DRHAFHNet: Dense Resolution High-Order Attention Forward Harmonic Network-based learning effectiveness of shopfloor employees with digital twin

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Abstract

The quick advances in the field of self-driving vehicles and connected automobiles have increased the commercial worth of automobile applications. Digital Twin is employed as a promising technology to modernize the automotive industry. Moreover, the development of digital twins has offered smart manufacturing systems with knowledge-making capabilities. Hence, the training in a virtual environment minimizes the errors on the shop floor. Still, the extraction of relevant insights to establish the optimal course sequence for the shop floor employees is computationally difficult. To overcome such issues, this paper develops the Dense Resolution High-order Attention Forward Harmonic Network (DRHAFHNet)-based course sequence recommendation for learning the effectiveness of shopfloor employees with digital twin. The shop floor owner collects the data from the physical space, and the cloud server stores the data from the shop floor owner. The twin manager collects the data from the cloud server and simulates in the virtual space. The virtual data is stored in the cloud, and the course sequence recommendation is performed by the DRHAFHNet using a digital twin E-learning platform. Moreover, the proposed model attains the Normalized Mean Square Error (MSE), Normalized Mean Absolute Percentage Error (MAPE), and Normalized Root MSE (RMSE) of 0.334, 0.332, and 0.342.

Keywords: Automobile Industry, Digital Twin, Shop Floor Employees, Dense-Resolution Network, Deep High-Order Attention Neural Network.

1. Introduction

Presently, smart manufacturing serves as an innovative approach for altering the necessities of industry, which has substantial advantages for minimizing the consumption of energy, increasing production efficiency, and safety operation [1] [2]. The shop floor in a typical manufacturing system offers sites and equipment for accomplishing numerous industrial tasks. The safety, and efficiency of the physical shop floor possess a significant impact on the efficiency, and quality of manufacturing [3]. Moreover, the shop floor is considered as a critical unit in the manufacturing unit, and intelligence digitization is needed to attain smart manufacturing. The creation of the Digital twin shop-floor and its utilization give better technical, and theoretical support for achieving efficient manufacturing. Furthermore, the Digital twin approach is utilized to create a deep mapping, and integration among the virtual, and physical worlds via digital means. The multi-scale and multi-dimensional virtualization of physical entities is needed for investigating the analysis, optimization, and simulation of physical entities. In addition, Digital twin shop-floor modeling is employed as an essential step to achieve the intelligent control of shop floors [4]. The digital twin shop floor comprises a virtual shop floor, a physical shop floor, and a service system.

The physical shop floor carries out the activities of actual production and transfers real-time statistics to the virtual shop floor. The virtual shop floor is powered by real-time data, which shows the data relationships, internal mechanism, and geometry of the physical shop floor [5] [3].

The digital twin shop-floor data covers the physical data gathered from the virtual model simulation and shop-floor information, which are recorded in the service system. The goal of Digital Twin is needed to monitor, optimize, manage, and control the work floor. Presently, the digital twin has become one of the most widespread research subjects in the digital sector [6]. Furthermore, the digital twin has been efficiently employed in numerous applications, such as scheduling [7] [8], shop-floor design, control [9], and management [10]. Numerous studies on digital twin highlight the requirement of real-time interaction data, consistency between the virtual and physical shop floors, as well as high-fidelity models [11]. A digital twin is employed as a nonphysical method, which has been used for representing the artificial, and physical systems. In the model, sensors are strategically located for gathering data on numerous elements. These data are fed into a data collection system and are subjected to the digital copy. Once the digital copy is upgraded with the essential data, the virtual model implements several simulations, which potentially leads to improved knowledge [12]. The improved ideas are subsequently brought back to the original structure in the physical scenario. It permits the physical processes and products, as well as their associated elements are used to define a cyber-world context [13] [14] [15]. As a result, a digital twin is regarded as a virtually and physically interconnected system. Moreover, it indicates the physical entities through high-fidelity virtual models for mapping, and connecting the data transmission [11].

The current achievement of Artificial Intelligence (AI) techniques such as Machine Learning (ML), and Deep Learning (DL) has offered better outcomes in manufacturing [16]. AI is described as the existence of specific features in computers, and robots that exhibit more capabilities in manufacturing. ML is employed as the heart of several developments in AI. Furthermore, ML is a branch of AI, which enables machines to adapt, and learn for computing specific tasks as per the incoming data. The deep neural network (DNN) and Artificial Neural Network (ANN) are frequently used ML approaches. ML algorithms are used in a variety of applications such as online process monitoring and process optimization for increasing the workpiece, and productivity [17]. Moreover, DL is part of ML approaches, which generate the essential representations in various applications like regression, clustering, pattern recognition, and classification. In addition, DL is widely applicable in the manufacturing industry, because it is a good choice to find complex structures in a massive volume of data. Numerous the applications such as data identification, stock management, image processing, and error detection and diagnostics are performed using the DL model and it offer exceptional performance. As a result, Digital twins and DL are used for enabling self-configuration, predictive services, and self-maintenance. In addition, DL has been utilized for providing independent operation with reliable success replication and minimizing the dependence on human decision-making [18].

In this work, the DRHAFHNet-based course sequence recommendation for learning the effectiveness of shopfloor employees with digital twin is devised. Initially, the shop floor owner collects the data from the physical space. After that, the cloud server stores the data from the shop floor owner. Thereafter, the twin manager collects the data from the cloud server and simulated in the virtual space. Moreover, the virtual data is stored in the cloud. At the server, the course sequence is recommended by the DRHAFHNet in a digital twin E-learning platform.

The key contribution is demonstrated below:

- **DRHAFHNet-based course sequence recommendation for learning the effectiveness of shopfloor employees with digital twin:** The learning effectiveness of shopfloor employees with digital twin is improved by recommending suitable course sequences. Here, the DRHAFHNet is used to recommend the course sequence to the employees. Moreover, the merging of Dense-Resolution Network (DRNet) and Deep High-Order Attention Neural Network (DHA-Net) forms the DRHAFHNet.

The remaining of the paper contains six parts: Section 2 explains the motivation and the survey of existing digital twin-based industrial systems. Section 3 portrays the system model and DRHAFHNet for learning effectiveness of shopfloor employees with a digital twin is explained in section 3. Moreover, section 4 describes the experimental result for DRHAFHNet for learning effectiveness of shopfloor employees with digital twin, and section 6 describes the conclusion.

2. Motivation

The automotive sector is digitalizing rapidly with increased robotics, innovative production, and automation methods. Currently, the knowledge-oriented workforce is critical to sustain production, safety, and efficiency. The Digital twin technology offers immersive, real-time, and data-driven training for shop floor employees. Hence, the learning effectiveness of shopfloor employees with digital twin is improved by recommending proper course sequences.

2.1 Literature Survey

S. Wang, *et al*. [16] devised the DL-enabled Digital Twin Technology for the manufacturing of human-robot collaborative processes. The DT framework continuously upgrade the digital depiction of the industrial system and minimized the downtime. However, the combination of DL with digital Twin necessitated a substantial computational resource that was not viable for small-scale manufacturing. F. Longo *et al*. [19] developed Evolutionary-based Fuzzy Cognitive Maps (E-FCM) for extracting workers’ implicit technical knowledge in smart factories. This model enhanced the knowledge transfer for industrial settings and attained an appropriate balance among procedural, and technical knowledge for non-routine performance. Nevertheless, this model failed to define a roadmap and cost analysis. K. Jarosz and T. Ozel [17]developed the AI+ML-based Shopfloor Employees Training using Digital Twin. It offered the growth of personalized machining processes as per the specific needs of customers, and improved market responsiveness, as well as customer satisfaction. Nevertheless, this model was susceptible to adversarial attacks, and data breaches. J. Song, *et al* [20] devised Digital Twin-Based Self-Organizing Manufacturing System (DT-SOMS). This model comprehended synchronized intelligence in the formation of resources. Nonetheless, it failed to consider bi-directional closed-loop synchronization to obtain secure, and reliable environment.

G. Ding, *et al*. [21] developed the workshop production scheduling method based on digital twin. This model reduced the processing end time, time deviation, machine deviation, and energy consumption. However, the processing time of the model was delayed and impacted the sensitivity of the scheduling decisions. Z. Huang, *et al*. [22]devised the Hybrid Learning-based Digital Twin for industrial manufacturing. This approach was employed for learning uncertainties from realworld scenarios and increased the dependability by disparate data accessibility. Nevertheless, the model failed to develop automatic reparameterization and enabled the digital twin in dynamic settings. H. Zhang, *et al*. [23] developed the digital twin shop floor (D2TS) based on cloud–fog computing as well as D2TS resource allocation (D2TSRA). This model increased the productivity and utilization of resources. Still, the model failed to minimize the manufacturing costs. S. R. Newrzella, *et al*. [24] developed the three-dimensional Digital Twin reference model for industrial application. This model highlighted the necessity of separating the life cycle as well as the functional and dependability dimensions. Nevertheless, this model did not include a suitable visualization tool to consolidate the digital twin concept in industries.

2.2. Challenges

The below-mentioned challenges are faced in Digital Twin-based industrial applications.

- In [19], the implementation of digital twin with cognitive training systems required more commercial investment in terms of software, training, and infrastructure. Hence, this model was not applicable for smaller companies.
- The AI+ML model in [17] was used to develop the machining systems with increased efficiency. However, it was unable to solve the overfitting problem while considering the unseen data.
- Improved scheduling process in workshop production using dynamic scheduling optimization is described in [21]. Nevertheless, this approach failed to overcome the issues of scalability.
- In [22], a hybrid learning-based digital twin for real-time workpiece quality monitoring achieved high dependability despite of varying fidelity, and data availability. However, it did not contemplate the cloud to store the data with high security.
- Effective communication among supervisors, management, and employees is challenging in shop floor management with real-time analysis. Hence, the unique system is designed to overcome the limitations.

3. System Model for automobile manufacturing system with Digital Twin

Figure 1 portrays the system model for an automobile manufacturing system, where elements like machinery equipment, product management systems, storage systems, robust communication network, and workspace layout are interconnected. These elements are working together to produce vehicles with good quality standards. The manufacturing devices, dedicated workspaces with suitable design, and product tracking software are also considered as the major components in the automobile industry. Moreover, the functioning of the automobile industry is virtualized using the cloud server, which interconnects the PMs to VMs. The digital twin upgrades the physical machine's real-time activity on a continual basis. Furthermore, the digital twin is utilized for changing automotive manufacturing by the real-time virtual representations of production lines, PMs, and whole factories.

3.1 Physical Space

In automobile manufacturing systems, PMs are needed for generating, assembling, and performing quality control. Moreover, the PMs like storage systems, communication systems, product management, workspace, as well as machinery, and equipment are stored in the cloud server.

3.2 Virtual System

VMs offer computing devices, where digital twins simulate, and process sensor data. Moreover, it provides real-time data processing, and computational power for simulating the production of vehicles. In virtual space, the twin manager gathers the stored data from the cloud server and simulates the received data.

3.3 Digital Twin-enabled E-Learning Platform

The physical representation of the virtual system is named as the digital twin [25]. It is a nonphysical system, which has been constructed as similar to the physical model. The sensors are positioned for gathering the data from various elements, and data are fed into a data collection system. Once the digital copy is upgraded with the required details, the virtual system implements the simulations and provides significant knowledge to subsequently be brought back to the original system. Moreover, it digitally transfers the physical processes, products, and their associated elements in a cyber-world environment. In a digital twin-enabled E-Learning platform, courses are given to employees as per their knowledge.

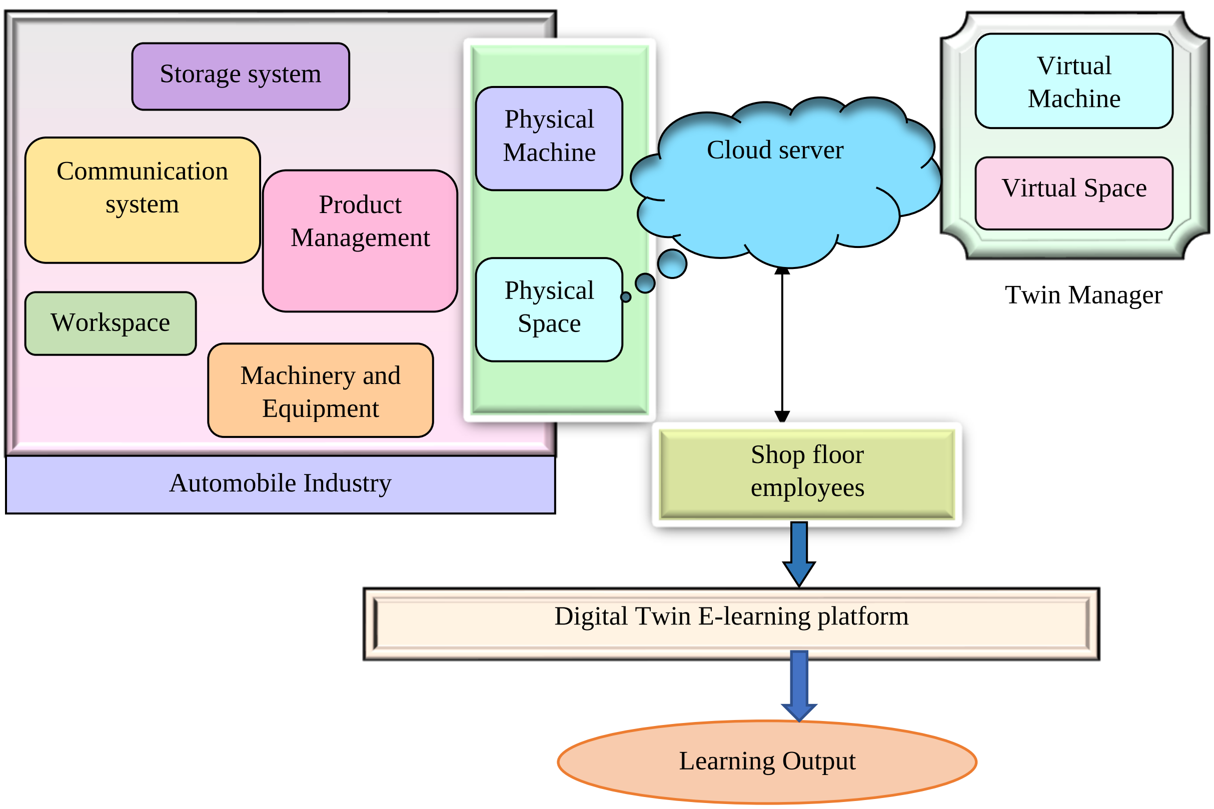

Figure 1. System model for automobile manufacturing system with Digital Twin

4. Proposed Dense Resolution High-order Attention Forward Harmonic Network for learning effectiveness of shopfloor employees with digital twin

A digital twin enables smart manufacturing, where the shop floor is considered as the key component in manufacturing. The digital twin shop floor (DTS) is employed for increasing its intellectualization. DTS provides the mapping of physical shop floor and offers intellectual services. Management sets the goals as per the defined processes, and deviations from the established goals are detected. Afterward, deviations are discussed in daily shop floor meetings. The impression of the deviation is identified, and the necessary training is given to the employees. Hence, this paper designs a framework for learning the effectiveness of shopfloor employees with digital twin based on course sequence recommendation using the proposed DRHAFHNet. Initially, the shop floor owner collects the data from the physical space. After that, the cloud server stores the data from the shop floor owner. Thereafter, the twin manager collects the data from the cloud server and simulated in the virtual space. Moreover, the virtual data is stored in the cloud. At the server, the course sequence is recommended by employing the proposed DRHAFHNet in a digital twin E-learning platform to obtain the learning output. Figure 2 illustrates a block diagram of DRHAFHNet-based learning effectiveness of shopfloor employees with digital twin.

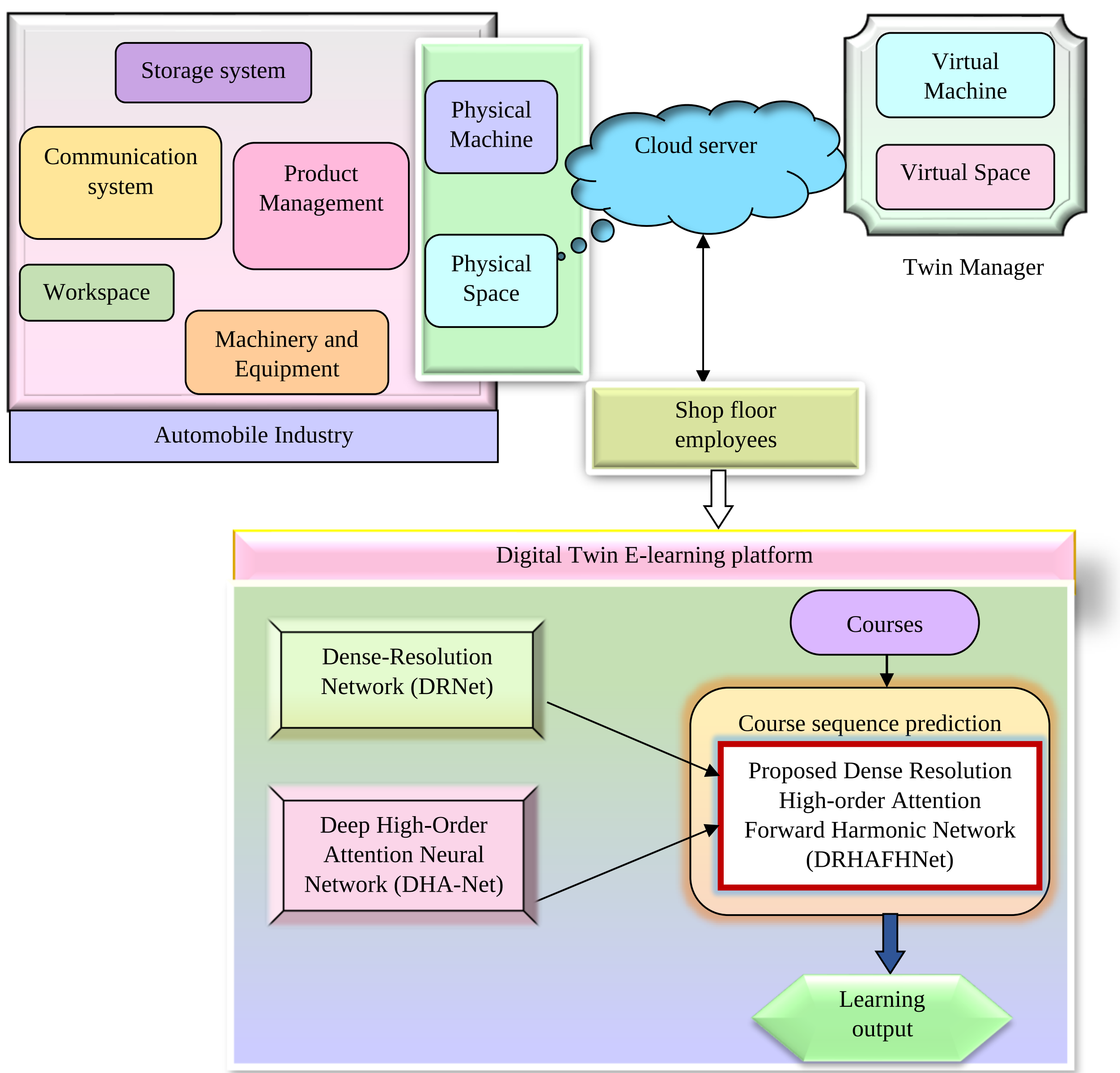

Figure 2. Block Diagram of DRHAFHNet for learning effectiveness of shopfloor employees with digital twin

4.1 Data Acquisition

The log files are gathered from the "Understanding Dropouts in Massive Open Online Courses (MOOCs) dataset [26], where the tracking log files contain the learning activities of all users. The logs include the supporting data, and the dropout prediction dataset contains the training and test set. Moreover, the user profile contains the details like birth year, education level, and gender of the user. The course data includes the start, and end date of the course, course type, and category. Moreover, the dataset is indicated by the term F .

4.1.1 User Profile Data

User profile data indicates the details about a user. In the dataset, the user profiles like birth year, education level, and gender of the user are contained. Table 1 shows the details of user profile data.

Table 1. User Profile Data

User ID	Birth year	Education level	Gender

4.1.2 Course Information Data

Course information data shows the structured details about the educational courses. The ID number of the course (number), course ID (String), start, and end date of the course, course type, and course category are considered as the course information data. Table 2 portrays the details of course information data.

Table 2. Course Information Data

ID number of the course	Course ID	Start Data	End Date	Course Type	Course Category

4.2 Extraction of features from the dataset

Feature extraction is needed to identify the essential attributes from the dataset F for improving, analyzing, and decision-making. Here, the birth year, education level, and gender of the user features are extracted from the user profile data as well as ID number of the course (number), course ID (String), start, and end date of the course, course type, and course category are extracted course information data. In addition, the following expression shows the extracted features.

$$A = \{A_1, A_2, ..., A_M\} \tag{1}$$

where, the extracted features are indicated by A, and M shows the total count of features.

4.3 Detection of Course sequence using the proposed DRHAFHNet

The detection of course sequence is essential, in which the employees can obtain personalized, and structured learning related to their skill levels, and role of employment. Moreover, the course sequence is needed to improve the efficiency of learning, diminish the training time, and increase workforce willingness for digital twin execution in automobile manufacturing. Here, the DRHAFHNet is devised for detecting the course sequence.

4.3.1 Structure of DRHAFHNet

Figure 3 shows the framework of DRHAFHNet, where the extracted features A is considered as the input. Initially, the feature A is applied to the DRNet [27] and DHA-Net [28]. The weight on the DRNet and DHN-Net models are denoted by N_1, and N_2. Likewise, the feature A is multiplied by the weight N_1 and then $\sum N_1$ is computed. Following that, the outcome from the DRNet is multiplied to $\sum N_1$ to yield S_1. On the other hand, the outcome of DHA-Net is multiplied with N_2, and then the outcome is multiplied to S_1 to yield S_2. Finally, S_1 and S_2 are applied to the forward harmonic analysis for getting the course sequence Y.

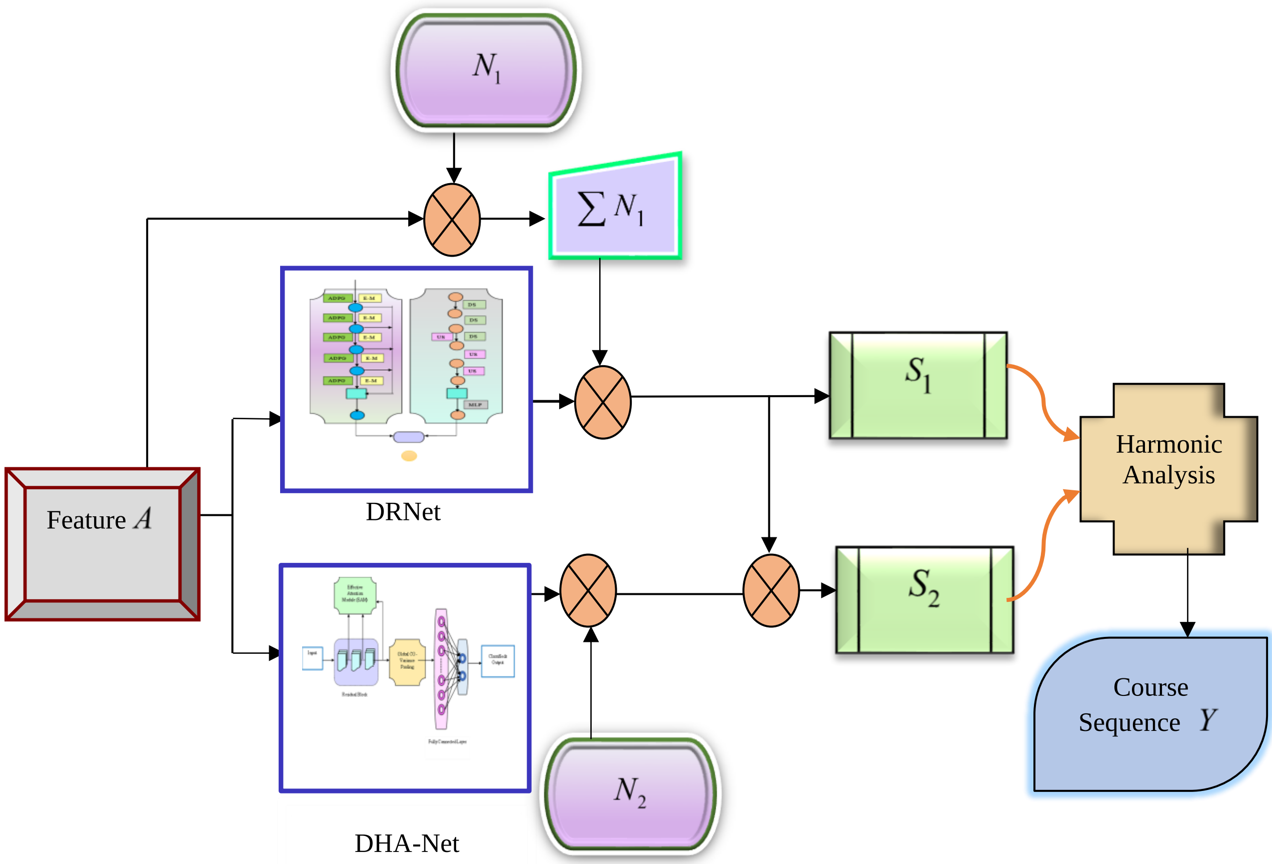

Figure 3. Structure of DRHAFHNet

a) DRNet

The schematic depiction of DRNet [27] is depicted in figure 4, where the Full-Resolution (FR), and Multi-Resolution (MR) are considered as the major components. Moreover, the Adaptive Dilated Point Grouping (ADPG) creates the indices of neighbors.

i) FR Branch

The Fully Convolution Layer (FC) acts as the FR branch, where a dependable count of points at diverse scales of embedding space are presented for feature learning. In upsampling, the per-point feature is retained without any error induced by numerical estimation. As a result, it is essential for learning precise depictions of point-wise features. Furthermore, the FR branch is made up of cascaded error-minimizing units that steadily learn the feature depiction from every point of its adaptive neighborhood at various embedding space scales. Moreover, the adaptive neighborhood is produced by ADPG. A full-resolution point cloud features are learned by a sequence of Error-minimizing modules (E-M). For obtaining a comprehensive understanding of the abstract embedding, the features learned from diverse scales are added and allied.

ii) MR Branch

The MR branch is indicated as the lightweight up/ down-sampling structure, which is employed for analyzing point clouds with minor resolutions. Here, the propagated features with skip links are densely related for improving the relationship between different feature embedding scales and point cloud resolutions. The MR provides detailed channel-wise details of point clouds.

iii) Feature Mapping

For merging the feature map from both the MR and FR branches, an acceptable merging approach is utilized. Typically, CNNs merges feature maps through concatenation, multiplication, and summation. These routine processes apply the identical dealing to all feature maps, regardless of attributes. The feature map from FR is fed as the per-point feature depiction. The channel-wise details of the feature map derived from the MR are utilized to increase the feature map of FR. The Multilayer Perceptrons (MLPs), and max-pooling are utilized for summarizing the knowledge of the MR branch. After computing the sigmoid activation α, a channel-wise augmentation for the per-point context in FR is realized by multiplication. The final output attained from the DRNet is given below,

$$S_1 = \left[A \times \alpha \left[\Re \left(\underset{M}{MAX} \left(A \right) \right) \right] \right] * \sum N_1 \times A \tag{2}$$

where, $\Re$ indicates the Error Minimizing (E-M) module, α specifies the activation function, and N_1 implies the weight. Furthermore, the outcome from DRNet is indicated by S_1.

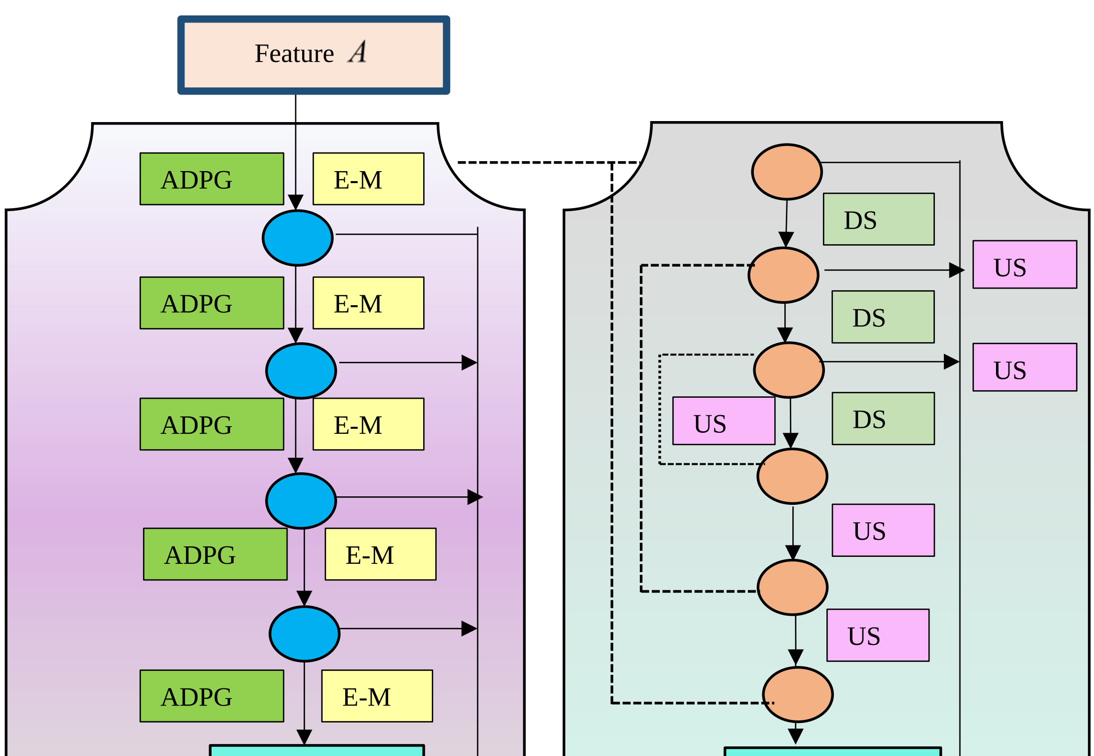

Figure 4. Schematic depiction of DRNet

b) DHA-Net

DHA-Net [28] contains the Effective Attention Module (EAM), which are connected behind every residual unit. The structure DHA-Net is shown in figure 5, where the EAM is utilized for weight revisions through channel attention learning, and a high-order pooling layer is linked for capturing complex higher-order mathematical details.

i) EAM

EAM are placed behind every residual unit, which is utilized to obtain the weight revisions through channel attention learning. A high-order pooling layer is included Before the final Fully Connected (FC) layer. The layer is utilized for gathering more sophisticated higher-order data. The EAM computes the dimension of the convolutional kernel and performs a single-dimensional convolutional (Conv) function. Afterward, a sigmoid function is employed to squeeze values in (0,1) range.

1)No Reduction in Dimension

The outcome of the Conv block is specified by $B \in C^{D \times G \times I}$, in which the feature map possesses the width and height of G , and I . The count of channels is specified by G . Moreover, the weight of the channel ϖ is computed as,

$$\varpi = \beta\left(Fn_{\{\beta_1,\beta_2\}}\left(\chi\left(b\right)\right)\right) \tag{3}$$

Here, the sigmoid function is denoted by β, and the global average pooling (GAP) $\chi(b)$ is computed by,

$$\chi(b)=\frac{1}{GI}\sum_{\varepsilon=1,\mu=1}^{G,I} B_{:,\varepsilon,\mu} \tag{4}$$

Consider $\eta=\chi(b)$, and the expression for $Fn_{\{\beta 1,\beta 2\}}$ becomes,

$$Fn_{\{\beta 1,\beta 2\}}(\eta)=G_2 \operatorname{Re}LU(G_1\eta) \tag{5}$$

The weights are indicated by the terms G_1, and G_2 .

Channel did not provide any direct connection to the weight; hence one FC layer computes the weights in every channel. For creating a direct communication among a channel and weights, EAM gathers the features from GAP, where a single-dimensional Conv of dimension y is utilized.

2) Local cross-channel interaction

Local interactions of the channel are needed for validating the effectiveness of the model. Here, A single-dimensional Conv of dimension y on the feature η is used to compute the cross-channel interactions as follows,

$$\varpi=\beta\left(\lambda_y(\eta)\right) \tag{6}$$

where, a single-dimensional Conv of dimension y is denoted by λ_y.

ii) High-order pooling module

High-order pooling is more effective than first-order pooling because it extracts the required statistical details about a set of features.

1)Higher-Order Normalization

Consider the input features $K\in C^{D\times P\times Q}$, where the feature map possesses the width, and height of P, and Q. Hence, the entire feature map is formulated by,

$$fm=\sigma(K;P,u) \tag{7}$$

Here, σ specifies the Convolution Neural Network (CNN) feature mapping, and u specifies the deviation. The feature map $\left(fm\in C^{D\times P\times Q}\right)$) is converted into $\hat{\lambda}$ dimensional feature matrix $fm\in C^{\hat{\lambda}\times X}$, in which $X=P\times Q$ features. Furthermore, the covariance matrix V is given by,

$$V=fmW\ fm^T \tag{8}$$

where, W specifies the identity matrix, and the transpose is specified by T .

2)Covariance Normalization

For estimating the high-order pooling layer, the eigenvalue decomposition is used. It is used for enhancing the feature representation through the removal of redundancy and increasing the decorrelation for learning features. Hence, the final outcome from the DHA-Net is obtained using the following expression,

$$S_2 = \frac{1}{2} S_{z-1}\left(3W - \hbar_{z-1} S_{z-1}\right) \times N_2 \times S_1 \tag{9}$$

where, the outcome from DRNet is indicated by S_1. Now Eq. (10) becomes,

$$S_2 = \frac{1}{2} S_{z-1}\left(3W - \hbar_{z-1} S_{z-1}\right) \times N_2 \times \left[A \times \alpha \left[\Re\left(\underset{M}{MAX}(A) \right) \right] \right] * \sum N_1 \times A \tag{10}$$

Here, the weight is specified by N_2.

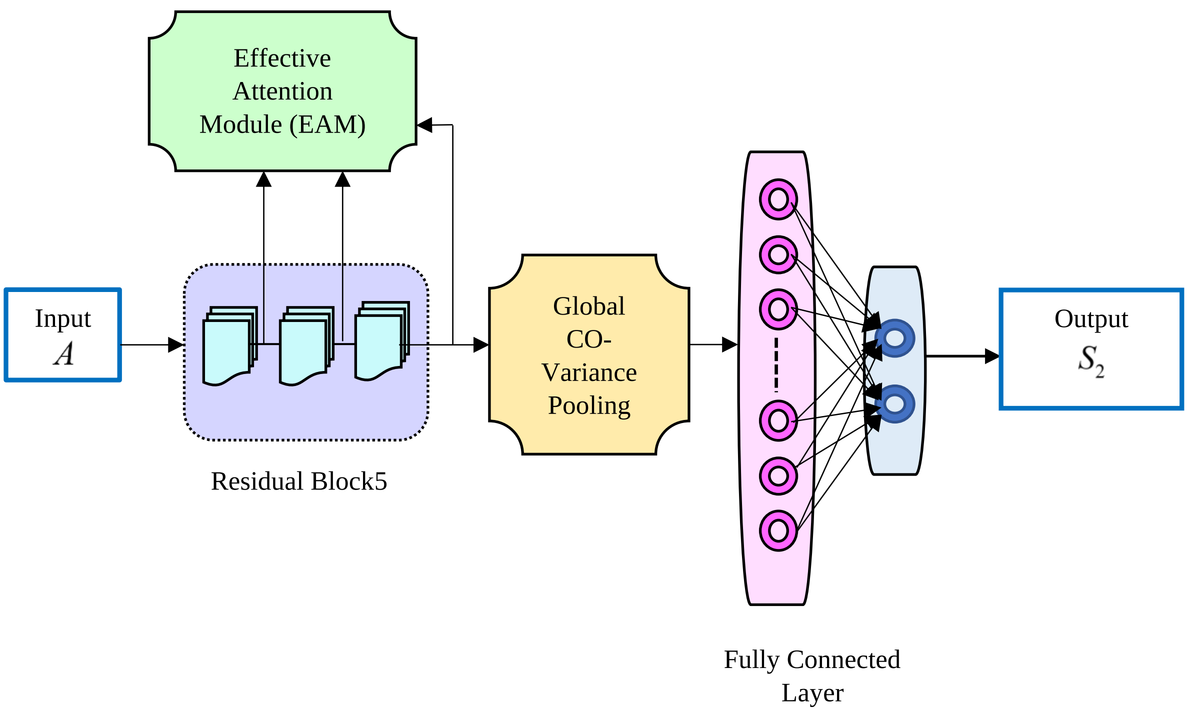

Figure 5. Structure of DHA-Net

c) Forward harmonic analysis

Harmonic analysis [29] is an algebraic process to represent the irregular functions through the utilization of sine, and cosine values. The outcome of DRNet (S_1) and the output of DHA-Net

(S_2) are considered as the input for estimating the harmonic. Using the time series $\Psi_{ts}\left(ts=1,2,...,\vartheta\right)$, the standard harmonics are given by,

$$\Psi(ts)=\ell_0+\sum_{i=1}^{v}\left(\ell_i\cos\left(2\pi its\ /\ y\right)+\delta_i\sin\left(2\pi its\ /\ y\right)\right) \tag{11}$$

where,

$$\ell_0=\frac{1}{y}\sum_{ts=1}^{y}\Psi(ts) \tag{12}$$

$$\ell_i=\frac{2}{y}\sum_{ts=1}^{y}\Psi(ts)\cos\left(2\pi its/y\right) \tag{13}$$

$$\delta_i=\frac{2}{y}\sum_{ts=1}^{y}\Psi(ts)\sin\left(2\pi its/y\right) \tag{14}$$

Consider $y=2, and\ v=1$. The substitute the values in Eq. (11), Eq. (12), Eq. (13), and Eq. (14).

$$\Psi(ts)=\ell_0+\ell_i\cos\left(2\pi ts\ /\ 2\right)++\delta_i\sin\left(2\pi ts\ /\ 2\right) \tag{15}$$

$$\Psi(ts)=\ell_0+\ell_i\cos\left(\ \pi ts\right)++\delta_i\sin\left(\pi ts\ \right) \tag{16}$$

$$\ell_0=\frac{1}{2}\sum_{ts=1}^{2}\Psi(ts) \tag{17}$$

$$\ell_0=\frac{1}{2}\left[\Psi_1+\Psi_2\right] \tag{18}$$

$$\ell_1=\frac{2}{2}\sum_{ts=1}^{2}\Psi(ts)\cos\left(2\pi ts/y\right) \tag{19}$$

$$\ell_1=\Psi_1\cos\left(2\pi/2\right)+\Psi_2\cos\left(2\pi\times 2/2\right) \tag{20}$$

$$\ell_1=\Psi_1(-1)+\Psi_2(1) \tag{21}$$

$$\delta_1=\frac{2}{2}\sum_{ts=1}^{2}\Psi(ts)\sin\left(2\pi its/y\right) \tag{22}$$

$$\delta_1=\Psi_1\sin\left(2\pi/2\right)+\Psi_2\sin\left(2\pi\times 2/2\right) \tag{23}$$

$$\delta_1=\Psi_1(0)+\Psi_2(0) \tag{24}$$

Substituting Eq. (18), Eq. (21), and Eq. (24) in Eq. (16).

$$\Psi(ts)=\frac{1}{2}\left[\Psi_1+\Psi_2\right]+\left[\Psi_1(-1)+\Psi_2(1)\right]\cos\left(\pi ts\right)+0\times\sin\left(\pi ts\right) \tag{25}$$

$$\Psi(ts)=\frac{1}{2}\left[\Psi_1+\Psi_2\right]+\left[\Psi_1(-1)+\Psi_2(1)\right]\cos(\pi ts) \tag{26}$$

The time series is given by,

$$\Psi(1)=\Psi(ts-1),\ \ \Psi(2)=\Psi(ts)\ ,and\ \Psi(ts)=\Psi(ts+1) \tag{27}$$

Applying Eq. (27) in Eqn. (26),

$$\Psi(ts+1)=\frac{1}{2}\left[\Psi(ts-1)+\Psi(ts)\right]+\left[\Psi(ts)-\Psi(ts-1)\right]\cos(\pi ts) \tag{28}$$

$$\Psi(ts)=S_1 \tag{29}$$

$$\Psi(ts-1)=S_2 \tag{30}$$

$$\Psi(ts+1)=Y \tag{31}$$

$$Y=S_1\left[\frac{1}{2}+\cos(\pi ts)\right]+S_2\left[\frac{1}{2}-\cos(\pi ts)\right] \tag{32}$$

Substitute the values of S_1, and S_2 in Eq. (32),

$$\begin{aligned}Y=&\left\{\left[A\times\alpha\left[\Re\left(\underset{M}{MAX}(A)\right)\right]\right]*\sum N_1\times A\right\}\left[\frac{1}{2}+\cos(\pi ts)\right]+\\&\left\{\frac{1}{2}S_{z-1}\left(3W-\hbar_{z-1}S_{z-1}\right)\times N_2\times\left[A\times\alpha\left[\Re\left(\underset{M}{MAX}(A)\right)\right]\right]*\sum N_1\times A\right\}\left[\frac{1}{2}-\cos(\pi ts)\right]\end{aligned} \tag{33}$$

where, Y indicates the outcome from DRHAFHNet.

5. Results and discussion

The experimental analysis of DRHAFHNet for learning effectiveness of shopfloor employees with digital twin is described. Moreover, the experimental outcome, dataset, metrics employed, performance estimation of DRHAFHNet, and comparative analysis of DRHAFHNet are illustrated.

5.1 Experiment setup

DRHAFHNet for learning effectiveness of shopfloor employees with a digital twin is implemented in the PYTHON tool.

5.2 Dataset description

The log files are collected from " MOOCs" dataset [26], where the tracking log files include the learning activities of all users. The logs contain the supporting data, and the dropout prediction dataset includes the training and test set. Furthermore, the user profile contains the details like birth year, education level, and gender of the user. The course data includes the start, and end date of the course, course type, and category.

5.3 Performance Estimating Parameters

The efficiency of DRHAFHNet for learning effectiveness of shopfloor employees with a digital twin is validated by the following metrics.

5.3.1 Normalized MSE

Normalized MSE [30] computes the average squared deviation between the expected and the detected outputs, which is given by,

$$Normalized\ MSE = \frac{1}{R}\sum_{1}^{R}\left[Y^{*} - Y\right]^{2} \tag{33}$$

The entire data are indicated R and the Y^{*} shows the expected value. Moreover, Y indicates the detected value.

5.3.2 Normalized MAPE

Normalized MAPE [30]is represented as the average absolute percentage errors between the expected, and real values as follows,

$$MAPE = \frac{1}{R}\sum_{1}^{R}\left|\frac{Y^{*} - Y}{Y}\right| \tag{34}$$

5.3.3 Normalized RMSE

The square root of the deviation between the estimated and detected values is termed as Normalized RMSE [30] and it is formulated as,

$$Normalized\ RMSE = \sqrt{\frac{1}{R}\sum_{1}^{R}\left[Y^{*} - Y\right]^{2}} \tag{35}$$

5.4 Performance Analysis

Figure 6 displays the performance estimation of DRHAFHNet for learning the effectiveness of shopfloor employees with digital twin. Figure 6 a) exhibits the performance estimation regarding Normalized MSE. The Normalized MSE attained by the DRHAFHNet regarding the epochs from 20-100 is 0.349, 0.341, 0.340, 0.338, and 0.334 at the training data of 90%. The performance analysis in terms of Normalized MAPE is depicted in figure 6 b). For the training data=90%, the values 0.338,0.338, 0.334, 0.334, and 0.332 are attained by the DRHAFHNet with the epochs of 20-100. The analysis concerning Normalized RMSE is portrayed in figure 6 c). For 90% of training data, the Normalized RMSE achieved by the DRHAFHNet with the epochs 20-100 are 0.347, 0.346, 0.344, 0.342, and 0.342.

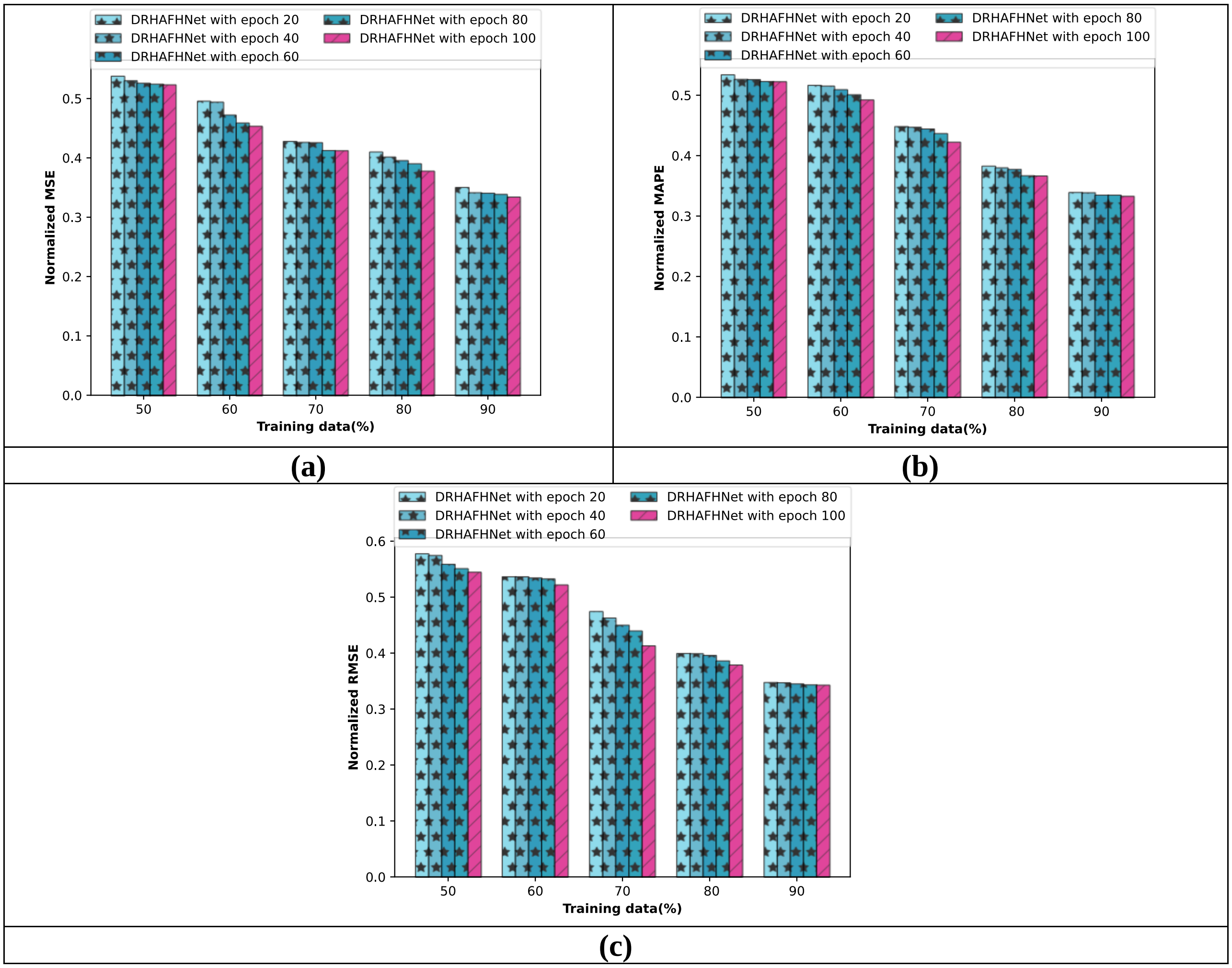

Figure 6. Performance analysis for DRHAFHNet for learning effectiveness of shopfloor employees with digital twin, a) Normalized MSE, b) Normalized MAPE, c) Normalized RMSE

5.5 Comparative techniques

The existing models like E-FCM [19], AI+ML [17], Dynamic scheduling strategy [21], and Hybrid learning-based DT [22] are considered as the comparative methods to validate the performance of DRHAFHNet for learning effectiveness of shopfloor employees with the digital twin.

5.6 Comparative evaluation

The comparative analysis of DRHAFHNet for learning effectiveness of shopfloor employees with a digital twin is described. Here, the training data, and delay are varied to measure the effectiveness of DRHAFHNet.

5.6.1 Assessment based on training data

Figure 7 displays the comparative assessment of DRHAFHNet using training data. Figure 7 a) portrays the evaluation concerning Normalized MSE. For 50% of the training data, the Normalized MSE of 0.510 is attained by the DRHAFHNet, in which the values 0.542, 0.540, 0.538, and 0.516 are attained by the E-FCM, AI+ML, Dynamic scheduling strategy, and Hybrid learning-based DT. Figure 7 b) demonstrates the estimation regarding Normalized MAPE. The E-FCM, AI+ML, Dynamic scheduling strategy, Dynamic scheduling strategy, Hybrid learning-based DT, and the DRHAFHNet attain the Normalized MAPE of 0.535, 0.533, 0.514, 0.506, and 0.504 with respect to the training data of 50%. The evaluation related to Normalized RMSE is exhibited in figure 7 c). While the training data=50%, the Normalized RMSE of 0.714 is attained by the DRHAFHNet, whereas values achieved by the E-FCM, AI+ML, Dynamic scheduling strategy, and Hybrid learning-based DT are 0.736, 0.735, 0.733, and 0.718.

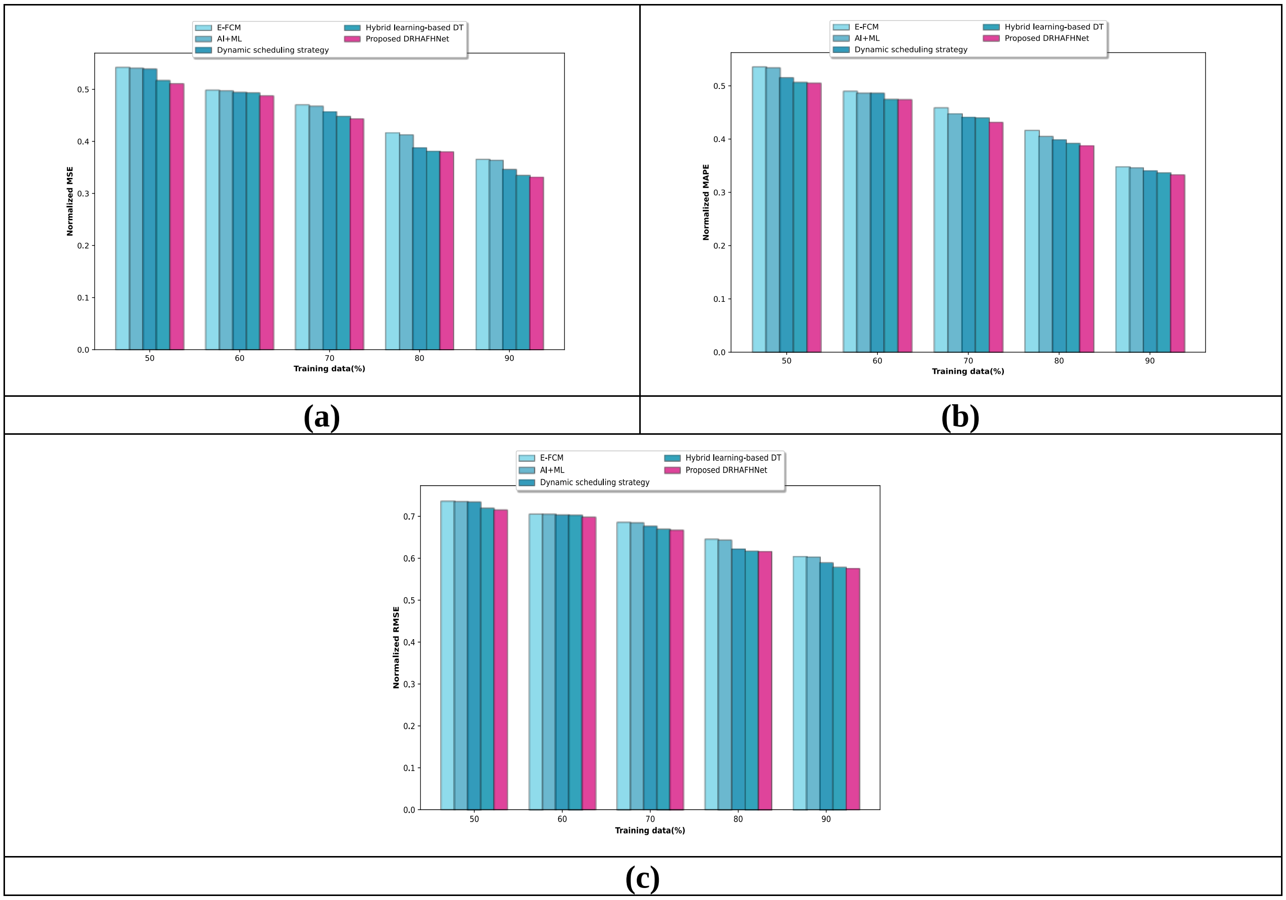

Figure 7. Comparative analysis for DRHAFHNet for learning effectiveness of shopfloor employees with digital twin based on training data, a) Normalized MSE, b) Normalized MAPE, c) Normalized RMSE

5.6.2 Assessment based on Delay

The comparative assessment of the DRHAFHNet using delay is shown in figure 8. The assessment related to Normalized MSE is exhibited in figure 8 a). The Normalized MSE achieved by the E-FCM, AI+ML, Dynamic scheduling strategy, Hybrid learning-based DT, and DRHAFHNet are 0.537, 0.529, 0.525, 0.523, and 0.522 under the delay of 1000 sec. The assessment in terms of Normalized MAPE is displayed in figure 8 b). For the delay of 1000 sec, the Normalized MAPE of 0.533, 0.526, 0.525, 0.522, and 0.522 are achieved by the E-FCM, AI+ML, Dynamic scheduling strategy, E-FCM, AI+ML, Dynamic scheduling strategy, Hybrid learning-based DT, and the proposed DRHAFHNet. Figure 8 c) depicts the assessment regarding Normalized RMSE. For the delay of 1000 sec, the Normalized RMSE attained by the DRHAFHNet is 0.544, in which the E-

FCM, AI+ML, Dynamic scheduling strategy and Hybrid learning-based DT attains the Normalized RMSE of 0.577, 0.574, 0.558, and 0.550.

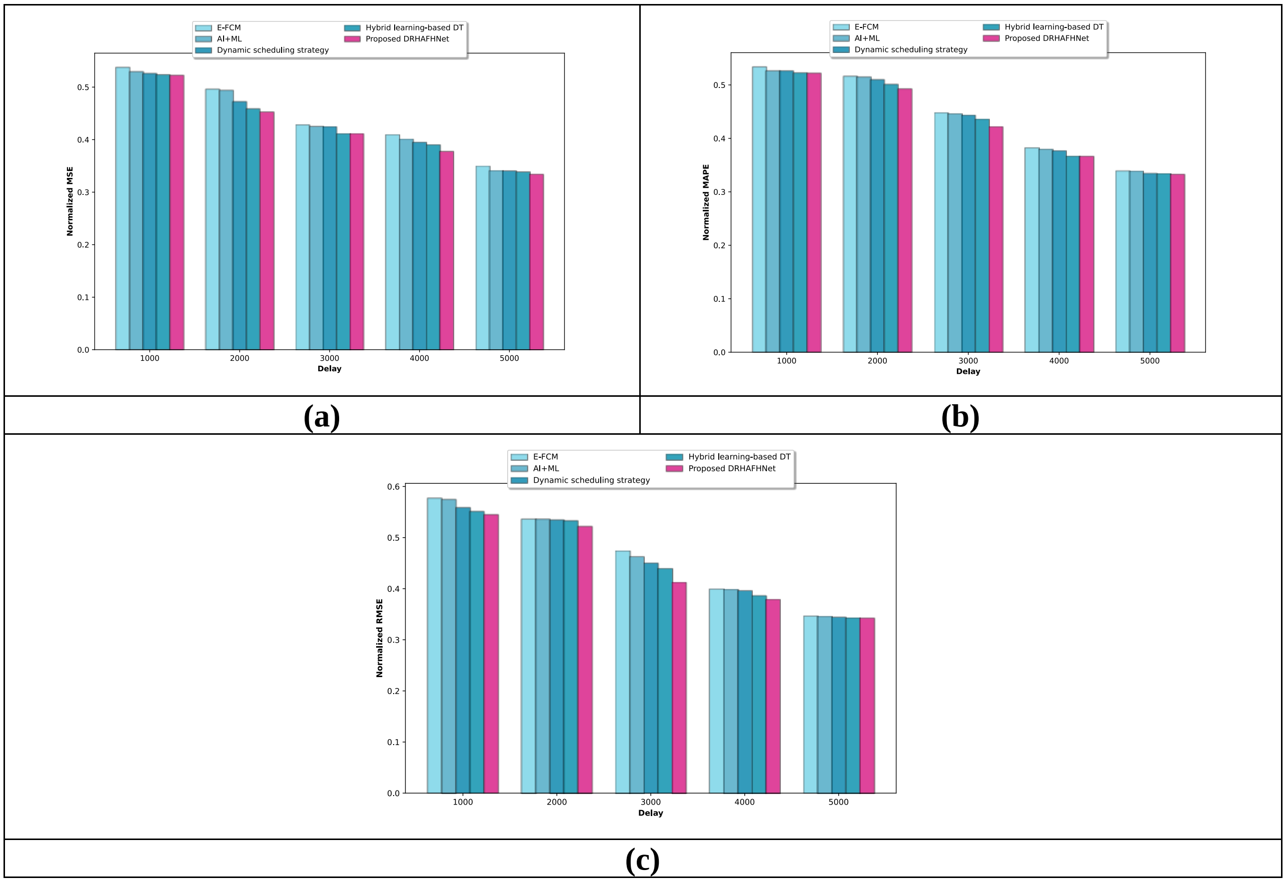

Figure 8. Comparative analysis for DRHAFHNet for learning effectiveness of shopfloor employees with digital twin based on Delay, a) Normalized MSE, b) Normalized MAPE, c) Normalized RMSE

5.7 Comparative discussion

Table 3 shows the comparative discussion for learning effectiveness of shopfloor employees with digital twin, where the performance of DRHAFHNet is compared to E-FCM, AI+ML, Dynamic scheduling strategy, and Hybrid learning-based DT. Here, the ideal outcomes are achieved by the DRHAFHNet using delay. The DRHAFHNet attains the Normalized MSE of 0.334**,** whereas the values 0.349, 0.341, 0.340, and 0.338 are attained by the E-FCM, AI+ML, Dynamic scheduling strategy, and Hybrid learning-based DT. The DRHAFHNet attains the MAPE of 0.332, in which the E-FCM, AI+ML, Dynamic scheduling strategy, and Hybrid learning-based DT attains the values of 0.338, 0.338, 0.334, and 0.334. The Normalized RMSE of 0.342 is attained by the DRHAFHNet, and the values attained by the E-FCM is 0.347, AI+ML is 0.346, Dynamic scheduling strategy is 0.344, and Hybrid learning-based DT is 0.342. Moreover, the DRHAFHNet achieves superior outcomes of 0.332, 0.332, and 0.576 under training data-based assessment.

Table 3. Comparative discussion

Variations	Metrics/ Methods	E-FCM	AI+ML	Dynamic scheduling strategy	Hybrid learning-based DT	Proposed DRHAFHNet
Training Data	*Normalized MSE*	0.365	0.363	0.346	0.334	0.332
	Normalized MAPE	0.347	0.345	0.340	0.336	0.332
	Normalized RMSE	0.604	0.602	0.588	0.578	0.576
Delay	*Normalized MSE*	0.349	0.341	0.340	0.338	**0.334**
	Normalized MAPE	0.338	0.338	0.334	0.334	**0.332**
	Normalized RMSE	0.347	0.346	0.344	0.342	**0.342**

6. Conclusion

The digital twin is considered as a decision-making solution for real-time communication, which requires strong collaboration between humans, technologies, and processes. The advance of digital twins has offered better outcomes in smart manufacturing systems. The training in a virtual environment reduces the occurrence of errors on the shop floor. However, the extraction of appropriate insights for establishing the ideal course sequence for the shop floor employees is complex. For solving such issues, the DRHAFHNet is developed to learn the effectiveness of shopfloor employees with digital twin based on course sequence recommendations. The shop floor owner gathers the data from the physical space, and the data from the shop floor owner are stored in a cloud server. The twin manager gathers the data from the cloud server and is simulated in the virtual space. The virtual data is stored in the cloud, and the DRHAFHNet detects the course sequence recommendation using a digital twin E-learning platform. In addition, the devised model achieves the MSE, MAPE, and RMSE of 0.334, 0.332, and 0.342. In the future, cloud-enabled DRHAFHNet will be developed to enable large-scale deployment over multiple industries.

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