the pandemic period. Similarly, the COVID-19 pandemic also dominates the currency market of the emerging countries associated with the Belt and Road (B&R) project (Wei et al., 2020). There are numerous studies reveal the influence of current global financial crises on the currency market of diverse economies of the world, which are presented in Table 1.

On the other hand, the current global financial crises are also disrupting the financial derivatives market as well as the currency market. The Vector Autoregression (VaR) model assessed that the COVID-19 pandemic increases the volatility of the OTC derivatives market, indicating higher currency risk hedging (Wybieralski, 2021). However, the unmatured derivatives contracts are devalued by increasing market volatility during the pandemic period. In this financial crisis, the 113 futures and options derivatives markets of 40 countries are strongly associated with rising the trading volume of derivatives contracts (Emm et al., 2021). By using GARCH and Ordinary Least Square (OLS) models, another study determined with using currency derivatives contracts between USD-TRY (Turkish New Lira) and EUR-TRY, the COVID-19 pandemic is negatively affected the futures derivatives market (Buyukkara et al., 2022). Thirteen significant derivatives markets are deviating by 40 % during the COVID-19 pandemic may alter the short-term

[1] The futures, forwards, swaps and options derivatives are widely used on foreign exchange, equities, interest rates and commodities assets. Fig. 1 represents the kinds of foreign exchange and commodity derivatives instruments which is presented in Appendix A.

[2] Fig. 3 exhibits the daily TFDC in the Bombay Stock Exchange (BSE) over the period 2014 to 2022 which is presented in Appendix A. The shaded area of the graph with light-gray colour is represented to the Covid-19 pandemic period.

[3] Fig. 4 plots the historical spot INR-CER against USD which is presented in Appendix A. The shaded area of the graph with light-gray colour is represented to the Covid-19 pandemic period. It should be noted that the futures, forward and spot markets are three primary markets of forex trading in India.

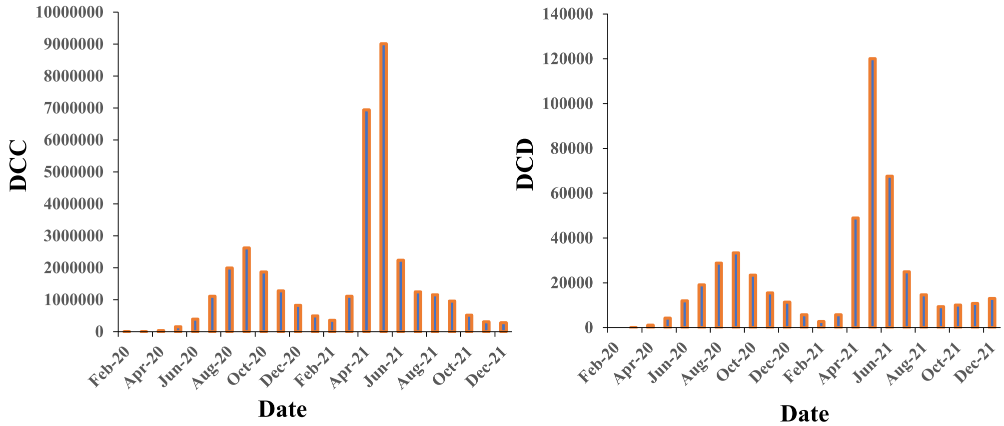

Fig. 2. Distribution of COVID-19 pandemic in India.

Table 1
Reviewing most similar studies.

Serial no.	Authors & (year)	Title	Variables	Approaches	Findings
1	Tan and Xue (2021)	Research on the Development of Digital Currencies under the COVID-19 epidemic	COVID-19 epidemic and Digital Currencies	Genetic Statistics	* * +
2	Xu and Lien (2021)	COVID-19 and currency dependences: Empirical evidence from BRICS	COVID-19 pandemic and CER of BRICS countries against USD	GARCH (1,1)-t	*+
3	Aslam et al. (2020)	On the efficiency of foreign exchange markets in times of the COVID-19 pandemic	COVID-19 outbreak and forex market efficiency	Multifractal Detrended Fluctuation Analysis (MF-DFA)	* * –
4	Phiri (2021)	Changing efficiency of BRICS currency markets during the COVID-19 pandemic	Efficiency of BRICS currency markets & COVID-19 pandemic	Wavelets neural network	*–
5	Li et al. (2021)	COVID-19 and currency market: A comparative analysis of exchange rate movement in China and USA during pandemic	COVID-19 confirmed cased & deaths and exchange rates	Autoregressive Distributed Lag (ARDL) model	*–
6	Sharma et al. (2022)	Impact of the COVID-19 Outbreak on the Currency Exchanges of Selected Countries	COVID outbreak and currency market	Generalized Autoregressive Conditional Heteroskedasticity (GARCH)	*±
7	Bazán-Palomino and Winkelried (2021)	FX markets' reactions to COVID-19: Are they different?	COVID-19 pandemic and FX markets	Traditional mean-variance portfolio, diversification ratio, maximally diversified (MD) portfolio & global minimum variance (GMV) portfolio	* * ±
8	Devpura (2021)	Effect of COVID-19 on the relationship between EUR/USD exchange rate and oil price	COVID-19, CER & futures oil prices	Predictive regression model	* * +
9	Iyke and Ho (2021)	Exchange rate exposure in the South African stock market before and during the COVID-19 pandemic	Exchange rate risk & COVID-19 pandemic	Exponential GARCH (1,1)	* * +
10	Salisu et al. (2021)	Global evidence of the COVID-19 shocks on real equity prices and real exchange rates: A counterfactual analysis with a threshold-augmented GVAR model	COVID-19 pandemic, CER, equity prices	Global Vector Autoregressive (GVAR) Model	* * –
12	Aloui (2021)	The COVID-19 pandemic haunting the transmission of the quantitative easing to the exchange rate	COVID-19 pandemic and CER,	BVAR with time-varying coefficients and stochastic volatility (TVP-BVAR-SV)	*+
13	Narayan (2022)	Understanding exchange rate shocks during COVID-19	CER returns and COVID-19 pandemic	Vector autoregression (VAR) model	* * –
14	Ekum and Ogunsanya (2020)	Application of Hierarchical Polynomial Regression Models to Predict Transmission of COVID-19 at Global Level	COVID-19 prediction	Machine learning based polynomial regression	**
15	Ullah (2022)	Impact of COVID-19 Pandemic on Financial Markets: A Global Perspective	COVID-19 pandemic and developed and emerging financial markets	Panel quantile regression and panel estimated generalized least square (EGLS)	**+

Note: * and ** represent the weak and strong effect of the COVID-19 pandemic on the financial market respectively.

discount rates (Berkman and Malloch, 2021). The VAR model was expanded to a Bivariate Asymmetric Dynamic Conditional (BADC) on the GARCH framework to estimate the contagion effect of COVID-19 syndrome on the futures derivatives markets of China and its major trading-partner countries. There is a financial contagion between developed and developing trading markets during the COVID-19 syndrome (Banerjee, 2021).

Although the numerous approaches have been using for currency risk management since several decades. According to our best knowledge, the foreign currency derivatives instrumental approach is comparatively more economical than other approaches, while this approach has been exceedingly used for currency risk management since a couple of decades (Elliott et al., 2003). However, hedgers highly use foreign currency derivatives to hedge their currency risk during the COVID-19 pandemic. The above literature concluded that the current global financial crisis has disrupted the currency and derivatives markets of developed, developing and under-developing economies. According to our best knowledge, the previous studies have strongly neglected the COVID-19 pandemic effect on both emerging financial markets simultaneously and the conditional effect of currency market volatility on the derivatives market given the percentage of COVID-19 pandemic effect. However, the present study estimates the influence of current global financial crises on both financial markets of an emerging economy and the conditional effect of currency market volatility on the derivatives market in the presence of the COVID-19 pandemic with advanced methodological approaches to fill the lacuna.

3. Data collection and research methodology

3.1. Data collection

The empirical dataset is classified into three subcategories for hypothetical testing. In the first category, the COVID-19 pandemic is measured by DCC and DCD in India. This empirical dataset has collected from the official website of GitHub (https://github.com). GitHub has significantly maintained the country-wise datasets regarding the COVID-19 pandemic. But the base-source of present dataset is the centre for systems science and engineering at Johns Hopkins University (CSSE-JHU) (https://systems.jhu.edu/). It is also supported by the ESRI living atlas team and the applied physics lab of Johns Hopkins University (APL-JHU). The second category of our empirical dataset comprises the TFDC with INR-EUR, INR-USD and INR-JPY, which is retrieved by the Bombay Stock exchange (BSE) of India (https://www.bseindia.com/). The present study uses the short-position of TFDC at one-month maturity level to predict the volatility of the Indian derivatives market during the COVID-19 pandemic. In third category of our empirical dataset, the domestic CER against USD has proposed to investigate the volatility of the Indian currency market during the COVID-19 pandemic. This empirical dataset has collected from the official website of the European Central Bank (ECB) (https://www.ecb.europa.eu/). More detail about our empirical dataset is given in the data availability and material part, which is presented after Section 5.

3.2. DNN-multivariate regression model

The DNN-based multivariate regression model is a supervised learning technique commonly used to predict continuous values by splitting data into input and output formats. Because the supervised machine learning and ANN approaches cannot predict the financial markets without data classification. However, we categorized our empirical datasets into input and output formats before to commence the training process. Let suppose the x & y are numeric input and output variables respectively at $n-th$ number of data samples $n = 1, 2, 3, \cdots, N$. Whereas, the $x(n)$ is a training input and $d(n)$is a desired output of the Q model. The $n-th$ is the number of $x(n)$ input datasets of the Q training model, whereas $x(n) = [x_1(n)x_2(n)\cdots x_n(n)]^T$are the number of training samples. The proposed model uses $L-th$ number of total dense layers for the optimal training process. Let's assume, $l-th$ is the input layer excluded from the Q training model while the input layer is represented by $l=0$ and the output by $l=L$. The m_l indicates the number of neurons in $l-th$ layers. In the training process, the specific weight of $i-th$ neuron from $(l-1)-the$ layer transfer to $j-th$ neuron of $l-th$ layer which expressed as $w_{l,j,i}^{[k]}$. The specific weight matrix associated with $l-th$ layer at $k-th$ iteration process is expressed as

$$w_l^k = \begin{bmatrix} w_{l,1,0}^{[k]} & w_{l,1,1}^{[k]} & \cdots & w_{l,1,m_{l-1}}^{[k]} \\ w_{l,2,0}^{[k]} & w_{l,2,1}^{[k]} & \cdots & w_{l,2,m_{l-1}}^{[k]} \\ \vdots & \vdots & \cdots & \vdots \\ w_{l,m_l,0}^{[k]} & w_{l,m_l,1}^{[k]} & \cdots & w_{l,m_l,m_{l-1}}^{[k]} \end{bmatrix}_{m_l \times m_{l-1}+1} \tag{1}$$

The $y_{l,\,j}(n)$ is representing the output of $j-th$ neuron at $l-th$ layer against the response of $x(n)$. Whereas, the output neurons of $l-th$ layer is $l = 1, 2, \cdots, l-1$ which is represented by $y_l(n) = [y_{l,\,0}(\,n\,)\,y_{l,\,1}(\,n\,)\cdots y_{l,\,m_l}(\,n\,)]^T$, whereas $y_{l,\,0}(n)$ is a bias-unit. The $y_l(n)$ output is the composition of $n-th$ number of activities of m_l neurons at $l-th$ layer. So, the activity of $j-th$ neuron on $l-th$ layer against the response of $n-th$ training data sample of $x(n)$ is provided by

$$v_{l,j}(n) = \sum_{i=0}^{m_{l-1}} w_{l,j,i}\, y_{l-1,i}(\,n) \tag{2}$$

The rectified linear unit (ReLU) and sigmoid activation functions are adjusted in hidden layers for efficient composition of financial predictions of the model. It should be noted that the ReLU function is used in hidden layers, while the sigmoid function is used in the output layer. Both activation functions are duly explained in Appendix B. Furthermore, the output of $j-th$ neuron $(j = 1, 2, \cdots, m_l)$ at $l-th$ layer is given by $y_{l,\,j} = \varphi_l(\,v_{l,\,j}(\,n))$, whereas the $\varphi_l(\bullet)$ is explained as

$$\varphi_l(Z) = \sigma(Z) = \frac{1}{1+e^{-Z}}\ l = 1, 2, \cdots, L-1 \tag{3}$$

So, the significant output of $j-th$ neuron in L layer is provided by

$$\mathrm{y_{L,j}(n)} = \sigma_L\left(\mathrm{v_{L,j}(n)}\right) = \frac{e^{\mathrm{v_{L,j}(n)}}}{e^{\mathrm{v_{L,1}(n)}} + e^{\mathrm{v_{L,2}(n)}}} \tag{4}$$

The overall numeric activity of $n-th$ number of neurons in l layer is written as $v_l(\,n\,) = [\,v_{l,\,1}(\,n\,)\,v_{l,\,1}(\,n\,)\cdots v_{l,\,m_l}(\,n\,)\,]^T$.

Fig. 5 exhibited that the proposed model contains on two numeric input and two output features, three hidden layers and one output layer. The first hidden layer takes 128 neurons, while the second and third hidden layers take 64 neurons. It should be noted that any number of input features could be assigned to the input layer, any number of hidden layers and any number of neurons to estimate the financial predictions. As following, we effectuate the forward propagation process for the DNN-based multivariate regression model in Fig. 5 via vector implementation. It should be pointed out that since w_l^k is an $m_l \times (m_l+1)$ matrix and $v_l(n)$ is an $m_l \times 1$ vector, an additional row represented by $v_{l,\,0}(\,n\,)$ has to be annexed to $v_l(\,n\,)$ before begin the forward propagation process.

Let's take a training example $(x(\,1\,), y_L(\,1\,))$ where $x(\,1\,)$ is a $m_0 \times 2$ input data feature vector, $y_L(\,1\,)$ is 2×1 ideal output vector and $x_0(1)$ is added as a bias-unit to input layer. The activity of the first hidden layer can be expressed by dropping index k from w_l^k.

$$\mathrm{y_1(\,1\,)} = \sigma((\boldsymbol{W}_1\mathrm{x}(\,1\,))(x_0(\,1\,))\ is\ added\ to(\mathrm{y_1}(\,1\,))) \tag{5}$$

The empirical activities of $l-th$ and $l+1$ layers $(l = 1, 2, \cdots, L)$ are expressed as

$$\mathrm{y}_{l+1}(\,1\,) = \sigma\left((\boldsymbol{W}_l y_l(1))\left(y_{l+1,0}(1)\right)\ is\ added\ to(\mathrm{y}_{l+1}(1))\right) \tag{6}$$

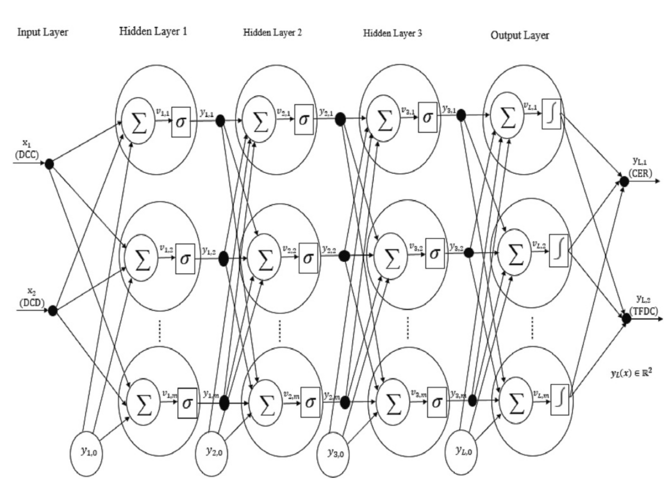

Fig. 5. Structure of the proposed model with three hidden layers (L = 4).

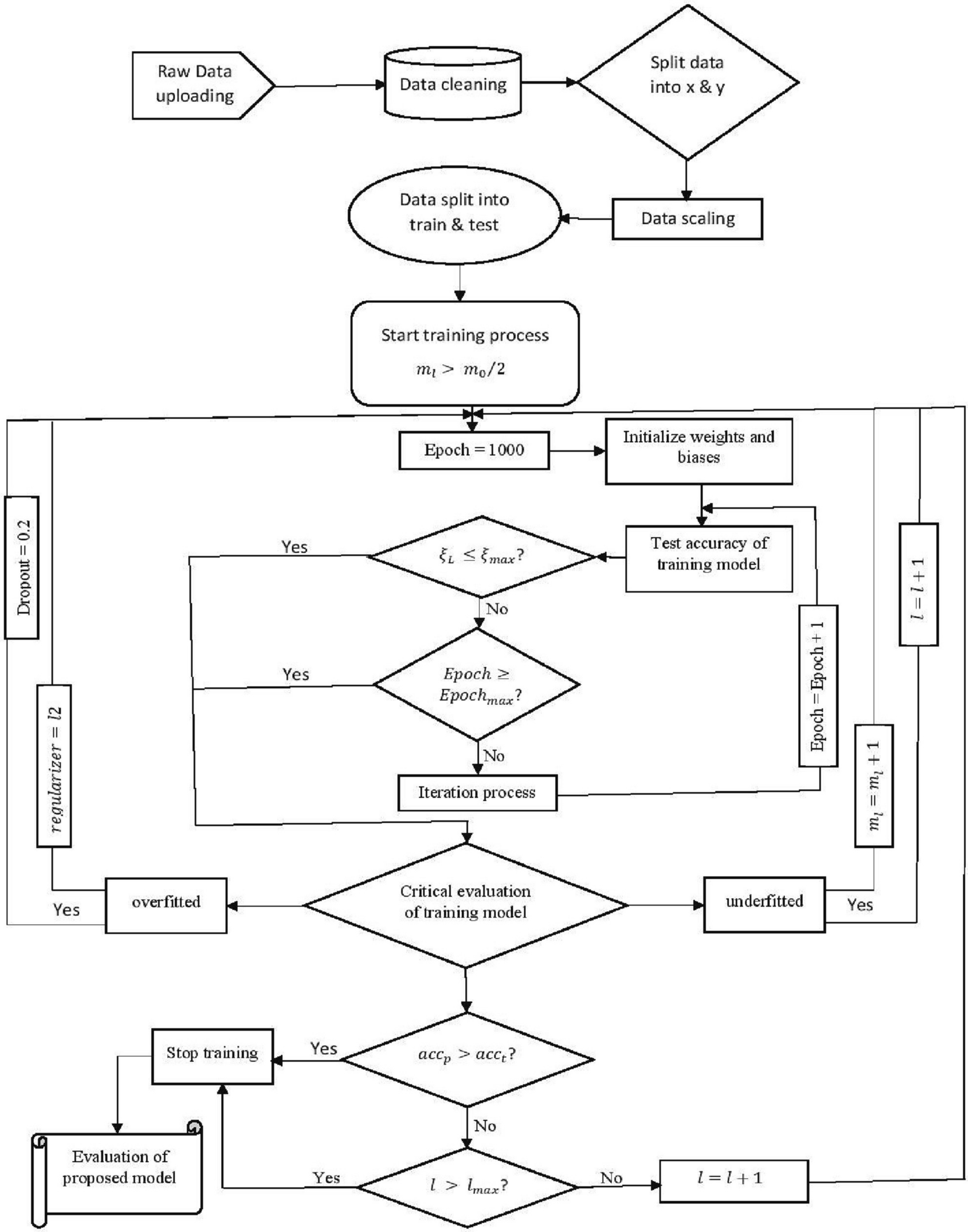

Fig. 6. Flowchart of the training process of the proposed model.

Whereas $y_{l,\,0}(1)$ is a bias unit at $l-th$ layer $l=1,2,\cdots,L$ initialized as 1, which is adjusted in the training process to enhance the financial prediction performance of the model as follows:

$$y_L(1)=\int\left(\sum_{j=1}^{m_L}W_L y_L(1)+\left(y_{L,0}(1)\right)\ is\ added\ to\ y_L(1)\right) \tag{7}$$

Whereas the m number of numeric features of output neurons in $L-th$ layer, which also included a bias-unit $y_{L,\,0}(1)$ added to $y_L(1)$. The significant decision rule at the output layer is unfolded as well:

$$y_L(n)=\left[y_{L,1}y_{L,2}\right]^T\Rightarrow\begin{cases}\text{"volatility in the CER"} & y_{L,1}>T_0\\ \text{"volatility in the TFDC"} & y_{L,2}>T_0\end{cases} \tag{8}$$

Whereas the T_0 is predetermined threshold $T_0=0.5$ of the model. Furthermore, suppose the desired error is less than the proposed model's output error. In that case, we must call back the backpropagation function to update the weights to optimize the model's performance.

3.2.1. Backpropagation training algorithm

The error between the desired output and the predicted output of $j-th$ neuron at $l-th$ layer can be summarized as

$$e_{l,j}(n)=d_{l,j}(n)-y_{1,j}(n) \tag{9}$$

It should be noted that only the cost of the output layer is explicit, while the error vector of the final layer can be expressed as

$$e_L(n)=\left[e_{L,1}(n)e_{L,2}(n)\right]^T \tag{10}$$

$$e_l(n)=\left(w_l^{[k]}\right)^T e_{l-1}(n)\circ(y_l(n)\circ(1-y_l(n))) \tag{11}$$

where the commutative ring $\circ$ represents the Hadamard product. Furthermore, the scholars will be trained our proposed model to minimize the error. So, the cumulative error of the model can be expressed as:

$$\xi_L(n)=\frac{1}{2}\parallel d(n)-y_L(n)\parallel=\frac{1}{2}\sum_{j=1}^{m_L}\left(d_{L,j}(n)-y_{L,j}(n)\right) \tag{12}$$

But the average error of the proposed model is given by

$$\overline{\xi}=\frac{1}{N}\sum_{n=1}^{N}\xi_L(n) \tag{13}$$

It should be noted that the main goal of the training process is to minimize the average cost of proposed model to enhance the financial prediction performance significantly. In the backpropagation process, the weights update in the training process against the response of the $n-th$ number of inputs. Particularly, the weight on $j-th$ neuron at the $l-th$ layer transmitting from $i-th$ neuron at the $(l-1)-th$ layer will be updated as

$$w_{l,j,i}^{[k+1]}=w_{l,j,i}^{[k]}+\Delta w_{l,j,i}(n) \tag{14}$$

Whenever,

$$\Delta w_{l,j,i}(n)=\alpha\Delta w_{l,j,i}(n-1)-\mu\frac{\partial\xi_l(n)}{\partial w_{l,j,i}^{[k]}} \tag{15}$$

Whereas the $\alpha\in[0,1]$, is a constant momentum, the $\partial(\bullet)/\partial(\bullet)$ represents the partial derivative function between updating weights and error of the proposed model and the λ represents the learning rate parameter during the backpropagation process. It should be noted that the steepest descent learning is diminished by zero constant momentum in Eqs. (14) and (15). Whereas the largest eigenvalue of the Hessian matrix gives the highest λ value. It is smoothly obtained when $l=L$

$$\frac{\partial\xi_L(n)}{\partial w_{L,j,i}^{[k]}}=\frac{\partial\xi_L(n)}{\partial e_{L,j}(n)}\frac{\partial e_{L,j}(n)}{\partial y_{L,j}(n)}\frac{\partial y_{L,J}(n)}{\partial v_{L,j}(n)}\frac{\partial v_{L,j}(n)}{\partial w_{L,j,i}^{[k]}}$$
$$=-e_{L,j}(n)\,\varphi_L'\left(v_{L,j}(n)\right)y_{L-1,i}(n) \tag{16}$$

Whereas, the prime symbol at φ_L' denotes the differentiation of output at $L-th$ layer with the iteration process updating the weights. So, we can further simplify the expression of Eq. (16) as

$$\delta_{L,j}=-e_{L,j}(n)\,\varphi_L'\left(v_{L,j}(n)\right)y_{L-1,i}(n) \tag{17}$$

Let assume, the $l\neq L$, then the $\partial(\bullet)/\partial(\bullet)$ is provided by

$$\left.\frac{\partial\xi_l(n)}{\partial w_{l,j,i}^{[k]}}\right|_{l\neq L}=\delta_{l,j}(n)\,y_{l-1,i}(n) \tag{18}$$

The $\delta_{l,\,j}(n)$ is further expressed as

$$\delta_{l,j}(n)=\frac{\partial\xi_l(n)}{\partial v_{l,j}(n)}=\sum_{p=1}^{m_{l+1}}\delta_{l+1,p}(n)\frac{\partial v_{l+1,p}(n)}{\partial v_{l,j}(n)} \tag{19}$$

Since,

$$\frac{\partial v_{l+1,p}(n)}{\partial v_{l,j}(n)}=\frac{\partial\left(\sum_{i=1}^{m_l}w_{l+1,p,j}\,\varphi_l\left(v_{l,j}(n)\right)\right)}{\partial v_{l,j}(n)}=w_{l+1,p,j}\,\varphi_l'\left(v_{l,j}(n)\right) \tag{20}$$

The Eq. (19) can be simplified as

$$\delta_{l,j}(n)=\varphi_l'\left(v_{l,j}(n)\right)=\sum_{p=1}^{m_{l+1}}\delta_{l+1,p}(n)\,w_{l+1,p,j}(n) \tag{21}$$

Besides, the cross-entropy loss function is also an effective cost function as well as the mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE). So, it can also be used for error evaluation of the model. This cost function measures the divergence between two likelihood distributions. The smaller cross-entropy value indicates the analogous distributions. At $k-th$ iteration process, the cost function in cross-entropy is given by.

$$J\left(W^{[k]}\right)=\frac{1}{N}\left\{\sum_{n=1}^{N}\sum_{j=1}^{J}\left[d_j(n)\log\left(y_{L,j}(n)\right)+\left(1-d_j(n)\right)\log\left(1-y_{L,j}(n)\right)\right]\right\}$$
$$+\frac{\lambda}{2N}\sum_{l=1}^{L}\sum_{j=1}^{m_l}\sum_{i=1}^{m_{l-1}}\left(w_{l,j,i}^{[k]}\right)^2 \tag{22}$$

Whereas, the $d_j(n)$ is the desired output of $j-th$ component in vector $d(n)$, and λ is a regulation parameter. The partial derivative of $J(W^{[k]})$ with respect to $w_{l,j,i}^{[k]}$ is counted to diminish the $J(W^{[k]})$, and the gradient descent learning can also be used to optimize the performance that expressed in Eqs. (14) and (15).

Fig. 6 shows the complete training process of the proposed model of the study. Before the training process, the uploaded dataset will be classified into input and output formats after the cleaning process. The classified datasets are further splitting into training (80 %) and testing (20 %) datasets. According to the thumb rule, the number of neurons in the hidden layer should be greater than half of the input variables in the training process, i.e., $\sum_{l=1}^{L-1}m_l>m_0/2$. The implicit features and hyperparameters of the training model are exhibited in Table 2, which is presented in Appendix B. The main goal is to maximize the predicted accuracy than target accuracy by reducing the error of the model. If the desired error $\leq$ obtained error of the training model, then we shall call to backpropagation function by adding more epochs; otherwise, it will forward for test evaluation. Let's suppose the desire error is greater than obtained error. It will refer to the estimate of the model's accuracy. Moreover, if the target accuracy $<$ predicted accuracy, then we will stop the training process and evaluate the financial prediction performance of the proposed model, otherwise, we will recall to iteration process by adding $l-th$ layer as $l+1$. This training process will continue until the

Table 4
Output of DNN-based regression model.

Model	Variables (IV)	C	β	R^2	MAE
M1 ($l = 3$)	DCC*	−0.0176	−0.1221	0.036	0.9648
M2 ($l = 3$)	DCD*	−0.0429	−0.2598	0.050	0.9648
M3 ($l = 3$)	DCC**	−0.2118	0.2571	0.109	0.9081
M4 ($l = 3$)	DCD**	−0.0423	0.2697	0.117	1.0666

Note: * and ** represent the association with TFDC and CER respectively.

goal does not achieve.

4. Results and discussion

The present study employed multiple ANN-based multivariate regression models to find an appropriate model for the given dataset.[4] Thereafter, the relative best model will be referred for the estimation of the influence of the COVID-19 pandemic on the dynamic and emerging financial markets. For this significant purpose, initially, we train our models at the given dataset and subsequently forecast the financial prediction performance of the proposed models. The summary of the empirical models is presented in Appendix C.[5] The output shows that our fourth model (M4) relatively gives best prediction performance with a small error. However, the DNN-based regression models are comparatively more useful for financial market predictions. On sound empirical evidence, we referred a DNN-based regression model for further financial predictions. The summary of our final recommended model is presented in Appendix C.

Table 4 represents the interaction between DCC, DCD, TFDC and CER, errors of the proposed models, external effect, per-unit effect and the overall effect of the COVID-19 pandemic on the dynamic and emerging financial markets. Our first model (M1) shows a negative relation between DCC and TFDC as indicated by beta value −0.1221, which represents that one-unit change in DCC becomes 12.21 units negative change in TFDC. The overall variation in the TFDC of an emerging financial market by 3.6 % due to DCC represents that the hedgers have hedged their currency risk by reducing the short-positing of TFDC during the COVID-19 pandemic. In addition, the intercept value −0.0176 of our first model shows a minor external effect, while higher internal effect is presented at TFDC in case of DCC. The present model gives optimal financial prediction with a small error 0.9648. Furthermore, our second empirical model (M2) shows that the TFDC is negatively associated with DCD as indicated by beta value −0.2598, which represents the one-unit change in DCD become 25.98 units negative change in TFDC. The r-square value shows the overall change in TFDC due to DCD, which is 5 %. Moreover, the intercept value −0.0429 of the present model indicates that there is no more external effect in TFDC in case of DCD. On the other hand, the error of the model is 0.9646 that indicates the prediction performance of the model. Thus, the empirical findings concluded that the futures derivatives market of India has been 3 % to 5 % inversely affected by the COVID-19 pandemic decreasing the short-position of TFDC.

Our third model (M3) shows the relationship between DCC and CER by using a DNN-based regression model. The output shows that the CER is positively associated with DCC as indicated by beta value 0.2571, which showed that the 1-unit change in DCC becomes 25.71 units positive change in CER. The overall variation in CER is 10.9 % by increasing the DCC in India during the period of the COVID-19 pandemic. Furthermore, our fourth model (M4) shows the relationship between DCD and CER by using a DNN-based regression model. The output of our proposed model shows that there has a strong positive relation between DCD and CER as indicated by beta value 0.2697, which represents that one-unit change in DCD becomes 26.97 units of positive change in CER of a dynamic and emerging financial market. The overall variation in CER is 11.7 % by increasing DCD in an emerging economy. The findings concluded that the Indian currency market has 10 % to 12 % inversely affected by the COVID-19 pandemic. Our findings are supported by (Banerjee, 2021; Li et al., 2021; Narayan, 2022; Narayan et al., 2020).

According to economic theory, the inflation rate, interest rates, public debt, political instability, economic health, international trade, current account deficit, market confidence, speculation, government intervention and global financial crisis are major factors of CER. All factors have more or less been affected by the global financial crisis. But the inflation has been severely affected by disturbing the global supply-chain of products during the current global financial crisis. According to the ministry of statistics and program implementation, the inflation rate in India increased by 5.59 % during the COVID-19 pandemic (Ministry of Statistics and Programme Implementation, 2021). Therefore, the market inflation increases the CER that itself raised by global supply-chain disorder during the COVID-19 pandemic. The CER directly affects the currency market and this effect spillover on the derivatives market to manage the currency risk while the usage of short-position of TFDC has been decreasing consistently since the outbreak of the COVID-19 pandemic. Furthermore, the graphical representation makes more apparent the direction of both financial markets during the COVID-19 pandemic as follows (Iqbal et al., 2021).

Fig. 10 shows the strength of the association between significant variables and the direction of both emerging financial markets during the COVID-19 pandemic. Fig. 10 contains on four 3D graphs and each graph takes a predictand variable at x-axis, a predictor variable at y-axis and a slope of coefficients at z-axis to estimate the emerging financial markets. Whereas, the colour-bar shows the strength of association of variables. Graph (a) of the M1 model represents that there is a strong relationship between DCC and TFDC as indicated by overwhelming red and yellow colours throughout the graph with few exceptions, which is presented at the extreme-lower part of the graph. The strength of association is divided into three parts as upper, middle and lower parts of the graph which demonstrated that the strong-positive, slight-positive and slight-negative association between DCC and TFDC respectively. But there is a negative slope of coefficients among the variables as indicated by the direction of the colour-scheme, which moves from dark-red colour to blue colour. The graph shows that the futures derivatives contracts sharply decreased over the pandemic period. Furthermore, Graph (b) of the M2 model shows the direction of the futures derivatives market of India in case of DCD. Our second empirical model gives the corresponding output as the previous model (M1). The graph shows that the futures derivatives contracts are sharply declining over the spreading DCD in India. Thus, the findings are concluded that the Indian futures derivatives market has been inversely affected by the COVID-19 pandemic while the futures derivatives contracts are consistently declining from the day first of the COVID-19 pandemic outbreak to hedge their currency risk.

Furthermore, Graph (c) of the M3 model shows the association between the Indian currency market and the COVID-19 pandemic in case of DCC. The output shows that the CER has a strong relation with DCC, as indicated by spreading light-green, yellow and light-red colours throughout the graph. The strength of association is divided into three

[4] The descriptive statistics of empirical data is shown in Table 3 which is presented in Appendix C.

[5] The output shows that the proposed models have absolutely trained on given dataset while non-trainable params are zero. Whenever, the Fig. 7 shows the loss of proposed model over the number of epochs on the back propagation algorithms which is presented in Appendix C. Our 1st model (M1) does not use any hidden layers within input and output layer while M1 is a SNN-based multivariate regression model for financial prediction. Similarly, the M2 and M3 are also SNN-based multivariate regression models as indicated by the application of one and two hidden layers respectively within input and output layers of the proposed models. But our fourth model M4 is a DNN-based multivariate regression model as indicated by $l = 3$ whenever $L = 4$ which is trained on backpropagation algorithms. In addition, the Fig. 8 plot the absolute error of proposed multivariate regression models which is presented in Appendix C.

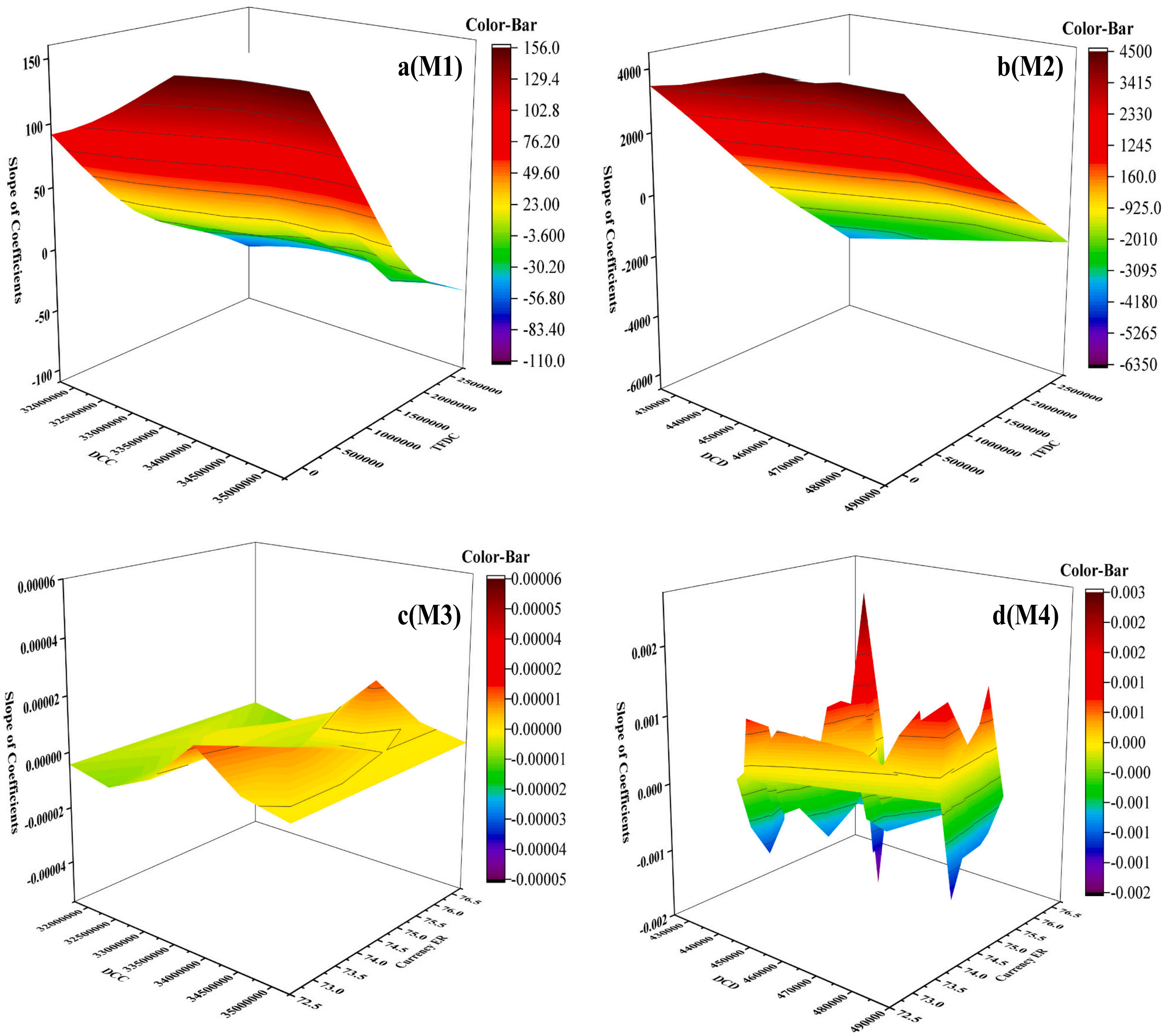

Fig. 10. Plot the slope of the coefficients.

Table 5
Strength of association between structural learning-based Bayesian network nodes.

X	Y	Mutual information	Symmetric	For X given Y	For Y given X	Entropy X	Entropy Y
(CER)	(TFCD)	0.006825	0.000856	0.004386	−0.000474	1.556012	14.395475
(DCC)	(DCD)	0.588054	0.056186	0.046467	0.071045	12.655250	8.277229
(DCC)	(CER)	0.009301	0.001309	0.000735	0.005978	12.655250	1.556012
(DCC)	(TFCD)	0.004390	0.000325	0.000347	−0.000305	12.655250	14.395475
(DCD)	(TFCD)	0.012691	0.001120	0.001533	−0.000882	8.277229	14.395475
(DCD)	(CER)	0.010919	0.002221	0.001319	0.007017	8.277229	1.556012

parts as upper, middle and lower parts of the graph which demonstrated a strong-positive, slight-positive and slight-negative association between DCC and CER respectively. Moreover, Graph (d) of the M4 model shows the direction of the currency market of India during the COVID-19 pandemic in case of DCD. The output indicates that the CER is comparatively more affected by DCD, as indicated by overwhelming the dark-yellow and dark-red colours throughout the graph with exception of few spikes at the lower part of the graph. The findings showed that the CER gradually increased during the pandemic period in India. Our graphical findings support our numerical findings remarkably.

4.1. Robustness estimation

The present study uses the structural learning-based Bayesian network approach for robustness estimation. It is a mechanism to explore the probabilistic distribution of random variables and the conditional effect of the variables. A structural learning-based Bayesian network provides expanded information about the relationships between all included variables. The structural learning-based Bayesian network uses score-based and constraint-based approaches to estimate the variable's probabilistic distribution and conditional effect. Whereas, the score-based approach searches maximal score at DAG (directed acyclic graph) principle and the constraint-based approach learns the conditional dependency of random variables and infer the presence or absence of particular arcs (Margaritis, 2003). Let's suppose, the W, X, Y and Z are four random variable nodes in $n - th$ Bayes network structure. In the first case of DAG, Z is a parent node of X & Y nodes, whereas X & Y are child nodes of a parent node. In the 2nd case of DAG, the X & Y are parent nodes of W node, whereas W is a child node of the parent nodes. But only the Z is a root node of W, X, and Y variables nodes in a particular DAG. Moreover, in the first case of DAG execution, the conditional dependency of random variables is written as P(X, Y | Z), which expressed how much probability of occurrence of X and Y variables when Z is already happened. Similarly, in the second case of DAG execution, the conditional dependency of random variables is written as P(W | X, Y), which represents that if the X & Y variables nodes are already happened, how much probability of occurrence of W variable node.

Fig. 11 shows the structural learning-based Bayesian network structure, which is presented in Appendix C. The present network structure gives the following relationships information: 1) the network represents the association between DCC, DCD and CER; 2) the network shows the association between DCC, DCD and TFDC; 3) the network demonstrates that the CER conditionally affects the TFDC given the percentage of DCC and DCD.

Table 5 shows that the currency market conditions represented by CER have the strongest positive relation with DCC and DCD. Moreover, the derivatives market conditions represented by TFDC have the strongest negative relation with DCC and DCD. In the case of conditional dependency, the TFDC is conditionally dependent on the CER given the percentage of DCC and DCD. We can see that the CER makes high strength relation with the percentage of DCC and DCD as well. Moreover, the transfer information loss of the variables in a particular network structure is measured by entropy. So, the entropy is always decreased by the deterministic processing of random data.

Fig. 12 represents the joint distribution of significant variables with the mesh-query approach. Each mesh-query graph contains on three variables, whereas the Z is a likelihood of X and Y variables. For this purpose, we placed the DCC and DCD at x-axis and CER and TFDC at y-axis to estimate the joint distribution of significant variables. The black colour in the surrounding of graphs a, b, c and d in Fig. 12 indicates the observations are quite rare when TFDC, DCC and DCD, and CER DCC and DCD are very low or very high. Whereas, the maximum observations are supporting to middle values of all significant variables.

4.2. Discussion

The commencement of 2020 portended gigantic lockdowns restraining activities of both private and public entities through gathering annulment in an attempt to prevent the distribution of the COVID-19 pandemic. Wide-ranging travel constraints were implemented, with social distancing and complete lockdown policies becoming day-to-day parts of producers' and customers' lives and an entire important impact on the market fluctuations.

The COVID-19 pandemic made worse global economic situation at a time when economies were at their fragile. Although the magnitude of the effect will not be exactly ascertained shortly, but damages are bound to be critical. The current macroeconomic vulnerability makes the market and the country more susceptible to economic and financial instability, which reduces the efficiency of support-oriented policies. The pandemic effects on the financial markets will be felt for a while, even with support.

The economies of emerging markets and developing countries are expected to be severely impacted, especially those having weak healthcare systems, financially fragile, highly dependent on tourism, trade, remittances from other countries, or export of primary commodities. Rising debt levels in emerging markets and developing economies make more vulnerable to financial instability than before the global financial crisis.

However, the fundamental key purpose of the present study is to estimate the absolute impact of the COVID-19 pandemic on the emerging currency and derivatives markets with new methodological approaches to support policies guide decisions, especially for monetary policymakers and financial risk hedgers in extreme financial crisis circumstances. Njindan Iyke (2020) determined that the great financial crisis negatively affected the currency market of emerging economies by enhancing the volatility of CER. But some scholars endorsed that it is just a transitory effect as follows (Narayan, 2020). The COVID-19 pandemic is enhancing the vulnerability of the Indian economy by squeezing the financial markets, especially their currency market turbulence (Padhan and Prabheesh, 2021). Mishra et al. (2020) estimated that the INR has depreciated by 7.2 % against the USD during the COVID-19 pandemic

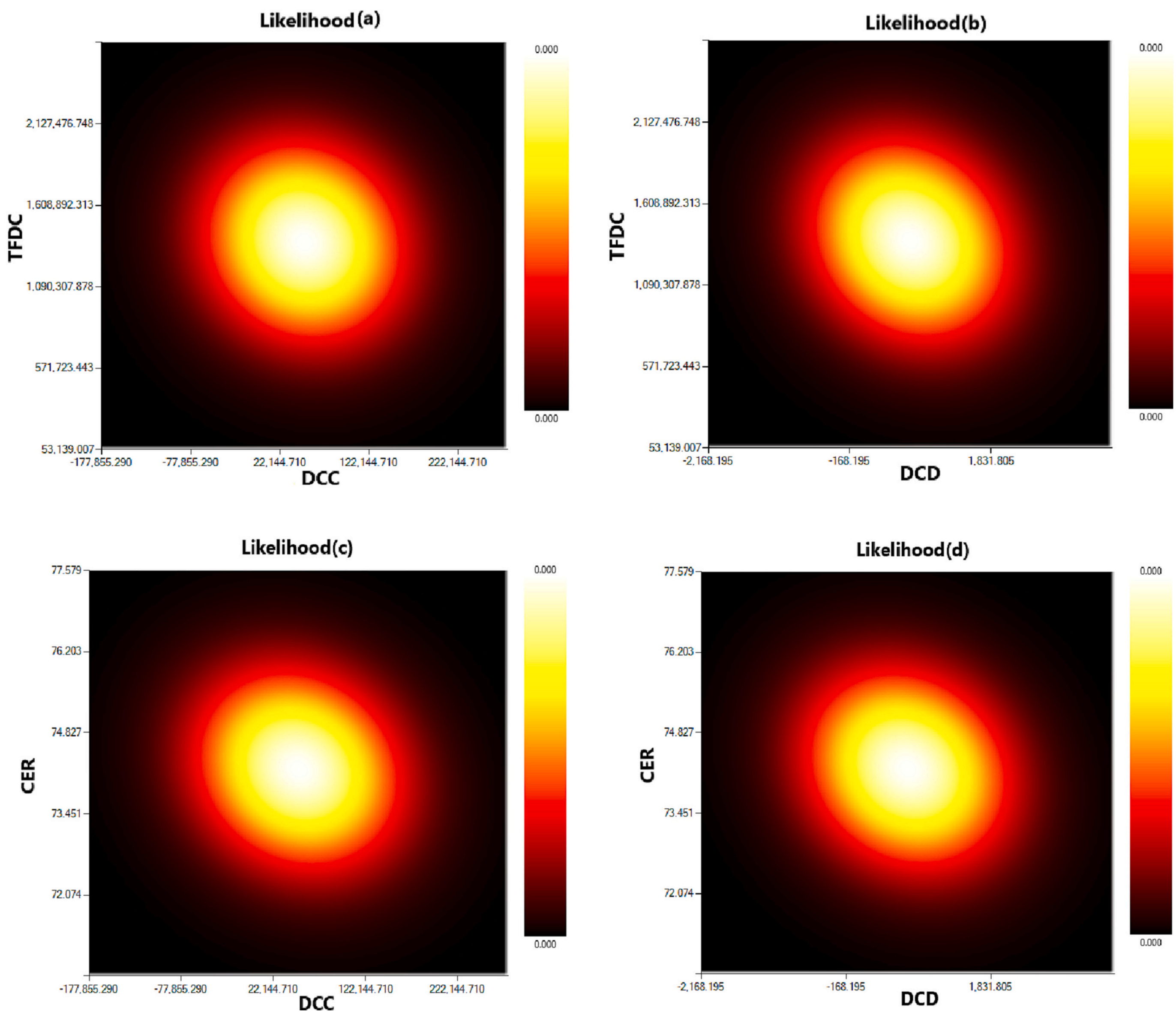

Fig. 12. Plot joint distribution of random variables with mesh-query.

period. So, the advanced and conventional approaches predicted that the Indian currency market efficiency has been affected by the COVID-19 pandemic (Phiri, 2022). The major findings of the present study regarding the COVID-19 pandemic effect on the Indian currency market are supporting to previous studies.

Furthermore, the numerous studies acknowledged the current global financial crisis has inversely affected the Indian currency market by enhancing the CER risk. The financial derivatives instrumental approach commonly uses to manage financial risk, which is poorly neglected in the largest economy of Asia during the current global financial crisis. Afrina et al. (2020) plotted the international financial derivatives markets' performance before and after the COVID-19 pandemic. The COVID-19 pandemic effect is dominant on the international financial derivatives market. Moreover, the COVID-19 pandemic has very bold impacted on the Indian derivatives market with decreasing the number of trading contracts for financial risk hedging (Dusmanta and Mohanty, 2022). Our findings regarding the COVID-19 pandemic and foreign currency derivatives are robust and supports previous study. However, the hedgers are suggested to decrease the short-position of futures derivatives to hedge the domestic currency risk specially during the crisis events line the COVID-19 pandemic.

Furthermore, with a new methodological approach, the present study has estimated the additional findings about the conditional effect of the Indian currency market on their derivatives market given the percentage of COVID-19 pandemic effect. Thus, we conclude with sound empirical evidence that the COVID-19 pandemic has destructively affected the currency market of an emerging economy by depreciating their currency value against USD while hedgers have been buying foreign safe-haven currencies against the local currency to manage CER risk since the outbreak of the COVID-19 pandemic.

4.3. Contribution of the study

This study makes several significant contributions to the literature in the theoretical, empirical and methodological.

4.3.1. Theoretical contributions

The financial literature showed that the global financial and nonfinancial crisis destructively affects the financial markets, and currency market instability effect spillover on the derivatives market to manage the financial risk, especially in global financial crises. While numerous studies have attempted to forecast the effect of the COVID-19 pandemic on the emerging currency market and its returns. The previous studies have poorly ignored the influence of the COVID-19 pandemic on the emerging derivatives market and the conditional effect of the currency market on the derivatives market in terms of the COVID-19 pandemic. However, the present study theoretically contributes by filling this lacuna by investigating the simultaneous effect of the COVID-19 pandemic on emerging currency and derivatives markets and the conditional effect of currency market volatility on the derivatives market given the percentage of the COVID-19 pandemic.

4.3.2. Empirical contributions

The present study contributes to the fast-growing literature seeking to use advanced ANN and structural learning-based Bayesian network to determine the influence of the COVID-19 pandemic on the emerging currency and derivatives markets. It makes a sustainable empirical contribution by predicting the absolute effect of the COVID-19 pandemic on the Indian derivatives market, which previous studies have poorly ignored. Moreover, this study empirically contributes by testing the conditional dependency of the Indian emerging derivatives market on the volatility of the currency market given the percentage of the COVID-19 pandemic via the Bayes network, which previous studies have strongly neglected.

4.3.3. Methodological contributions

Most previous studies have employed the TEMs, MLMs and SNNs to examine the COVID-19 pandemic effect on emerging financial markets. But a complex multidimensional highly volatile nonlinear financial market data can be poorly predicted by conventional approaches (HongXing et al., 2022; Wookjae Heo et al., 2020). So, to overcome this challenge, three methodological contributions were made. First, we employed an advanced DNN-based multivariate regression model with a back propagation function to determine the absolute impact of the COVID-19 pandemic on the Indian emerging currency and derivatives markets. Second, we applied a structural learning-based Bayesian Network approach with a constraint algorithm to robust the relationship between the COVID-19 pandemic and emerging financial markets. Third, we expanded the usage of the structural learning-based Bayesian Network to find the conditional effect of the Indian currency market on their derivatives market given the percentage of the COVID-19 pandemic. All contributions gave interesting information regarding changes in Indian currency and derivation markets during the COVID-19 pandemic and its associated mechanism.

5. Conclusion and implications of the study

The present study focused on the influence of the COVID-19 pandemic on dynamic emerging financial markers by using a DNN-based multivariate regression. Several findings are documented as follows: first, the DNN-based multivariate regression model gives optimal financial predictions with a small error than the SNN-based multivariate regression model at a complex multidimensional high volatile nonlinear financial market dataset. Second, the structural learning-based Bayesian network is a useful approach to forecasting the probabilistic distribution of random variables and conditional effect. Third, the current global financial crisis has destructively affected the Indian currency market. The findings concluded that the Indian currency market has 10 % to 12 % damaged by the current global financial crisis, which is indicated by sharply appreciating the domestic CER from 70.03₹ to 75.57₹ against USD. Fourth, the COVID-19 pandemic has strongly influenced the Indian derivatives market while an emerging futures derivatives market has 3 % to 5 % damaged during the current global financial crisis that is indicated by consistently reducing the short-position of TFDC throughout the pandemic period. Fifth, the Indian currency market conditionally affects their emerging futures derivatives market given the percentage of the COVID-19 pandemic. Indeed, the Indian currency continuously losing their values throughout the pandemic period while the hedgers hedge their currency risk by reducing the short-position of TFDC during the pandemic period. By sound empirical evidence, we concluded that the COVID-19 pandemic has negatively influenced the Indian dynamic emerging currency and derivatives markets.

This study provides various significant implications for a wider audience. First, financial researchers and data analysts understanding knowledge about ANN with backpropagation algorithm and structural learning-based Bayesian network with constraint algorithm for financial predictions. By sound empirical evidence of the financial prediction performance of the proposed model suggests that researchers and data analysts should be considered both empirical approaches for examining the absolute effect of the financial crises on the emerging financial markets and the conditional effect of the currency market on the derivatives market at extreme financial crisis conditions. Second, monetary policymakers of emerging financial markets' understanding of whether there is a strong influence of resent global financial crisis on the currency market will support guide decisions about whether specific policies are needed to equilibrium the currency market by extreme fluctuations, especially during the financial crises. The evidence of a strong influence of the current global financial crisis on an emerging currency market suggests that policymakers should make appropriate policies to control CER volatility that may promote currency market stability to enhance currency market activities and boost the confidence of foreign investors in extreme financial crisis circumstances. This study may support financial risk hedgers to manage their currency risk through a buy-hold-and-sell strategy with foreign currency derivatives at extreme CER volatility during the financial crises. In future studies, the COVID-19 pandemic effect on the emerging financial markets is still a developing issue; we believe that further studies can obtain the significant theoretical and empirical contributions on this matter with panel-country-data and advanced computational approaches.

Data sources

The COVID-19 pandemic dataset is easily accessible from https://github.com at the following URL: https://github.com/owid/covid-19-data/owid-covid-latest.csv.The gethub reported that this empirical dataset has retrieved from https://systems.jhu.edu/ which is also supported by https://engineering.jhu.edu/covid-19/support-the-csse-covid-19-dashboard-team/. The TFDC dataset is easily accessible from https://www.bseindia.com/ at the following URL: https://www.bseindia.com/markets/currencyDerivatives/CurrDeriArchiveSum.aspx. Moreover, the CER dataset is also easily accessible from https://www.ecb.europa.eu/ at the following URL: https://www.ecb.europa.eu/stats/html/index.en.html.

CRediT authorship contribution statement

Hafiz Muhammad Naveed: Conceptualization, Writing - Original Draft. **Shoaib Ali, Jan Muhammad Sohu, Hafiz Muhammad Naveed:** Data Curation. **Hafiz Muhammad Naveed, Mohammed Ismail Alhussam:** Methodology, Software, Formal Analysis. **Yao HongXing, Bilal Ahmed Memon, Shoaib Ali:** Writing-Review and Editing. **Yao HongXing:** Resources, Investigation, Visualization: Supervision, Project Administration, Funding Acquisition. All respected authors have read prudently and agreed to publish this manuscript. Moreover, authors declare no potential conflicts of interest to the research, authorship, and publication of this article.

Declaration of competing interest

The authors declare no potential conflicts of interest to the research, authorship, and publication of this article.

Data availability

Data will be made available on request.

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Appendix A

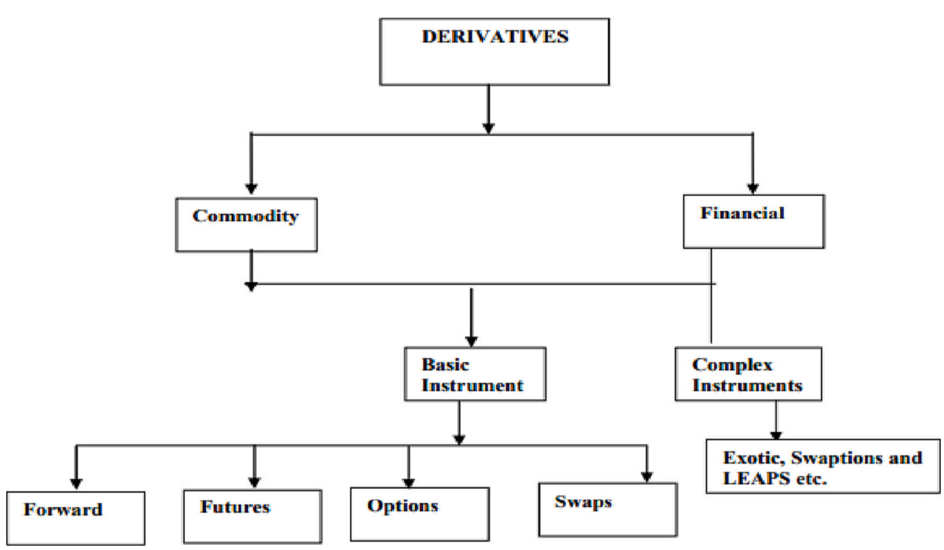

Fig. 1. Architecture of foreign derivatives instruments.

Fig. 1 shows that the financial and commodities are two main kinds of derivatives which trade internationally. In addition, the forward, futures, options and swaps are key instruments of financial and commodities derivatives used to hedge their currency and commodities risks. It should be noted that the present study is using currency futures derivatives to examine the effect of the COVID-19 pandemic on the financial derivatives market of an emerging economy.

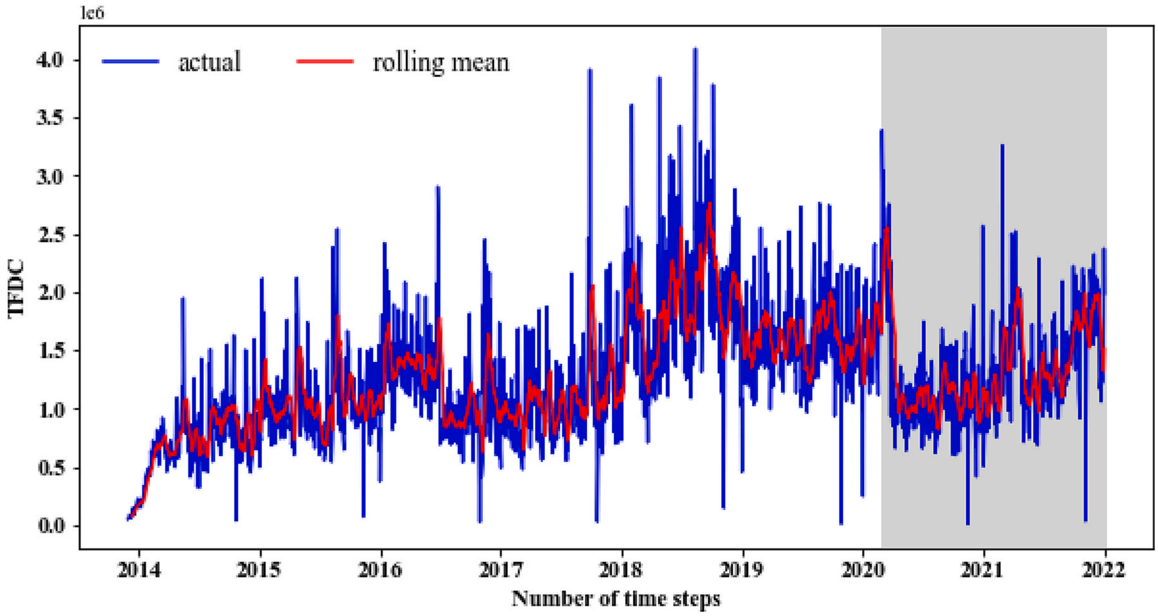

Fig. 3. Plotting daily TFDC in the BSE.

Fig. 3 demonstrates the short-position of TFDC in the BSE. It should be noted that these currency futures derivatives are traded between INR-USD, INR-EUR and INR-JPY remarkably. A historical dataset is used in the above Graph to explicit the COVID-19 pandemic effect on the financial derivatives market. The shaded area with light-gray colour represents the pandemic effect on the futures derivatives market, which is indicated by reducing the number of contracts to hedge their currency risk.

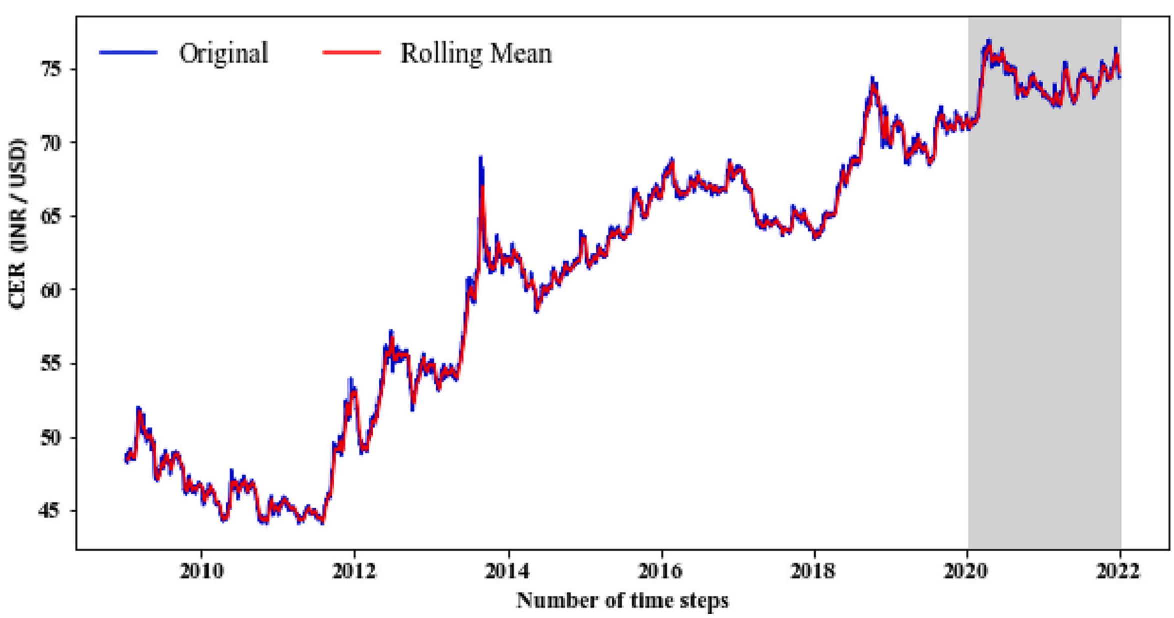

Fig. 4. Plotting daily currency exchange rate.

Fig. 4 shows the Indian CER against the international currency over the period 02-01 2009 to 01-01-2022. The graph shows that the CER is consistently increasing over the data sample. But it was surprisingly jumped upward after the outbreak of the COVID-19 pandemic which indicated by a shaded area with light-gray colour.

Appendix B

ReLU activation function

Let $\mathbb{A}$ be a deep neural network architecture. Let F be the class of functions-outputs $f = N\ (\Phi, \cdot)$ of all deep ReLU neural networks Φ having the architecture A. Let $a \in \mathbb{R}$ and H be the class of all functions $h_f : \mathbb{I}^d \rightarrow \{0, 1\}, f \in F$, defined by threshold:

$$h_f(x) := \begin{cases} 0 \text{ if } f(x) \leq a \\ 1 \text{ if } f(x) > a \end{cases}$$

Whereas

$$\text{VCdim}(\ H\ ) \leq \text{CW}(\mathbb{A})^2$$

For some positive constant C, Moreover, exists a $C' > 0$ such that

$$VCdim(H) \leq C^{'} L(\mathbb{A}) W(\mathbb{A}) log(W(\mathbb{A})\ )$$

Sigmoid activation function

The sigmoid activation function is also called the standard logistic function, that is expressed as

$$S(x) = \frac{1}{1 + e^{-1}} = \frac{e^x}{e^x + 1} = x \in (\,-\infty, \infty)$$

So, the 1st and 2nd derivatives given as

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

$$S^{'}{'}(x) = \frac{e^x(1 - e^{x)}}{(1 + e^x)^3} = S(x)(1 - S(x)\ )(1 - 2S(x)\ )$$

For $x \in (-\infty, \infty)$, it follows to Barry (2017), where $S(x)$ is increasing on $(-\infty, \infty)$ and $y = S(x)$ is a solution of autonomous differential equation.

$$\frac{dy}{dx} = y(1 - y)$$

Whereas the initial condition is $y(0) = 0.5$, and then the activation function may satisfy with the following properties.

$$S(x) + S(\,-x) = 1$$

$$S^{'}(x) = s(x)S(x)$$

$$S^{'}(x) = S^{'}(\,-x)$$

$$\lim_{x \to \infty} S(x) = 1$$

$$\lim_{x \to 0} S(x) = \frac{1}{2}$$

$$\lim_{x \to -\infty} S(x) = 0$$

$$\lim_{x \to \pm\infty} S^{'}(x) = 0$$

$$\lim_{x \to 0} S^{'}(x) = \frac{1}{4}$$

$$\int S(x)dx = ln(1 + e^x) + C$$

where the C is a constant of integration. The function $\ln(1 + e^x)$is known in the literature as softplus function

Appendix C

Table 2
Hyperparameters of the proposed model.

Functions	Application	Features
Model	**	sequential
Random state	**	42
Activation function	**	ReLU & Sigmoid
Kernel initialier	**	he_normal
Regularizer	**	*l*2
Dropout	*	0
Optimizer	**	adam
Earlystopper	**	monitor = val_loss
Patience	**	10
Callback function	**	monitor
Mode	**	auto
Batch size	**	32
Validation split	**	0.2
Maximum epochs	**	10,000
Shuffle	**	False

Note: ** represents the application of implicit function in the proposed model.

Table 3
Descriptive statistics.

Statistics	DCC	DCD	TFCD	CER
Observations	703	703	703	703
Mean	49,649	687	1,349,600	74
Median	26,382	392	1,265,739	74
Maximum	414,188	7374	3,392,499	77
Minimum	0	−1	6753	71
Std. Dev.	75,889	952	432,461	1
Skewness	3	3	1	0
Kurtosis	12	11	4	3
Jarque-Bera	3645	2851	145	4
Sum	34,903,105	482,975	949,000,000	52,120
Sum Sq. Dev.	4,040,000,000,000	637,000,000	131,000,000,000,000	925

Summary of the proposed model

M1($l = 0$)			M2($l = 1$)			M3($l = 2$)			M4($l = 3$)		
Layer (type)	Output shape	Param #	Layer (type)	Output shape	Param #	Layer (type)	Output shape	Param #	Layer (type)	Output shape	Param #
dense_1(Dense)	128	384	dense_1(Dense)	128	384	dense_1(Dense)	128	384	dense_1(Dense)	128	384
dense_2(Dense)	2	258	dense_2(Dense)	64	8256	dense_2(Dense)	64	8256	dense_2(Dense)	64	8256
			dense_3(Dense)	2	130	dense_3(Dense)	64	4160	dense_3 (Dense)	64	4160
						dense_4(Dense)	2	130	dense_4(Dense)	64	4160
									dense_5(Dense)	2	130
NTP: 0	TAP: 642	TP: 642	NTP: 0	TAP: 8770	TP: 8770	NTP: 0	TAP: 12930	TP: 12930	NTP: 0	TAP: 17090	TP: 17090

Note: NTP: Non-trainable params; TAP: Trainable params; TP: Total params.

The above table contains on four absolute trained models. The M1 is an SNN-based multivariate regression model, which comprised without hidden layers, one input layer and one output layer. The dense input layer takes two numeric inputs with 128 neurons, whereas the output layer gives two numeric outputs. The summary of our first proposed model indicates that it is a fully trained model because TP = TAP while NTP = 0. Furthermore, the M2 model contains on one hidden layer, one input layer and one output layer. The present model uses homogeneous numeric inputs and outputs as the previous SNN-based multivariate regression model. The summary of the present model shows that the trainable params are 384 at the input layer with using 128 neurons. In addition, the trainable params are 8256 in the first hidden layer by using 64 neurons. Similarly, the output layer is contained on 130 params and 2 numeric outputs. This is another absolute fully connected trained model. Furthermore, the M3 model contains on one input layer, one output layer and two hidden layers. The model summary demonstrates that the trainable params are 384 in the input layer by comprising two numeric inputs with 128 hidden neurons. Moreover, the strength of trainable params is 8256 and 4160 at the first and second hidden layers respectively by using the homogeneous number of neurons. In addition, the trainable params are 130 in the output layer at 2 numeric outputs. The model summary indicates that it is another fully trained model while TP = TAP and NTP = 0. Furthermore, our fourth DNN-based multivariate regression model is contained on one input layer, one output layer, and three hidden layers. We are adjusting 128 number of neurons in the input layer and using 64 number of neurons in all rest of the layers. Our DNN-based multivariate regression model is an absolute train model while TP = TAP and NTP = 0.

Fig. 7 demonstrates the loss and validation loss of various ANN-based multivariate regression models. In M1, the loss and validation loss are smoothly declining throughout the graph. It should be noted that we have used auto-function in the training process to stop the training process automatically at a minimum error of the model. Graph 1 in Fig. 7 indicates that our first model is expending 1400 epochs to accomplish the training process. Similarly, the 2nd, 3rd and 4th graphs indicate that the M2, M3 and M4 proposed models are expending 600, 400, and 300 number of epochs to accomplish the training process as well. The loss and validation loss are correspondingly declining throughout the graphs while there is no overfitting and underfitting problems. But our DNN-based multivariate regression model accomplishes the training process by comparatively expending a small number of epochs. Therefore, the loss and validation loss are more efficiently and smoothly declined by the M4 model than competitive models.

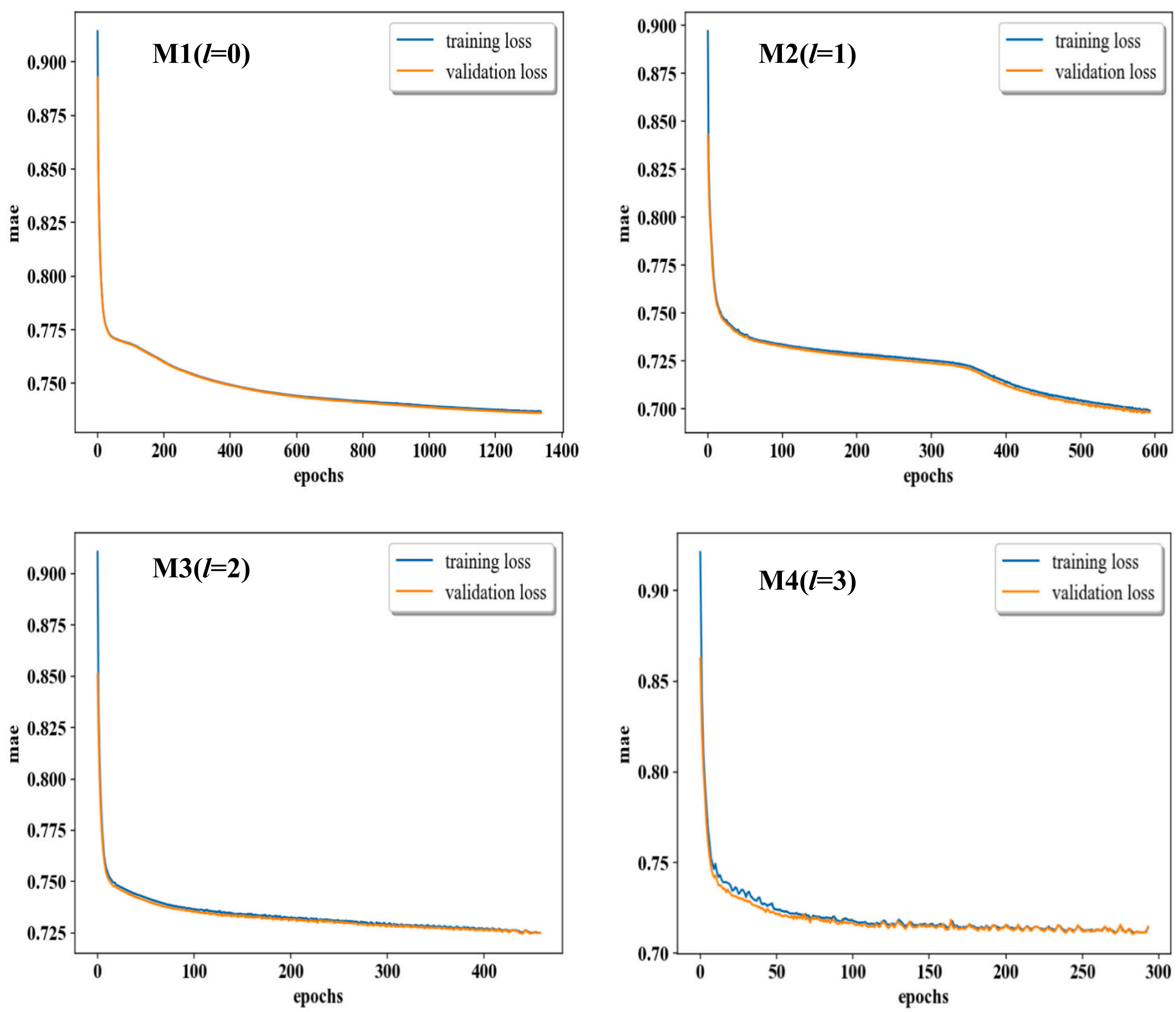

Fig. 7. Training and validation loss of the proposed model.

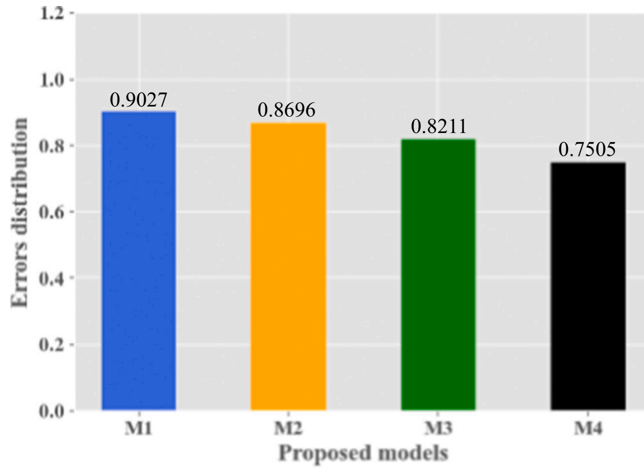

Fig. 8. Plot absolute errors of proposed models.

Fig. 8 plots the absolute errors of proposed DNN-based multivariate regression models for financial predictions. For this purpose, we are placed the number of empirical models at x-axis and error distribution of proposed models at y-axis. Fig. 8 indicates that the overall errors of proposed models (M1, M2, M3, & M4) are 0.9027, 0.8696, 0.8211 and 0.7505 respectively. The output shows that the M4 gives optimal financial predictions with a small error by expending relatively less-number of epochs and training time to accomplish the training process at given dataset. With sound empirical evidence, we concluded that the DNN-based multivariate regression model is relatively an appropriate model than the SNN-based multivariate regression model for financial predictions using a complex high volatile multidimensional time series data. However, we referred the DNN-based regression model for our further predictions.

Summary of the optimal proposed models

M1($l = 3$)			M2($l = 3$)			M3($l = 3$)			M4($l = 3$)		
Layer (type)	Output shape	Param #	Layer (type)	Output shape	Param #	Layer (type)	Output shape	Param #	Layer (type)	Output shape	Param #
dense_1(Dense)	128	256	dense_1(Dense)	128	256	dense_1(Dense)	128	256	dense_1(Dense)	128	256
dense_2(Dense)	64	8256	dense_2(Dense)	64	8256	dense_2(Dense)	64	8256	dense_2(Dense)	64	8256
dense_3 (Dense)	64	4160	dense_3 (Dense)	64	4160	dense_3 (Dense)	64	4160	dense_3 (Dense)	64	4160
dense_4(Dense)	64	4160	dense_4(Dense)	64	4160	dense_4(Dense)	64	4160	dense_4(Dense)	64	4160
dense_5(Dense)	1	65	dense_5(Dense)	1	65	dense_5(Dense)	1	65	dense_5(Dense)	1	65
NTP: 0	TAP: 16897	TP: 16897	NTP: 0	TAP: 16897	TP: 16897	NTP: 0	TAP: 16897	TP: 16897	NTP: 0	TAP: 16897	TP: 16897

Note: NTP: Non-trainable params; TAP: Trainable params; TP: Total params.

The above table comprises the summary of proposed models, which are recommended by models' evaluation process. All recommended models use homogeneous features and hyperparameters for the financial predictions. Every model has one input layer, one output layer and three hidden layers. We used 128 neurons in the input layer and 64 neurons in the hidden layers based on features of recommended models from the previous prediction segment. The model summary showed that there are no non-trainable params while TP = TAP which indicates that the training model has trained remarkably.

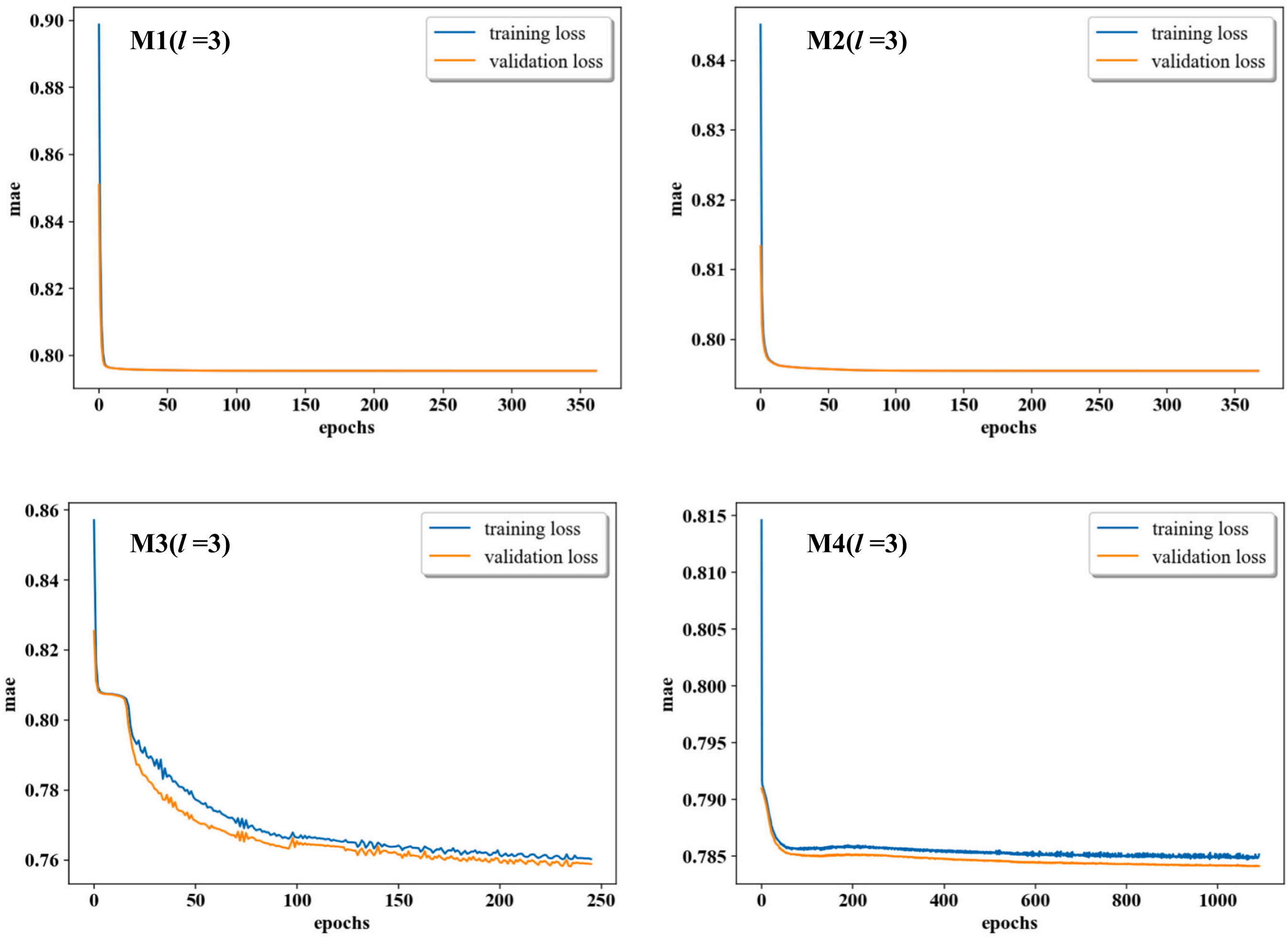

Fig. 9. Training and validation loss of optimal proposed model for estimation.

Fig. 9 comprises the loss of the models. For this purpose, we have taken the number of epochs at x-axis and loss (MAE) at y-axis. Every graph in Fig. 9 has two different downward curves representing the loss and validation loss of the proposed model. Both curves are correspondingly declining throughout the graphs, indicating no underfitting and overfitting problems in our trained models. Our proposed M1, M2, and M3 models are expending 350, 350 and 250 number of epochs to accomplish the training process respectively. But our 4th model is relatively taking few more epochs and training time than our previous models to accomplish the training process.

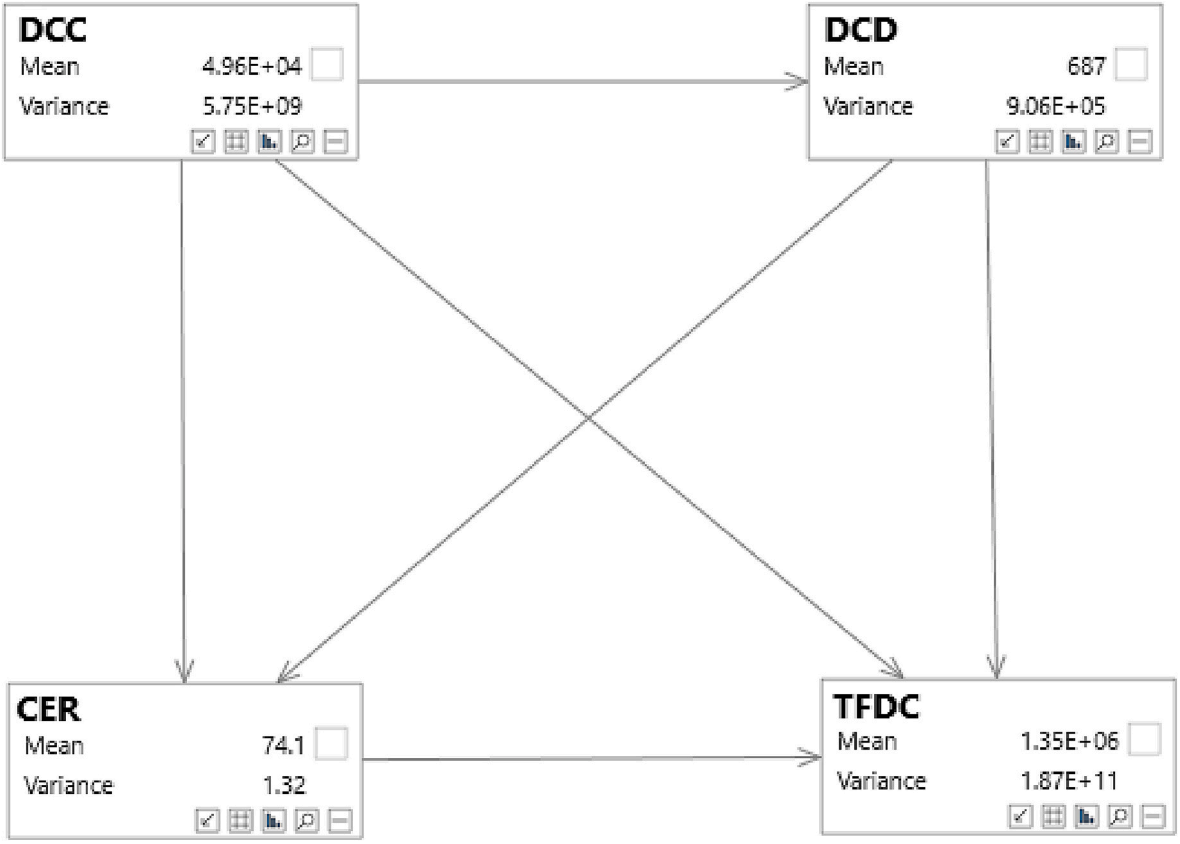

Fig. 11. A Bayesian network structure.

Fig. 11 shows a Bayesian network structure at given variable nodes. This network structure contains on four significant variable nodes and each variable node is interconnected with another variable node with a solid edge to transfer the unique information. The network shows relationships between all random variables and the conditional dependency of the variable.

References

Abedin, M.Z., Moon, M.H., Hassan, M.K., Hajek, P., 2021. Deep learning-based exchange rate prediction during the COVID-19 pandemic. Ann. Oper. Res. 1–52 https://doi.org/10.1007/s10479-021-04420-6.

Afrina, T., Beg, T.H., Zayed, N.M., Hossain, M.S., Shahi, S.K., 2020. An analysis of the effects of corona virus (COVID-19) on international financial derivatives market, 2020. Indian J. Finance Bank. 4 (2), 93–98. https://doi.org/10.46281/ijfb.v4i2.757.

Aloui, D., 2021. The COVID-19 pandemic haunting the transmission of the quantitative easing to the exchange rate. Financ. Res. Lett. 43, 102025 https://doi.org/10.1016/j.frl.2021.102025.

Álvarez-Díez, S., Alfaro-Cid, E., Fernández-Blanco, M.O., 2016. Hedging foreign exchange rate risk: multi-currency diversification. Eur. J. Manag. Bus. Econ. 25 (1), 2–7. https://doi.org/10.1016/j.redee.2015.11.003.

Antonakakis, N., Money, 2012. Exchange return co-movements and volatility spillovers before and after the introduction of euro. J. Int. Financ. Mark. Inst. Money 22 (5), 1091–1109. https://doi.org/10.1016/j.intfin.2012.05.009.

Aslam, F., Aziz, S., Nguyen, D.K., Mughal, K.S., Khan, M., 2020. On the efficiency of foreign exchange markets in times of the COVID-19 pandemic. Technol. Forecast. Soc. Chang. 161, 120261 https://doi.org/10.1016/j.techfore.2020.120261.

Banerjee, A.K., 2021. Futures market and the contagion effect of COVID-19 syndrome. Financ. Res. Lett. 43, 102018 https://doi.org/10.1016/j.frl.2021.102018.

Barry, P.J.A.P.A., 2017. Sigmoid Functions and Exponential Riordan Arrays. School of Science Waterford Institute of Technology Ireland.

Bazán-Palomino, W., Winkelried, D., 2021. FX markets' reactions to COVID-19: are they different? Int. Econ. 167, 50–58. https://doi.org/10.1016/j.inteco.2021.05.006.

Beckmann, J., Czudaj, R.L., 2022. Exchange rate expectation, abnormal returns, and the COVID-19 pandemic. J. Econ. Behav. Organ. https://doi.org/10.1016/j.jebo.2022.02.002.

Benzid, L., Chebbi, K., 2020. The Impact of COVID-19 on Exchange Rate Volatility: Evidence Through GARCH Model. https://doi.org/10.2139/ssrn.3612141. Available at SSRN 3612141.

Berkman, H., Malloch, H., 2021. Stock valuation during the COVID-19 pandemic: an explanation using option-based discount rates. J. Bank. Financ., 106386 https://doi.org/10.1016/j.jbankfin.2021.106386.

Bernoth, K., Herwartz, H., 2021. Exchange rates, foreign currency exposure and sovereign risk. J. Int. Money Financ. 117, 102454 https://doi.org/10.1016/j.jimonfin.2021.102454.

Buyukkara, G., Kucukozmen, C.C., Uysal, E.T., 2022. Optimal hedge ratios and hedging effectiveness: an analysis of the turkish futures market. Borsa Istanbul Rev. 22 (1), 92–102. https://doi.org/10.1016/j.bir.2021.02.002.

Choudhry, T., Hassan, S.S., Money, 2015. Exchange rate volatility and UK imports from developing countries: the effect of the global financial crisis. J. Int. Financ. Mark. Inst. Money 39, 89–101. https://doi.org/10.1016/j.intfin.2015.07.004.

Dash, D.P., Sethi, N., Dash, A.K., 2021. Infectious disease, human capital, and the BRICS economy in the time of COVID-19. MethodsX 8, 101202. https://doi.org/10.1016/j.mex.2020.101202.

Devpura, N., 2021. Effect of COVID-19 on the relationship between Euro/USD exchange rate and oil price. MethodsX 8, 101262. https://doi.org/10.1016/j.mex.2021.101262.

Dimitriou, D., Kenourgios, D., Simos, T., 2017. Financial crises, exchange rate linkages and uncovered interest parity: evidence from G7 markets. Econ. Model. 66, 112–120. https://doi.org/10.1016/j.econmod.2017.06.003.

Dusmanta, K., Mohanty, N., 2022. Impact of COVID-19 waves on Indian derivative market: special reference to financial derivative segment. Int. J. Sci. Res. https://doi.org/10.21275/SR22511114609.

Ekum, M., Ogunsanya, A., 2020. Application of hierarchical polynomial regression models to predict transmission of COVID-19 at global level. Int. J. Clin. Biostat. Biom. 6 (1), 27. https://doi.org/10.23937/2469-5831/1510027.

Elliott, W.B., Huffman, S.P., Makar, S.D., 2003. Foreign-denominated debt and foreign currency derivatives: complements or substitutes in hedging foreign currency risk? J. Multinatl. Financ. Manag. 13 (2), 123–139. https://doi.org/10.1016/S1042444X(02)00039-7.

Emm, E.E., Gay, G.D., Ma, H., Ren, H., 2021. Effects of the Covid-19 pandemic on derivatives markets: evidence from global futures and options exchanges. J. Futur. Mark. https://doi.org/10.2139/ssrn.3994700.

Farhi, E., Werning, I., 2014. Dilemma not trilemma? Capital controls and exchange rates with volatile capital flows. IMF Econ. Rev. 62 (4), 569–605. https://doi.org/10.1057/imfer.2014.25.

Gadanecz, B., Miyajima, K., Shu, C., 2018. Emerging market local currency sovereign bond yields: the role of exchange rate risk. Int. Rev. Econ. Financ. 57, 371–401. https://doi.org/10.1016/j.iref.2018.02.004.

Garg, B., Prabheesh, K., 2021. The nexus between the exchange rates and interest rates: evidence from BRIICS economies during the COVID-19 pandemic. Stud. Econ. Financ. https://doi.org/10.1108/SEF-09-2020-0387.

Güler, K., Tepecik, A., 2019. Exchange rates' change by using economic data with artificial intelligence and forecasting the crisis. Procedia Comput. Sci. 158, 316–326. https://doi.org/10.1016/j.procs.2019.09.057.

Gunay, S., 2021. Comparing COVID-19 with the GFC: a shockwave analysis of currency markets. Res. Int. Bus. Financ. 56, 101377 https://doi.org/10.1016/j.ribaf.2020.101377.

Hau, H., 2014. The exchange rate effect of multi-currency risk arbitrage. J. Int. Money Financ. 47, 304–331. https://doi.org/10.1016/j.jimonfin.2014.05.001.

HongXing, Y., Naveed, H.M., Answer, M.U., Memon, B.A., Akhtar, M., 2022. Evaluation optimal prediction performance of MLMs on high-volatile financial market data. Int. J. Adv. Comput. Sci. Appl. 13 (1) https://doi.org/10.14569/IJACSK.2022.0130129.

Hossain, M., 2021. The effect of the Covid-19 on sharing economy activities. J. Clean. Prod. 280, 124782 https://doi.org/10.1016/j.jclepro.2020.124782.

Investhub.agency, 2022. Currency trading in India. https://investhub.agency/blog/currency-trading-in-india/.

Iqbal, N., Fareed, Z., Wan, G., Shahzad, F., 2021. Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market. Int. Rev. Financ. Anal. 73, 101613 https://doi.org/10.1016/j.irfa.2020.101613.

Iyke, B.N., Ho, S.-Y., 2021. Exchange rate exposure in the south african stock market before and during the COVID-19 pandemic. Financ. Res. Lett. 43, 102000 https://doi.org/10.1016/j.frl.2021.102000.

Kim, K.-H., Kim, N.-U., Ju, D.-C., Ri, J.-H., 2020. Efficient hedging currency options in fractional brownian motion model with jumps. Physica A 539, 122868. https://doi.org/10.1016/j.physa.2019.122868.

Kumar, R., 2014. Stock markets, derivatives markets, and foreign exchange markets. In: Strategies of Banks Other Financial Institutions Theories Cases. Academic Press, pp. 125–164. https://doi.org/10.1016/B978-0-12-416997-5.00005-1.

Levy, D., Mayer, T., Raviv, A., 2022. Economists in the 2008 financial crisis: slow to see, fast to act. J. Financ. Stab., 100986 https://doi.org/10.1016/j.eap.2021.06.014.

Li, C., Su, Z.-W., Yaqoob, T., Sajid, Y., 2021. COVID-19 and currency market: a comparative analysis of exchange rate movement in China and USA during pandemic. Econ. Res. 1–16. https://doi.org/10.1080/1331677X.2021.1959368.

Long, W., Zhong, Y., Li, R., Zhao, M., 2022. Does the emotional tendency of COVID-19 news affect financial markets? Procedia Comput. Sci. 199, 532–539. https://doi.org/10.1016/j.procs.2022.01.065.

Louhichi, W., Ftiti, Z., Ameur, H.B., 2021. Measuring the global economic impact of the coronavirus outbreak: evidence from the main cluster countries. Technol. Forecast. Soc. Chang. 167, 120732 https://doi.org/10.1016/j.techfore.2021.120732.

Margaritis, D., 2003. Learning Bayesian Network Model Structure From Data Carnegie-Mellon Univ Pittsburgh Pa School of Computer Science].

Ministry of Statistics and Programme Implementation, 2021. CONSUMER PRICE INDEX report december 2021. https://mospi.gov.in/web/mospi/home.

Mishra, A.K., Rath, B.N., Dash, A.K., 2020. Does the indian financial market nosedive because of the COVID-19 outbreak, in comparison to after demonetisation and the GST? Emerg. Mark. Financ. Trade 56 (10), 2162–2180. https://doi.org/10.1080/1540496X.2020, 1785425.

Monge-Naranjo, A., 2014. Currency returns during the financial crisis and great recession. In: Economic Synopses, p. 4. https://doi.org/10.20955/es.2014.4.

Narayan, P.K., 2020. Has COVID-19 changed exchange rate resistance to shocks? Asian Econ. Lett. 1 (1), 17389. https://doi.org/10.46557/001c.17389.

Narayan, P.K., 2022. Understanding exchange rate shocks during COVID-19. Financ. Res. Lett. 45, 102181 https://doi.org/10.1016/j.frl.2021.102181.

Narayan, P.K., Devpura, N., Wang, H., 2020. Japanese currency and stock market—what happened during the COVID-19 pandemic? J. Econ. Anal. Policy 68, 191–198. https://doi.org/10.1016/j.eap.2020.09.014.

Njindan Iyke, B., 2020. The disease outbreak channel of exchange rate return predictability: evidence from COVID-19. Emerg. Mark. Financ. Trade 56 (10), 2277–2297. https://doi.org/10.1080/1540496X.2020.1784718.

Padhan, R., Prabheesh, K., 2021. The economics of COVID-19 pandemic: a survey. Econ. Anal. Policy 70, 220–237. https://doi.org/10.1016/j.eap.2021.02.012.

Phiri, A., 2021. Changing efficiency of BRICS currency markets during the COVID-19 pandemic. Econ. Chang. Restruct. 1–27. https://doi.org/10.1007/s10644-021-09363-3.

Phiri, A., 2022. Changing efficiency of BRICS currency markets during the COVID-19 pandemic. Econ. Chang. Restruct. 55 (3), 1673–1699. https://doi.org/10.1007/s10644-021-09363-3.

Rambo, R.G., Main, D., Beaubien, L., 2011. Reducing reporting risk: designating foreign currency forward contracts as cash flow hedges. J. Account. Educ. 29 (4), 284–294. https://doi.org/10.1016/j.jaccedu.2012.03.003.

Salisu, A.A., Ayinde, T.O., Gupta, R., Wohar, M.E., 2021. Global evidence of the COVID-19 shock on real equity prices and real exchange rates: a counterfactual analysis with a threshold-augmented GVAR model. Financ. Res. Lett., 102519 https://doi.org/10.1016/j.frl.2021.102519.

Sarno, L., Valente, G., 2005. Empirical exchange rate models and currency risk: some evidence from density forecasts. J. Int. Money Financ. 24 (2), 363–385. https://doi.org/10.1016/j.jimonfin.2004.12.011.

Sethi, M., Dash, S.R., Swain, R.K., Das, S., 2021. Economic consequences of Covid-19 pandemic: an analysis of exchange rate behaviour. Organ. Mark. Emerg. Econ. 12 (2), 258–284. https://doi.org/10.15388/omee.2021.12.56.

Sharma, S., Yadav, M.P., Jha, B., 2022. Impact of the COVID-19 outbreak on the currency exchanges of selected countries. Int. J. Sociotechnology Knowl. Dev. 14 (2), 73–91. https://doi.org/10.4018/IJSKD.2022040105.

Tan, L., Xue, L., 2021. Research on the development of digital currencies under the COVID-19 epidemic. Procedia Comput. Sci. 187, 89–96. https://doi.org/10.1016/j.procs.2021.04.037.

Thaker, H.M.T., Sakaran, K.C., 2021. Covid-19, financial markets (Islamic vs non-Islamic), and exchange rate: does the malaysian market offers diversification opportunities to the Investors? Glob. Rev. Islam. Econ. Bus. 9 (1), 019–027. https://doi.org/10.14421/grieb.2021.091-02.

Ullah, S., 2022. Impact of COVID-19 pandemic on financial markets: a global perspective. J. Knowl. Econ. 1–22. https://doi.org/10.1007/s13132-022-00970-7.

Umar, Z., Gubareva, M., 2020. A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. J. Behav. Exp. Financ. 28, 100404 https://doi.org/10.1016/j.jbef.2020.100404.

Wei, Z., Luo, Y., Huang, Z., Guo, K., 2020. Spillover effects of RMB exchange rate among B&R countries: before and during COVID-19 event. Financ. Res. Lett. 37, 101782 https://doi.org/10.1016/j.frl.2020.101782.

Wookjae Heo, J.M.L., Park, Narang, Grable, John E., 2020. Using Artificial Neural Network techniques to improve the description and prediction of household financial rations. J. Behav. Exp. Financ. 25, 100273 https://doi.org/10.1016/j.jbef.2020.100273.

World Bank Organization, 2020. World Bank national accounts data, and OECD National Accounts data files. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=IN&most_recent_value_desc=true.

Wuyts, W., Marin, J., Brusselaers, J., Vrancken, K., 2020. Circular economy as a COVID-19 cure? Resour. Conserv. Recycl. 162, 105016 https://doi.org/10.1016/j.resconrec.2020.105016.

Wybieralski, P., 2021. Challenges in currency derivatives management in the OTC market in Poland during the Covid-19 pandemic. In: Toward the „new normal" After COVID-19–a Post-transition Economy Perspective. Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu, pp. 254–263. https://doi.org/10.18559/978-83-8211-061-6/III5.

Xu, Y., Lien, D., 2021. COVID-19 and currency dependences: empirical evidence from BRICS. Financ. Res. Lett., 102119 https://doi.org/10.1016/j.frl.2021.102119.

Xu, Y., Lien, D., 2022. COVID-19 and currency dependences: empirical evidence from BRICS. Financ. Res. Lett. 45, 102119 https://doi.org/10.1016/j.frl.2021.102119.

Yu, X., Wan, Z., Tu, X., Li, Y., 2020. The optimal multi-period hedging model of currency futures and options with exponential utility. J. Comput. Appl. Math. 366, 112412 https://doi.org/10.1016/j.cam.2019.112412.

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