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Deep Belief Kronecker Forward Harmonic Net for Financial Distress Prediction using Federated Learning

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ABSTRACT

Due to the globalization of the world financial system, the prediction of financial distress is essential for enterprises, especially for financial organizations. Accurate bankruptcy prediction is needed for every financial organization to make careful financing decisions. Owing to financial regulations, the prediction of financial distress becomes complex. For resolving the complexity, the Federated Learning (FL) approach is utilized. FL improves the data privacy and eliminates the security threats, and it is required for the institutions to control the risks in large-scale applications. Hence, this paper devises the FL-based Deep Belief Kronecker Forward Harmonic Net (FL_DBKFHNet) for Financial Distress Prediction (FDP). The servers and nodes are considered as the major part of the FL approach. The local training is carried out using the local data from each device, and updates are passed to the server. After completing the aggregation in the server, the upgraded data is downloaded by the global model. For each epoch, the updated training is iterated in the local model via the utilization of downloaded data. The FDP is done in the training model, where the input data is utilized to detect the financial distress using the proposed FL_DBKFHNet. Moreover, FL_DBKFHNet-based FDP achieved better accuracy, loss function, Mean Square Error (MSE), Root MSE, and Mean Average Precision of 93.99%, 0.251, 0.066, 0.258, and 0.915.

Keywords: Federated Learning, Financial Distress Prediction, Deep Learning, Deep Belief Network, Deep Kronecker Network.

1. Introduction

FL is considered as the distributed machine learning (ML) approach, which permits the edge agents for creating the models data, in which the aggregated data is created on the server using the edge agents. Furthermore, Agents distribute the created algorithm or model without the direct transmission of data to the server. Hence, data privacy is maintained moderately since the data remains on the device. In addition, there is a massive count of agents present, who are interested in joining in the FL model. Yet, the subset of the agents is considered as part of the training function in the FL, and the agents simplifies the FL function. If a massive count of agents is considered in the FL, a subclass of the agent handles a lesser count of agents. The second advantage is that the activities of the agents are monitored efficiently [1]. Furthermore, FL applications have attained popularity due to the capability of preserving user privacy. The FL approach is employed to handle data that are not individual and are distributed identically (non-IID) [14]. Hence, the FL domain achieved more popularity owing to its privacy data sharing capability, sharing of computational power, the requirement of less communication overhead, and handling of non-IID data. The FL model protects privacy by not revealing any agent's confidential data throughout the training of the on-device model [15], and computational complexities are distributed amongst the agents rather than the necessity of a fusion center [16].

The prediction of financial distress is also termed as known as business failure or bankruptcy prediction, which is essential for decision-makers like credit lenders, executives of the companies, and investors. On the other hand, managers must evaluate the company's risk while creating a development strategy. The investors or credit lenders must assess the financial status of the company such as solvency, profitability, and liquidity, earlier than deciding whether to expand the investment or credit. Therefore, FDP is considered as critical component for enterprise risk management,

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and it is also essential to enterprise the theory of financial distress [17] [6]. Because of the universal financial crisis, the lot of companies declaring bankruptcy has increased severely. Therefore, it is more necessary to consider the FDP models for corporate sustainable development [21]. The stakeholders of the company attained more benefits with the aid of FDP [18]. As a result, the utilization of FDP is investigated in more studies. In addition, the prediction of FDP is dictated not only through the methods or models employed but also by the utilization of available information [2]. The FDP models are applied in numerous applications such as the managing of business solvency, assessing the risks of bond and loan defaults, the derivatives of pricing credit, and other credit-based activities [19][4]. The avoidance of Bankruptcy not only increases the economic level of the company but also improves the overall economic status of the country. As a result, the effectual FDP model is utilized as a popular research topic among practitioners and academics [3].

The researchers have put a lot of effort for creating effective approaches for the prediction of business financial emergencies, which consider two major objectives. The first approach is to develop and increase the analytical features through standard statistical methods like logit regression models, Multivariate Discriminated Analysis (MDA), and probity regression models [8]. A lot of studies have discovered that some organizations neglect the financial risks, which is the prime cause of their business failure [20]. Moreover, the businesses faced a lot of financial risks but they did not suffer by considerable losses. Because they effectively detect the probable financial dilemma in a timely manner. The market and business participants established an FDP model with high predictive accuracy, large application scope, and considerable operability. Therefore, several kinds of ML methodologies are employed for FDP. Due to the advancement of the ML model, the combination of multiple ML models during the FDP process is employed as a new trend [23] [6]. The hybrid ML model combining the least absolute shrinkage and selection operator (LASSO), stepwise regression (SR), random forests (RF), and categorization and regression trees (CART) are utilized to develop FDP models [4]. Deep Learning (DL) is considered as a subset of ML techniques. The DL-based FDP using the time series data offered a better solution [24]. The Deep Recurrent Neural Networks (DRNNs), and Convolutional Neural Network (CNN) is considered as the most effective DL architectures for accessing the financial time-series data [25] [6].

In this paper, the FL_DBKFHNet is developed for FDP, where the servers, and nodes are the two major part. At first, the local training utilizes the local of every node and then the local updates is given to the server. Once the aggregation is performed on the server, the global model downloads the data at each node. Here, the updated training is iterative on each epoch. Moreover, the FDP is performed in the training model by the DBKFHNet.

The prime contribution of this paper is illustrated below:

• **Proposed FL_DBKFHNet for FDP:** In the financial organization, distress prediction is needed to mitigate financial losses. Here, the DBKFHNet is developed for FDP. Moreover, the merging of Deep Belief Network (DBN), and the Deep Kronecker Network (DKN), in which the Forward Harmonic Analysis Network is used to modify the layers.

The remaining parts of the paper includes five sections. In section 2, the motivation and the existing FDP techniques are specified. Section 3 portrays the FL_DBKFHNet-based FDP, and section 4 depicts the experimental outcome for FL_DBKFHNet-based FDP. The conclusion is given in section 5.

2. Motivation

The FDP is essential for the companies to detect financial issues and take preventive measures to mitigate the risks. Moreover, the FDP is needed for the investors, creditors, and stakeholders for sustaining their growth. The FDP also influences the loan decisions, investment choices, and strategic deals of the companies. As a result, the FL_DBKFHNet-based FDP is developed.

2.1 Literature Survey

Imteaj, A. and Amini, M.H., [1] developed the FL for predicting financial distress. This approach was more robust even though numerous straggler agents were presented in the network and it offered faster convergence. Still, it did not predict the malicious agents and facilitate fairness consideration of agents for the merging of the global model. Liu, J., *et al.* [2] developed the GA-based gradient boosting method for FDP. This model inherited the utilization of network data and GA-enabled selection of parameters. However, the hyperparameters training was challenging and time-consuming. Sun, J., *et al.* [3] devised the One-Versus-One (OVO)-Support Vector Machine (SVM) for FDP. The decomposition approaches, and numerous feature sets offered a comprehensive understanding of the company's

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financial status. However, numerous feature selections were not considered for different fusion and decomposition methods. Jan, C.L., [4] devised the Deep neural networks (DNN) and CNN for FDP. This model was used to fit the needed parameters throughout the learning. Nevertheless, the accuracy of the model depends on the quality of input data; hence, the incorrect predictions was occurred due to the incomplete data.
Safi, S.A.D., *et al.* [5] developed the Metaheuristic Optimization-Based Artificial Neural Network (MHOANN) for FDP. This approach offered effectual sensitivity for attaining better prediction in the imbalanced datasets with minor classes. However, it failed to explore other techniques for the hyperparameter tuning. Al Ali, A., *et al.* [6] developed the Genetic algorithm Long Short-Term Memory based FDP (GALSTM-FDP) This model was more useful for the market participants policymakers, and corporations. In this model, macroeconomic and other business aspects were not integrated to attain more effective predictions. Elhoseny, M., *et al.* [7] developed the Adaptive Whale optimization algorithm with deep learning (AWOA-DL)-based FDP. In this model, the prediction was based on the effectual tuning and adaptation of hyperparameters. However, it failed to enhance the accuracy by considering clustering and feature selection approaches. Chen, Y., *et al.* [8] developed the FDP-based Sparse Neural Networks (FDP-SNN). This model considered the FDP from multiple aspects without the limitation of input variables. Nonetheless, it failed to include accounting, and finance such as corporate cultures, organizational identification, and managers' personalities for distress prediction.

2.1 Major Challenges

The complexities faced in the existing FDP methods are given below:

- The module introduced in [1] was not capable of detecting financial distress whether an agent was malicious or not. Moreover, it failed to provide fairness while allotting the computational tasks throughout the training.
- In [2], the GA-based gradient boosting handled non-linear relations among the financial variables. Still, this model created overfitting, when it was not regularized properly, and it led to inaccurate performance for new data.
- The GALSTM-FDP model in [6] was employed in different financial datasets. Still, the hybrid behavior of the model increased more complexity in terms of processing time, and cost.
- In [7], the AWOA-DL effectively handled the large datasets, that were suitable for high-dimensional data. However, the model was easily overfitted when the training dataset was unbalanced.
- The DL-based FDP offered significant merits in terms of better adaptability, and predictive power. Still, the financial data collected from different sources with different formats contained noise owing to the external factors, and market volatility. These are the major challenges for FDP.

3. Proposed FL_DBKFHNet for Financial Distress Prediction

FDP is crucial for enterprise risk control, particularly for financial organizations. The financial organization must create various risk management systems, which include credit rating, and bankruptcy prediction. Financial organizations require an accurate bankruptcy prediction for creating careful financing decisions. Moreover, financial distress prediction is essential for internal and external stakeholders in the organizations. Due to financial regulations, the consistency and comparability of financial data are affected. Hence, it is complex to predict the financial distress. As a result, this work introduces the FL_DBKFHNet-based financial distress prediction using FL. The local training is done by the local data from every device and then the updates is sent to the server. Once, the aggregation is performed in the server, the upgraded data is downloaded via the global model. The updated training is iterative at every epoch by means of the downloaded data. In the training model, the input data is obtained from the specified database [9]. Thereafter, financial distress prediction is accomplished using FL_DBKFHNet. Figure 1 shows the block diagram of FL_DBKFHNet-based FDP.

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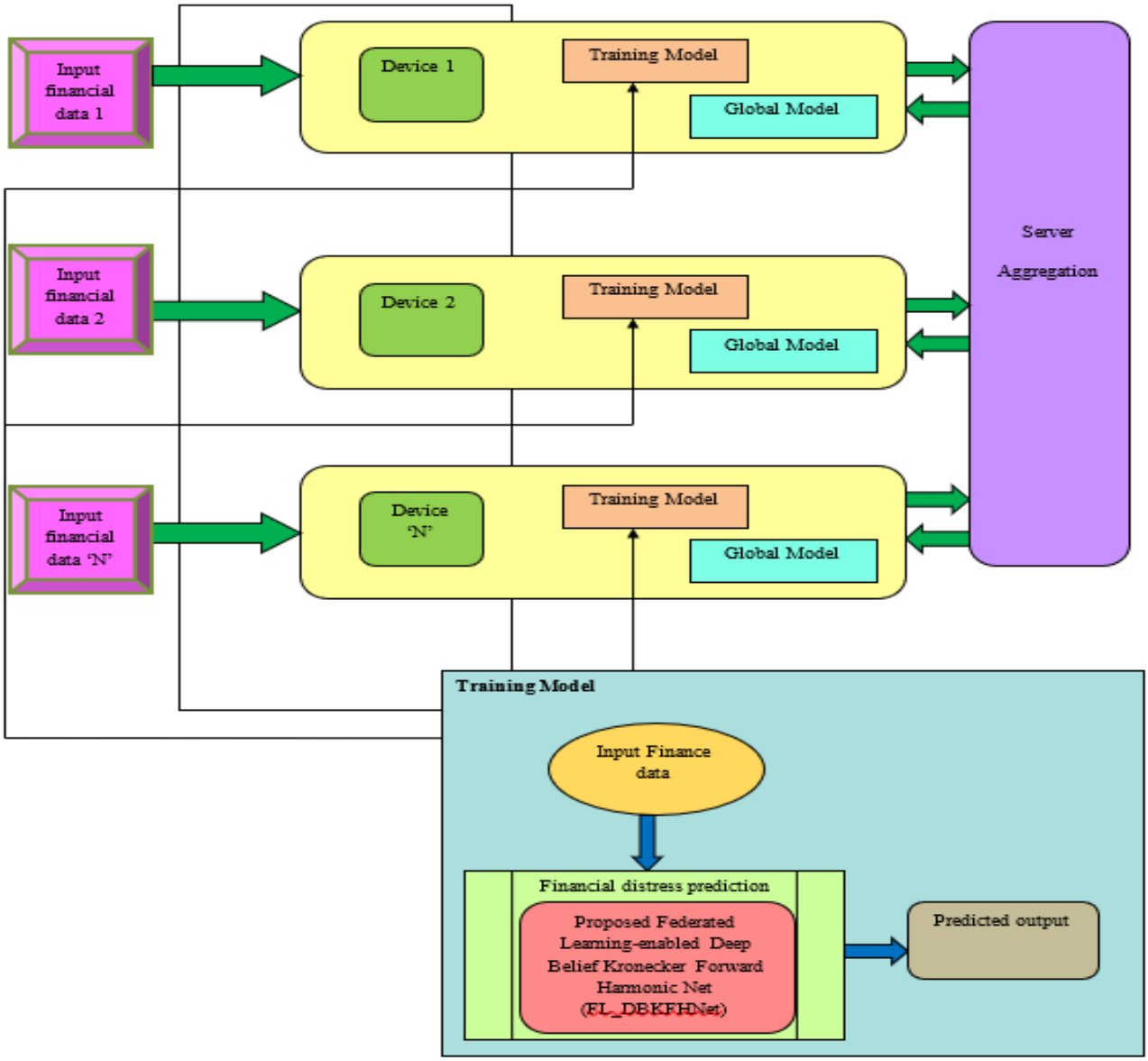


Figure 1. Block diagram of financial distress prediction utilizing FL_DBKFHNet

3.1 Local training based on local data

The local data is employed to train the local model, which considers a set of devices. Moreover, the aggregation is done in the server, and then the global training downloads the upgraded data until the accurate constraint is reached.

3.1.1 Training for every node

The validation of local model is done with the help of the local data from each device at the interval τ .

3.1.2 Training model

In training, the prediction of financial distress is done using the proposed FL_DBKFHNet. Here, the financial data is given to the FL_DBKFHNet for predicting financial distress. Hence, data acquisition and FDP are the two major processes of this model.

i) Data Acquisition

The financial data gathered from the dataset [9] is formulated using the following expression,

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$$J = \left\{ J_1, J_2, ..., J_n, .., .\ J_y \right\} \tag{1}$$

The total counting of financial data is specified as y and J_n implies the n^{th} data.

b) FDP using the proposed DBKFHNet

FDP is employed for monitoring the investment decisions and risk management for the financial institutions, and banks. The earlier prediction of financial distress is essential for the companies to make appropriate decisions and estimate the risk related to investing or lending in a company. Here, the DBKFHNet is proposed for FDP, and the schematic view of DBKFHNet is portrayed in figure 2. Initially, the data J_n is multiplied by the weight L_1 to form $\sum L_1$. Simultaneously, the data J_n is given to DBN [10], and the resultant outcome is multiplied with $\sum L_1$ to obtain A. Moreover, the data J_n is fed to the DKN [11], and the corresponding output is multiplied with the weight L_2, and the output is multiplied with A to generate B. Here, B implies the output of the DKN. Finally, A and B is applied to the forward harmonic analysis [12] for attaining the FDP termed as M.

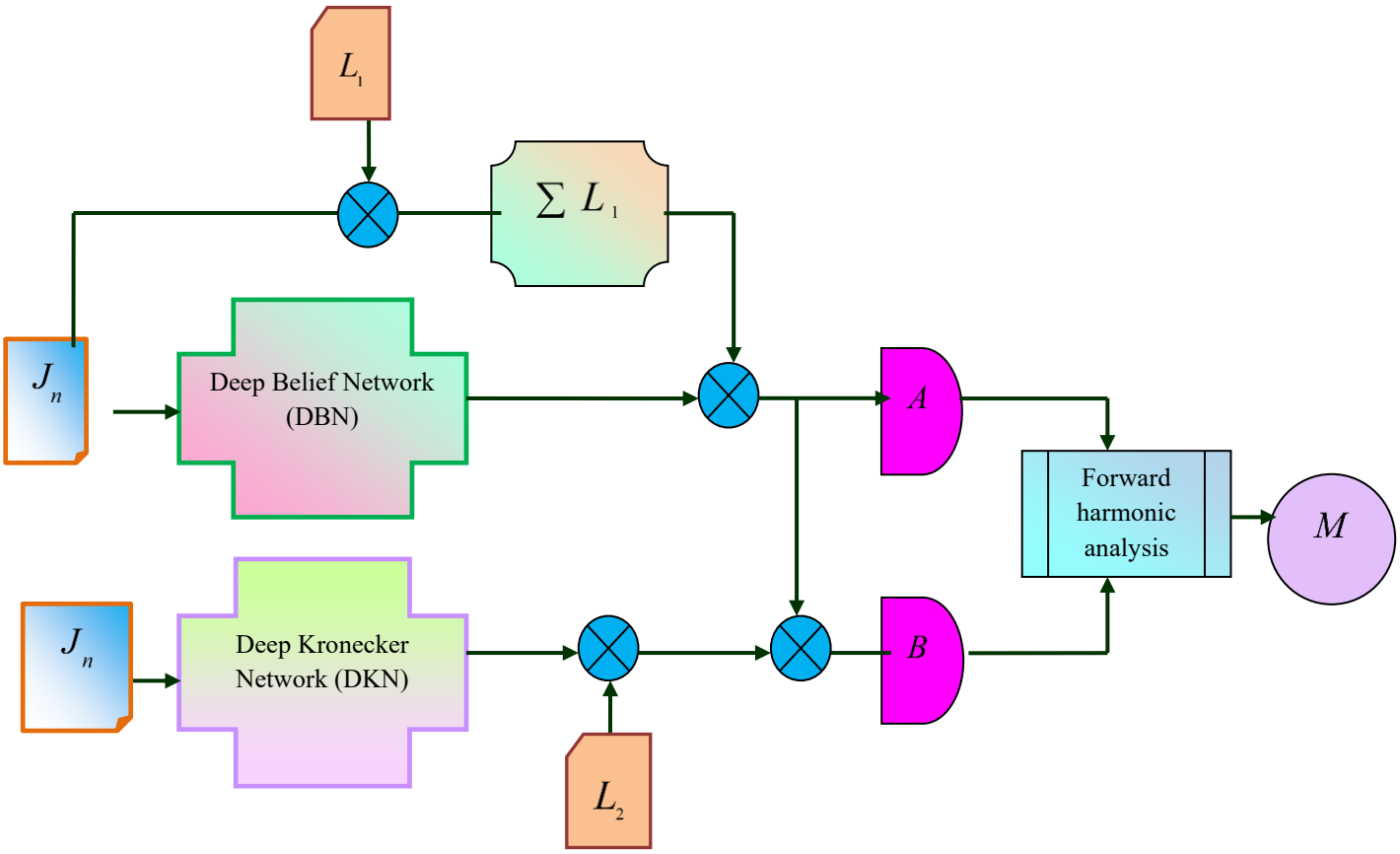


Figure 2. Schematic representation of DBKFHNet

i) DBN Model

DBN [10] is considered as one of the effectual DL models. In pretraining, the generative model is employed, and the finetuning considers the back-propagation. In DBN, less volume of training samples detects the optimal parameters in a rapid manner. The schematic illustration of DBN is portrayed in figure 3, where the Restricted Boltzmann Machine

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(RBM), and the Logistic Regression (LR) are presented. In the RBM, the hidden unit $\hbar = \{0,1\}^I$, and the visible unit $a = \{0,1\}^H$ are included. Hence, the output of DBN is formulated as,

$$A = \left(-\sum_{b=1}^{H} v_b . J_n - \sum_{g=1}^{I} u_g . \hbar_g - \sum_{b=1}^{H} \sum_{g=1}^{I} \varpi_b . a_b \hbar_g \right) * \sum L_{1`} * J_n \tag{2}$$

$$= -v^T a - u^T \hbar - a^T W \hbar \tag{3}$$

Here, $\theta = \left\{ v_b, u_g, \varpi_{b,g} \right\}$, and the weight among the hidden and the visible unit b is denoted by $\varpi_{b,g}$. The bias in the hidden, and visible layers are specified as u_g and v_b. The joint distribution of the unit is given by,

$$R(a,\hbar;\theta) = \frac{1}{C(0)} Exp\left(-e(a,\hbar;\theta)\right) \tag{4}$$

$$C(0) = \sum_{a} \sum_{\hbar} e(a,\hbar;\theta) \tag{5}$$

where, $C(0)$ implies the normalization constant and the energy required for the joint configuration is indicated as e. Moreover, the conditional distribution in the hidden unit $\hbar$ and the visible unit b is formulated as,

$$\delta\left(\hbar_g = 1 \mid a\right) = \gamma\left(\sum_{b=1}^{H} W_{bg} a_b + u_g\right) \tag{6}$$

$$\delta\left(a_b = 1 \mid \hbar\right) = \gamma\left(\sum_{b=1}^{I} W_{bg} \hbar_g + v_b\right) \tag{7}$$

$$\gamma(\varepsilon) = \frac{1}{1 + Exp(-\varepsilon)} \tag{8}$$

Here, δ is utilized to detect the sparsity. After the hidden unit selection, the data is recreated, and the states of hidden units are upgraded. Furthermore, W is learned by the contrastive divergence approach, and the variations in the weight are expressed as,

$$\Delta \varpi_{bg} = \eta\left(a_b \hbar_{g\,Data} - a_b \hbar_{g\,\mathrm{Re}\,construction}\right) \tag{9}$$

where, the learning rate is specified as η. In the reconstruction stage, the data in hidden units are learned as input features. In case, the model exactly recovers the input, then the hidden units maintain enough data about the input. Hence, the learned biases and weight are used to estimate input data. The RBM with a single hidden unit is not effective in capturing the data features. The type of layer-by-layer learning is utilized for designing DBNs. Therefore, the DBN extracts the deep features from incoming data using the hierarchical pretraining approach. The input data from the zeroth layer is converted into a first-layer feature, and it is trained in a similar way as the aforesaid RBM. After completing the training, the subsequent layers in the RBM are learned by the outcome of the prior layer. Moreover, the LR layer is presented after the RBM units, which are employed for the fine-tuning of the entire pre-trained system.

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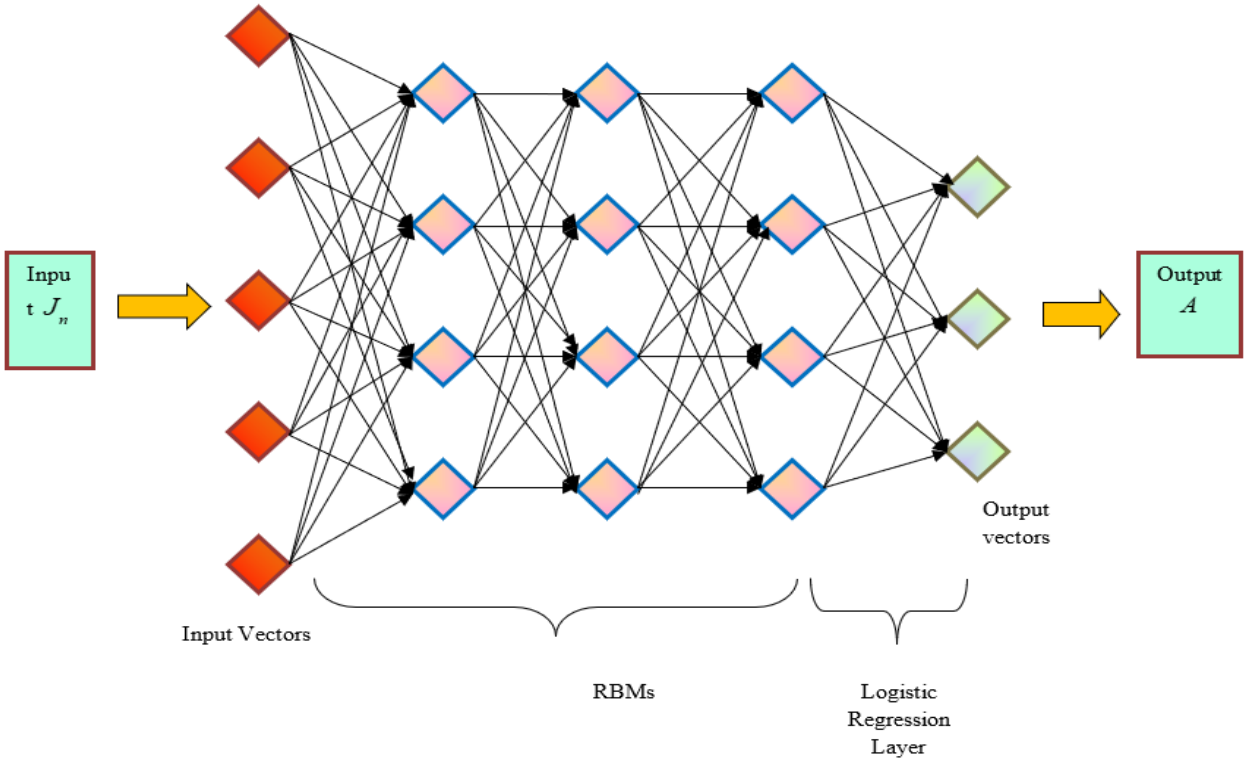


Figure 3. Schematic view of DBN

ii) DKN Model

The DKN [11] is a kind of neural network, which is designed for handling huge data with compound structures. The DKN includes the Kronecker product to carry out the interactions between the features and it is employed for learning high-dimensional data specification. It is used for dealing with multiple views of data, like the interactions of user items, auxiliary data, and contextual information. This multi-view technique can improve the capability of precise predictions. The Convolution (Conv), flatten, multiply, and dense layers are present in the DKN, which is shown in figure 4. The data J_n fed to DKN as input, which creates the outcome B as follows,

$$B = \left[t(\mu_x) Exp\left\{ \mu_x \left\langle (J_n)_x, K \right\rangle - \xi\left(\left\langle (J_n)_x, K \right\rangle \right) \right\} * L_2 \right] * A \qquad (10)$$

$$B = \left[t(\mu_x) Exp\left\{ \mu_x \left\langle (J_n)_x, K \right\rangle - \xi\left(\left\langle (J_n)_x, K \right\rangle \right) \right\} * L_2 \right] * \left(- \sum_{b=1}^{H} v_b . J_n - \sum_{g=1}^{I} u_g . \mathrm{h}_g - \sum_{b=1}^{H} \sum_{g=1}^{I} \varpi_b . a_b \mathrm{h}_g \right) * \sum L_{1'} * J_n \qquad (11)$$

The function of known univariates is represented as $t(.)$ and $\xi(.)$, and the function of certain known link functions $\lambda(.)$ is formulated as,

$$\lambda\left(\Re(t_x) \right) = \left\langle (J_n)_x, K \right\rangle \qquad (12)$$

The coefficient K, as well as the rank Z for the Kronecker product decomposition $P(\geq 2)$ is expressed as,

$$K = \sum_{z=1}^{Z} S_P^z \otimes S_{P-1}^z \otimes \ldots \otimes S_1^z \qquad (13)$$

The Kronecker factor is portrayed as $z = 1, \ldots, Z$, where the dimension of S_P^z is unknown. Moreover, $p = 1, \ldots, P$ represents a identified matrix. Using Kronecker product, $\sigma = \Pi_{p=1}^{P} \sigma_p$ and $\psi = \Pi_{p=1}^{P} \psi_o$ is reached. Here, the simplified

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form is given as $S_{p'} \otimes S_{p'-1} \otimes \ldots \otimes S_{p''} = \overset{p''}{\underset{p=p'}{\otimes}} S_{\kappa}$. Here, $K = \sum_{z=1}^{Z} \otimes_{p=P}^{1} S_p^z$ specifies the decomposition of every matrix.

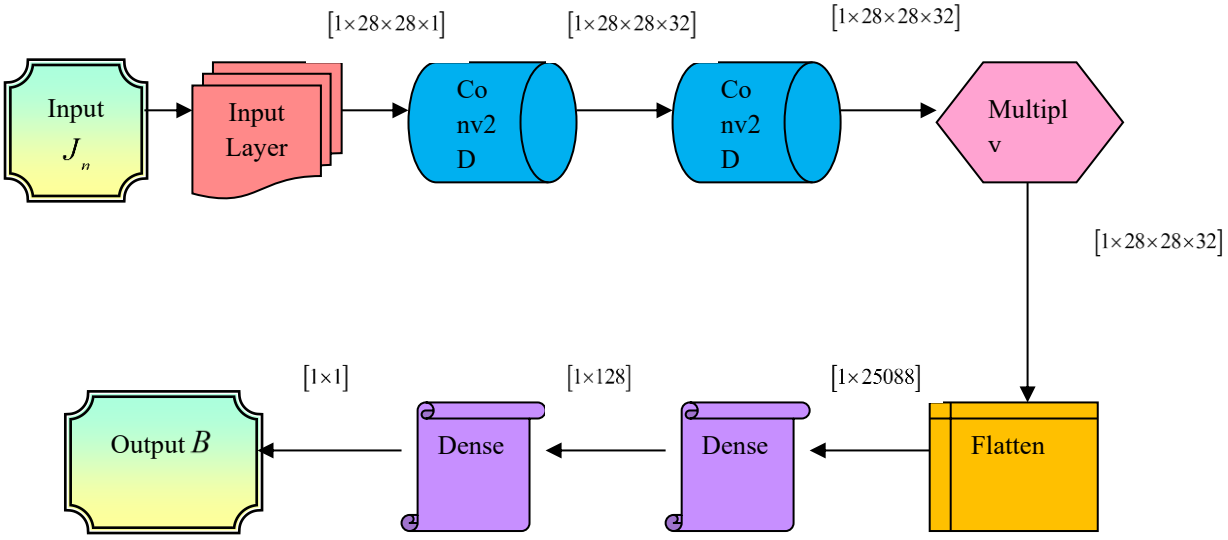


Figure 4. Structure of DKN

iii) Forward Harmonic Analysis

Forward harmonic analysis [12] is a numerical approach for representing the periodic functions with sines and cosines functions. The fundamental idea is to split up the periodic functions into the harmonics contents, which resulting the logical depiction of the function.

The outcome of DBN (A) and the outcome of DKN (B) are fed as the input of harmonic analysis.

The time series $c_{(1)}, c_{(2)}, \ldots, c_{(d)}, \ldots, c_{(r)}$ is considered, and the standard form of the harmonic analysis is formulated by,

$$c_{(d)} = h_0 + \sum_{i=1}^{j} \left(h_i \cos\left(2\pi d / r\right) + k_i \sin\left(2\pi i d / r\right) \right) \tag{14}$$

Consider, $r = 2$ and $j = 1$; hence the above equation is expressed as,

$$c_{(d)} = h_0 + h_1 \cos\left(\frac{2\pi d}{2}\right) + k_1 \sin\left(\frac{2\pi d}{2}\right) \tag{15}$$

$$c_{(d)} = h_0 + h_1 \cos\left(\pi d\right) + k_1 \sin\left(\pi d\right) \tag{16}$$

The mathematical form of h_0, h_1 and k_i is given as,

$$h_0 = \frac{1}{2}\left[c_{(1)} + c_{(2)}\right] \tag{17}$$

$$h_i = \frac{2}{r} \sum_{d=1}^{r} c_d \cos\left(\frac{2\pi d}{2}\right) \tag{18}$$

$$h_1 = \frac{2}{2}\left[c_{(1)} \left(\frac{\cos 2\pi}{2}\right) + c_{(2)} \cos\left(\frac{2\pi 2}{2}\right) \right] \tag{19}$$

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$$h_1 = c_{(1)}(-1) + c_{(2)}(1) \tag{20}$$

$$k_i = \frac{2}{r}\sum_{d=1}^{r} c_1 \sin(2\pi id / r) \tag{21}$$

$$b_1 = \frac{2}{2}\left[c_{(1)} \sin\left(\frac{2\pi}{2}\right) + c_{(2)} \sin\left(\frac{2\pi 2}{2}\right)\right] \tag{22}$$

$$k_1 = c_{(1)} \sin(\pi) + c_{(2)} \sin(2\pi) \tag{23}$$

Consider $\sin \pi = 0$ and $\sin 2\pi = 0$; therefore, the above equation is written as,

$$k_1 = c_{(1)} * 0 + c_{(2)} * 0 \tag{24}$$

The time series $c(d-1), c(d), c(d+1)$ are given as,

$$c_{(1)} = c(d-1) \tag{25}$$

$$c_{(2)} = c(d) \tag{26}$$

$$c_{(d)} = c(d+1) \tag{27}$$

Substitute Eq. (25), Eq. (26), and Eq. (27) in Eq. (16), Eq. (17), Eq. (20), and Eq. (24). The expession become,

$$c(d+1) = h_0 + h_1 \cos 2\pi d + k_1 \sin \pi d \tag{28}$$

$$h_0 = \frac{1}{2}\left[c(d-1) + c(d)\right] \tag{29}$$

$$h_1 = -c(d-1) + c(d) \tag{30}$$

$$k_1 = 0 \tag{31}$$

Substitute Eq. (29), Eq. (30) and Eq. (31) in Eq. (28), the equation becomes,

$$c(d+1) = \frac{1}{2}\left[c(d-1) + c(d)\right] + \left(-c(d-1) + c(d)\right)\cos 2\pi d \tag{32}$$

$$c(d+1) = \frac{1}{2}c(d-1) + \frac{1}{2}c(d) - c(d-1)\cos 2\pi d + c(d)\cos 2\pi d \tag{33}$$

$$c(d+1) = c(d)\left[\frac{1}{2} + \cos 2\pi d\right] + c(d-1)\left[\frac{1}{2} - \cos 2\pi d\right] \tag{34}$$

$$c(d+1) = c(d)\left[\frac{1+2\cos 2\pi d}{2}\right] + c(d-1)\left[\frac{1-2\cos 2\pi d}{2}\right] \tag{35}$$

Let us consider,

$$c(d) = A \tag{36}$$

$$c(d-1) = B \tag{37}$$

$$c(d+1) = M \tag{38}$$

Therefore, Eq. (35) becomes,

$$M = A\left[\frac{1+2\cos 2\pi d}{2}\right] + B\left[\frac{1-2\cos 2\pi d}{2}\right] \tag{39}$$

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$$M=\left[\left(-\sum_{b=1}^{H}v_b.J_n-\sum_{g=1}^{I}u_g.\hbar_g-\sum_{b=1}^{H}\sum_{g=1}^{I}\varpi_b.a_b\hbar_g\right)*\sum L_{1'}*J_n\right]\left[\frac{1+2\cos 2\pi d}{2}\right]+$$
$$\left[t(\mu_x)Exp\left\{\mu_x\left\langle(J_n)_x,K\right\rangle-\xi\left(\left\langle(J_n)_x,K\right\rangle\right)\right\}*L_2\right]*\left(-\sum_{b=1}^{H}v_b.J_n-\sum_{g=1}^{I}u_g.\hbar_g-\sum_{b=1}^{H}\sum_{g=1}^{I}\varpi_b.a_b\hbar_g\right)*\sum L_{1'}*J_n\left[\frac{1-2\cos 2\pi d}{2}\right] \quad (40)$$

Here, M implies the financial distress prediction, A shows the outcome of DBN, and B represents the output of DKN.

3.2 Aggregation at the Server

In the server, the weights of the local models are aggregated. Here, two local models are considered. The Conditional Autoregressive Value at Risk by Regression (CAViar) [13] model performs the aggregation of weight from numerous local trainings and the weights are averaged on the server. Here, χ_1 and χ_2 specifies the weights on the local models 1, and 2. Figure 5 exhibits the data aggregation.

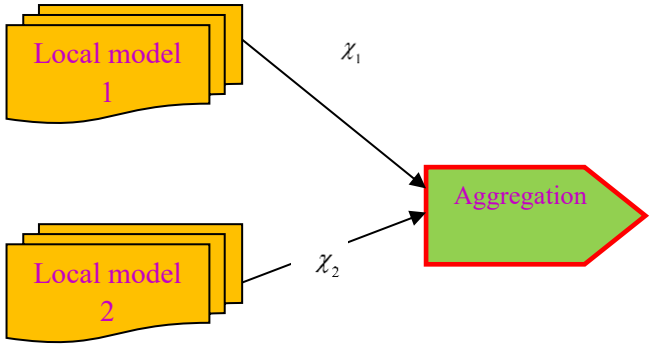


Figure 5. Schematic depiction of data aggregation

Using CAViaR [13], the global weight is derived using the following expressions,

$$\chi_{global}=D_0+D_1\chi_1(\ell-1)+D_2\chi_2(\ell-2)+D_1\,fun\left(\chi_1(\ell-1)\right)+D_2\,fun\left(\chi_2(\ell-2)\right) \quad (41)$$

Here, $D_1\chi_1(\ell-1)$ and $D_2\chi_2(\ell-2)$ shows the weight of local nodes 1,2 at the iterations $(\ell-1)$, and $(\ell-2)$. The term D denotes a vector with an unknown parameter. Moreover, $fun\left(\chi_1(\ell-1)\right)$ and $fun\left(\chi_2(\ell-2)\right)$ implies the fitness of local nodes 1, 2 at the iterations $(\ell-1)$, and $(\ell-2)$.

3.3 Application of global trained model on each local node

The weights are fed to the models and server. Following that, the global model downloads the upgraded data, and the process is reiterated till attaining the ideal result.

4. Results and discussion

The experimental assessment of FL_DBKFHNet-based FDP is described in this part. Furthermore, the software used, estimating parameters, performance assessment, and comparative evaluation are exhibited.

4.1 Experimental setup

The implementation of FL_DBKFHNet-based FDP is done in the Python tool.

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4.2 Dataset description

In this work, the Financial Distress Prediction dataset [9] is employed. It is an imbalanced dataset, where the first column specifies the companies, and the following column includes the data at different periods. Column 3 specifies the target variables, and the fourth to the final column specifies the features (x1 to x83), which indicate the non-financial and financial condition of the companies.

4.3 Performance metrics

The effectiveness of FL_DBKFHNet-based FDP is computed by using the performance measuring parameters like accuracy, loss function, MSE, RMSE, and mean average precision are given below:

4.3.1 Accuracy

Accuracy [22] is represented as the metric, which identifies the exact values over the entire sample. The accuracy is expressed as,

$$Accuracy = \frac{E_+ + E_-}{E_+ + F_+ + E_- + F_-} \tag{42}$$

Here, E_+ and E_+ represents the true positive and false positive. Moreover, the indicates the true negative and false negative are indicated as E_- and F_-.

4.3.2 Loss function

The loss function is termed as the error values, which is defined as the square of real and computed values. The expression for loss function is given by,

$$Loss\ function = \left(U_f - O_f\right)^2 \tag{43}$$

where, O_f implies the estimated f^{th} value and the actual f^{th} value is indicated by U_f.

4.3.3 MSE

MSE [26] is defined as the average of the square of difference among the actual and predicted values. The mathematical form of MSE is given as,

$$MSE = \frac{1}{f}\sum_{f=1}^{\varsigma}\left(U_f - O_f\right)^2 \tag{44}$$

where, and ς portrays the whole value.

4.3.4 RMSE

RMSE [26] is described as the root value of MSE, which is formulated using the following expression,

$$RMSE = \sqrt{\frac{1}{f}\sum_{f=1}^{\varsigma}\left(U_f - O_f\right)^2} \tag{45}$$

where, the RMSE is portrayed as Ψ_4.

4.3.5 Mean Average Precision

Mean Average Precision defines the mean value average precision across each class, which is the precision is expressed by,

$$\Pr ecision = \frac{E_+}{E_+ + F_+} \tag{46}$$

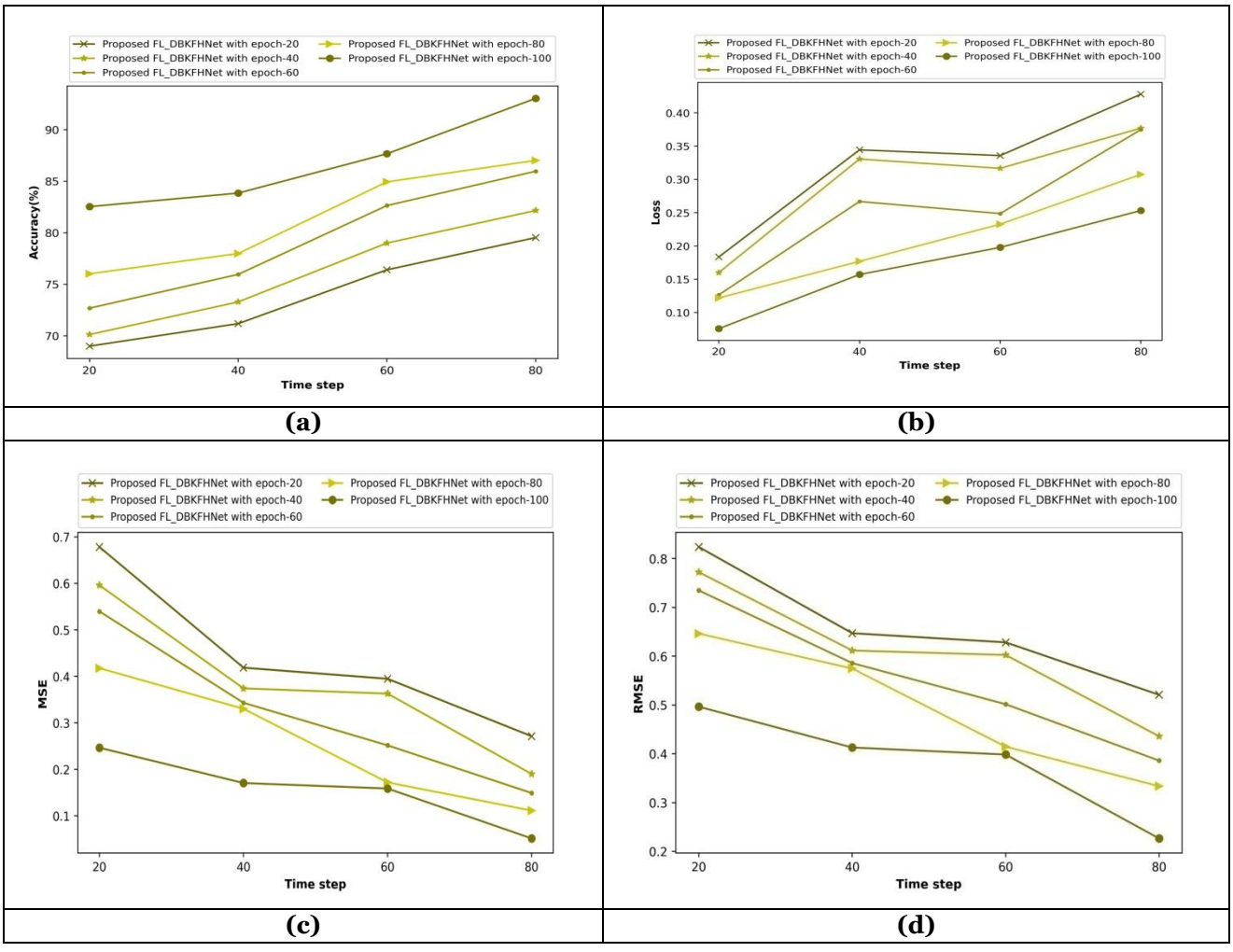
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4.4 Performance Estimation

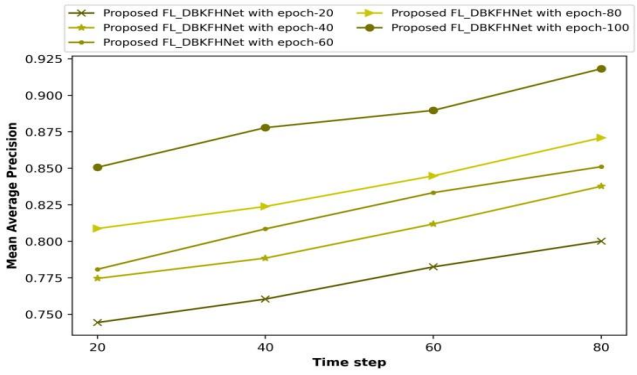
The performance analysis of FL_DBKFHNet-based FDP is shown in figure 6. The performance of FL_DBKFHNet is estimated by varying the epochs from 20 to 100 regarding the time step from 20 to 80. Figure 6 a) portrays the performance assessment concerning accuracy. While considering the time step=80, the accuracy of FL_DBKFHNet with the epochs of 20, 40, 60, 80 and 100 are 79.52%, 82.15, 85.96%, 87.01%, and 93.03%. The analysis in terms of loss function is shown figure 6 b). The loss function of FL_DBKFHNet is 0.428, 0.377, 0.374, 0.307, and 0.253 in the epochs of 20, 40, 60, 80, and 100 using the time step of 80. Figure 6 c) exhibits the assessment in connection with MSE. Here, the FL_DBKFHNet attained the MSE of 0.271 in the 20th, 0.190 in the 40th, 0.149 in the 60th, 0.111 in the 80th, and 0.051 in the 100th epochs using the time step =80. The estimation in terms of RMSE is depicted in figure 6 d). For the time step of 80, the RMSE of FL_DBKFHNet in the epochs 20 is 0.520, 40 is 0.436, 60 is 0.386, 80 is 0.333 and 100 is 0.226. Figure 6 e) deliberates the estimation regarding mean average precision. For the time step of 80, the mean average precision of FL_DBKFHNet in the epochs 20, 40 60, 80, and 100 are 0.800, 0.837, 0.851, 0.870, and 0.918.



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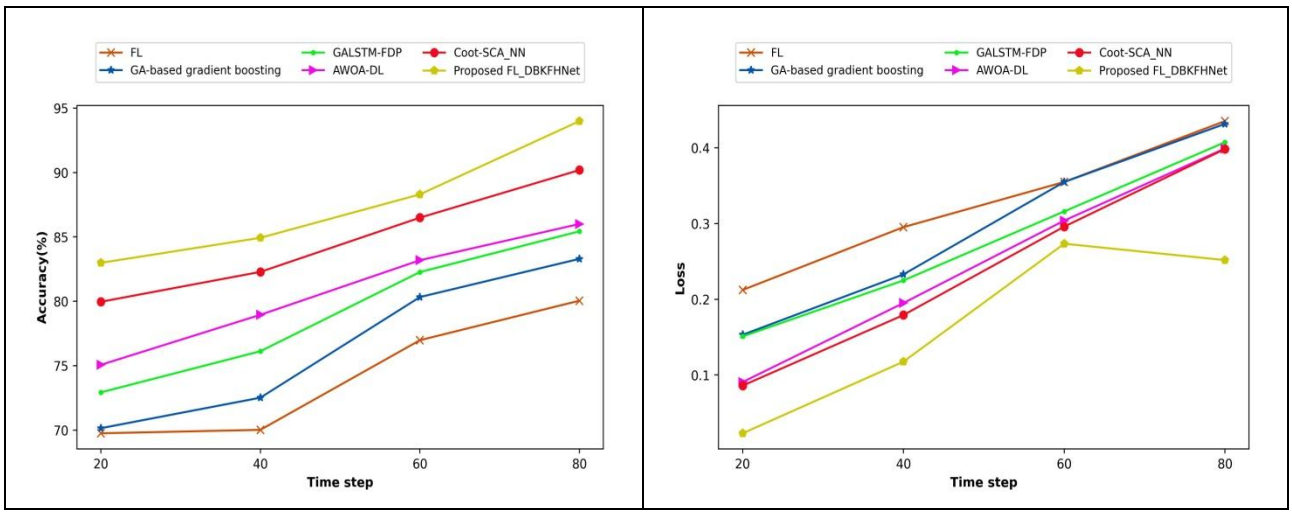
`Figure 6. Performance analysis, a) accuracy, b) Loss Function, c) MSE, d) RMSE, e) Mean Average Precision

4.5 Comparative Methods

The existing techniques like FL [1], GA-based gradient boosting [2], GALSTM-FDP [6], AWOA-DL [7], and Coot-SCA_NN are considered as the comparative methods to validate the efficiency of FL_DBKFHNet-based FDP.

4.6 Comparative Analysis

Figure 7 portrays the comparative analysis of FL_DBKFHNet-based FDP. The estimation concerning accuracy is shown in figure 7 a). While considering the time step =20, the accuracy of FL_DBKFHNet is 82.98%, In which the existing models like FL, GA-based gradient boosting, GALSTM-FDP, AWOA-DL, and Coot-SCA_NN attained the accuracy of 69.74%, 70.14%, 72.92%, 75.06% and 79.96%. The evaluation concerning the loss function is exhibited in figure 7 b). The loss function of FL_DBKFHNet is 0.022, where the loss function of 0.212, 0.153, 0.150, 0.090, and 0.085 are attained by the FL, GA-based gradient boosting, GALSTM-FDP, AWOA-DL and Coot-SCA_NN under the time step of 20. The estimation related to MSE is shown in figure 7 c). For the time step of 20, the FL_DBKFHNet achieved the MSE of 0.303, whereas the MSE of the FL is 0.598, GA-based gradient boosting is 0.573, GALSTM is 0.496, AWOA-DL is 0.458, and Coot-SCA_NN is 0.407. Figure 7 d) deliberates the assessment related to RMSE. While considering the time step of 20, the RMSE of FL_DBKFHNET is 0.550, in which the RMSE of FL, GA-based gradient boosting, GALSTM-FDP, AWOA-DL, and Coot-SCA_NN are 0.773, 0.757, 0.704, 0.676 and 0.637. Figure 7 e) depicts the assessment regarding mean average precision. For the time step of 20, the mean average precision of FL, GA-based gradient boosting, GALSTM-FDP, AWOA-DL, Coot-SCA_NN, and FL_DBKFHNet are 0.752, 0.760, 0.797, 0.804, 0.814 and 0.840.



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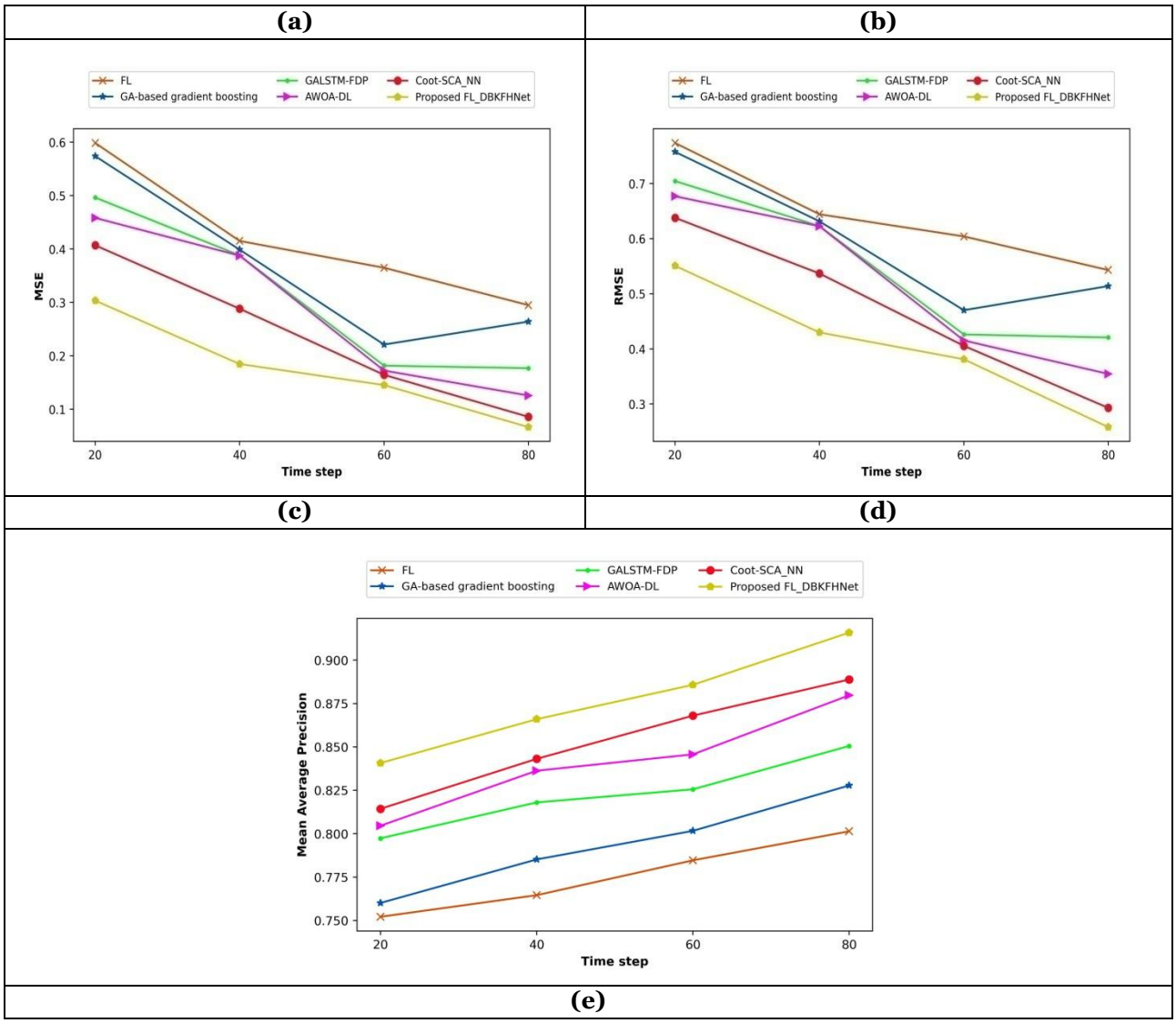


Figure 7. Comparative analysis, a) accuracy, b) Loss Function, c) MSE, d) RMSE, e) Mean Average Precision

4.7 Comparative discussion

The discussion of FL_DBKFHNet-based FDP with respect to the existing methods is given in table 1. The highest accuracy, and mean average precision, as well as the minimum loss function, MSE, and RMSE, are considered as the better outcomes. The optimal results are achieved in the time step of 80. The maximum accuracy of FL_DBKFHNet-BASED is 93.99%, whereas the accuracy of FL, GA-based gradient boosting, GALSTM-FDP, AWOA-DL, and Coot-SCA_NN are 80.04%, 83.29%, 85.43%, 86.00%, and 90.19%. The FL_DBKFHNet achieved the lowest loss function of 0.251, whereas the FL, GA-based gradient boosting, GALSTM-FDP, AWOA-DL, and Coot-SCA_NN got the loss function of 0.435, 0.431, 0.407, 0.399, and 0.398. The lesser MSE of FL_DBKFHNet is 0.066, whereas the MSE of 0.294, 0.264, 0.177, 0.125, and 0.085 are obtained by the GA-based gradient boosting, GALSTM-FDP, AWOA-DL, and Coot-SCA_NN. The minimum RMSE of FL_DBKFHNet is 0.258, whereas the RMSE of FL is 0.543, GA-based gradient boosting is 0.513, GALSTM is 0.420, AWOA-DL is 0.354, and Coot-SCA_NN is 0.293. The FL_DBKFHNet got the highest mean average precision of 0.915, whereas the FL, GA-based gradient boosting, GALSTM-FDP, AWOA-DL, and Coot-SCA_NN obtained the mean average precision of 0.801, 0.827, 0.850, 0.879 and 0.888. Moreover, the finest outcomes of 82.98%, 0.0229, 0.303, 0.550, and 0.840 are attained by the FL_DBKFHNet. Due to the effectual training and parameter selection, the FL_DBKFHNet attained better prediction.

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Table 1. Comparative discussion

Variations	Metrics/Methods	FL	GA-based gradient boosting	GALSTM-FDP	AWOA-DL	Coot-SCA_NN	Proposed FL_DBKFHNet
Time step=20	*Accuracy (%)*	69.74	70.14	72.92	75.06	79.96	82.98
	Loss Function	0.212	0.153	0.150	0.090	0.085	0.0229
	MSE	0.598	0.573	0.496	0.458	0.407	0.303
	RMSE	0.773	0.757	0.704	0.676	0.637	0.550
	Mean Average Precision	0.752	0.760	0.797	0.804	0.814	0.840
Time step=80	*Accuracy (%)*	80.04	83.29	85.43	86.00	90.19	**93.99**
	Loss Function	0.435	0.431	0.407	0.399	0.398	**0.251**
	MSE	0.294	0.264	0.177	0.125	0.085	**0.066**
	RMSE	0.543	0.513	0.420	0.354	0.293	**0.258**
	Mean Average Precision	0.801	0.827	0.850	0.879	0.888	**0.915**

5. Conclusion

In financial institutions, FDP is crucial for allowing them to evaluate the financial rate of individuals, and enterprises. Credit rating and Bankruptcy prediction are two major issues in FDP. Financial distress happens when a corporation does not control its liabilities above its assets. Still, the FDP is complex due to the structured and unstructured data. Therefore, this research develops the FL_DBKFHNet for FDP. The nodes and servers are the part in the FL approach. The local training is performed through the local data from every device and send the updates to the server. Once, the aggregation is done in the server, the global model downloads the upgraded data. In every epoch, the downloaded data from the global models iterate the updated training. The detection of financial distress is done in the training model, in which the proposed DBKFHNet is utilized. In addition, optimal accuracy, loss function, MSE, RMSE, and Mean Average Precision achieved by the FL_DBKFHNet for FDP are 93.99%, 0.251, 0.066, 0.258, and 0.915. In the future, the feature extraction, and data augmentation will be used to obtain the prediction result with even more high accuracy.

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