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RESEARCH ARTICLE

Evaluation of the Digital Transformation Effects in Manufacturing Using the DEA-BP Model and the Internet of Things

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ABSTRACT This work aims to comprehensively evaluate the effects of digital transformation in the manufacturing industry by employing a combined approach of data envelopment analysis (DEA) and Back Propagation (BP) neural network to construct the DEA-BP model. Firstly, the digital transformation effects are more comprehensively revealed by constructing the DEA-BP model, leveraging the efficiency evaluation of DEA and the nonlinear learning capabilities of BP neural networks. Secondly, critical input factors are selected. This work considers the manufacturing environment driven by the Internet of Things (IoT) to assess the core influencing factors of digital transformation more practically and operationally. Finally, through experiments utilizing simulated manufacturing process data, the performance of various models is compared in terms of overall efficiency, prediction performance, and classification performance. The research results indicate that the DEA-BP model significantly outperforms other models in overall efficiency evaluation, reaching a maximum efficiency of 93%, fully capitalizing on the flexibility of DEA and the nonlinear learning capabilities of the BP model. Regarding prediction performance for digital transformation, the DEA-BP model exhibits higher accuracy. In classification performance, the DEA-BP model remarkably improves accuracy, precision, and recall, demonstrating higher stability than other models. This work provides a new approach to evaluating the effects of digital transformation in the manufacturing industry, offering feasibility and guidance for practical applications, and it possesses high research and application value. Future research could further optimize model interpretability and computational efficiency, explore additional evaluation indicators, and enhance comprehensiveness and applicability.

INDEX TERMS Evaluation of effects, data envelopment analysis, back propagation neural network, Internet of Things, manufacturing industry.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

With the rapid advancement of information technology, the application of the Internet of Things (IoT) in the manufacturing industry has gradually become a core force driving digital transformation [1]. The application of IoT in the manufacturing industry exhibits various characteristics. First, IoT establishes connections among diverse nodes within the production environment, including production equipment, sensors, production lines, and products [2]. This extensive connectivity empowers manufacturing enterprises to capture real-time production data, furnishing comprehensive and precise information support for the production process [3]. Besides, IoT technology facilitates intelligent interconnection between devices in the manufacturing industry [4]. Through embedded sensors and communication modules, production equipment achieves real-time communication and data exchange, thereby enhancing the intelligence and automation of the production process [5]. This intelligent collaboration among devices enables production to respond more flexibly and efficiently to changes in market demand.

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The digital transformation of the manufacturing industry is one of the vital global development trends currently faced by the manufacturing industry, bearing undeniable significance [6]. Digital transformation, through the integration of advanced information technologies such as IoT, big data analytics, and artificial intelligence, reshapes the operational models of traditional manufacturing [7]. It augments production efficiency and flexibility by monitoring production processes in real-time, optimizing supply chain management, and embracing intelligent manufacturing technologies. This, in turn, enables manufacturing enterprises to swiftly adapt to market demand shifts, enhance production efficiency, and curtail costs. Digital transformation strengthens product quality and innovation capabilities [8]. Through data-driven analysis, companies can better understand product performance and market feedback, optimize product design and manufacturing processes, improve product quality, and better meet customer needs [9]. In addition, digital transformation encourages companies to achieve intelligent operations and sustainable development. The widespread application of intelligent manufacturing equipment enables companies to achieve automated production, predictive maintenance, and resource optimization. This aids in reducing energy consumption, mitigating environmental impact, and fostering sustainable operations [10].

This work aims to deepen the understanding of the effects of digital transformation driven by the IoT on the manufacturing industry. The introduction meticulously outlines the research background, motivation, and importance. The literature review scrutinizes the prevailing applications of IoT in the manufacturing industry and underscores the pivotal role of digital transformation in manufacturing. The research innovation is primarily reflected in proposing and constructing an evaluation method that integrates Data Envelopment Analysis (DEA) and Back Propagation (BP) models. The objective is to comprehensively and accurately assess the effects of digital transformation. The section on experimental design and performance evaluation meticulously delineates steps such as dataset collection and model parameter settings, laying the foundation for empirical research. The conclusion emphasizes the research contribution and indicates future research directions, conferring significant innovative value on both theoretical and practical levels.

B. RESEARCH OBJECTIVES

This work aims to delve into the role of IoT in the manufacturing industry, particularly its impact on digital transformation. Through a systematic assessment, it uncovers the key roles of IoT in optimizing production processes, enhancing the level of intelligent manufacturing, and strengthening the digital capabilities of enterprises. It provides profound insights into achieving a more efficient and intelligent digital transformation in the manufacturing industry. Additionally, this work is committed to constructing an innovative DEA-BP model. By integrating the efficiency evaluation of DEA and the learning capabilities of the BP neural network (BPNN), it seeks to comprehensively assess the effects of digital transformation in the manufacturing industry. This work's practical significance and potential impact are not only to propose an evaluation method of manufacturing digital transformation based on the DEA-BP model but also to actively promote the practice and development of the manufacturing industry. By combining IoT technology with cutting-edge data analytics methods, it is possible to more accurately assess the effects of digital transformation in manufacturing, providing more operational and practical decision support for enterprises. The successful application of this work helps manufacturing enterprises make better use of digital technology, improve production efficiency, reduce costs, and promote industrial upgrading and transformation, thus promoting the sustainable development of the manufacturing industry.

II. LITERATURE REVIEW

Numerous researchers conducted in-depth studies on the application of IoT technology in manufacturing processes. For instance, Amiri et al. explored the practical application of IoT technology in manufacturing. They found that IoT technology, through embedded sensors and smart devices, enabled real-time monitoring and data collection in the production environment [11]. This real-time data flow allowed production managers to monitor equipment status and production efficiency more accurately, thus implementing timely production adjustments.

In a profound exploration of the impact of IoT on manufacturing efficiency and quality, Feroz et al. found that the widespread application of IoT technology significantly enhanced the overall efficiency of the manufacturing industry [12]. By monitoring equipment operational status and production data in real-time, manufacturing companies could quickly identify and address potential issues, reducing the risk of production interruptions and substantially improving production efficiency [13]. Additionally, the proliferation of IoT technology could bring about digitalized production process management, providing manufacturing companies with a more flexible and transparent production environment. Furthermore, Pourghebleh et al. [14] emphasized IoT's positive impact on manufacturing quality. Through precise real-time data monitoring, manufacturing companies could rapidly identify and adjust factors that may lead to quality issues in the production process [14].

Regarding the application of advanced models in the evaluation of digital transformation, Yang et al. [15] provided crucial insights. The research indicated that using advanced models to evaluate digital transformation had notable advantages. The fusion application of DEA and the BPNN was particularly noteworthy. Moreover, DEA can measure the efficiency of production factors, providing an overall assessment of the production effectiveness of digital transformation [15]. Meanwhile, by learning from historical data, the BPNN can uncover potential correlations and trends, offering more accurate predictions for digital transformation [16]. Wagner and Cozmiuc deepened the understanding of the role of advanced models in digital transformation and guided the adoption of the DEA-BP model to evaluate the effects of digital transformation in the manufacturing industry [17]. In addition, Kumari et al. combined taxonomy and process models to carry out multimedia big data computation and IoT application [18]. Kumari et al. verified the loss of big data analysis in IoT environment [19]. Moreover, integrated with reinforcement learning research methods, Kumari and Tanwar proposed a reinforcement learning-based security requirement response scheme for smart grid systems [20].

Existing research highlights the critical role of IoT in manufacturing, emphasizing its importance in real-time monitoring, data collection, and connectivity in the production process, and providing robust support for digitization. However, there still exists a lack of comprehensive evaluation of digital effects. Current model applications emphasize efficiency and quality improvement but fall short in comprehensive evaluation. Based on the DEA-BP model, this work aims to comprehensively and accurately evaluate the effects of digital transformation in the manufacturing industry, addressing the shortcomings in existing research.

III. RESEARCH MODEL

A. THE APPLICATION OF THE DEA-BP MODEL

Regarding efficiency evaluation, the DEA model is widely applied as a powerful tool [21]. DEA quantifies the relationship between inputs and outputs to assess the efficiency level of units in resource utilization [22]. The digital transformation of the manufacturing industry refers to the comprehensive transformation and upgrading of production, management, marketing, and other aspects through the application of modern information technology such as information technology, IoT, and big data, driven by digital technology. It aims to achieve intelligence, networking, and digitization of the production process. This transformation is to simply move the traditional production process to the Internet. Moreover, through the deep integration of digital technology, it also achieves intelligent and fine management of the production process and improves production efficiency, product quality, and enterprise competitiveness. Digital transformation enables the manufacturing industry to respond more flexibly to changes in market demand, accelerate the speed of product iteration and update, and achieve customized production and personalized services, thus better meeting the diversified needs of consumers. Simultaneously, digital transformation can also advance the upgrading and transformation of industrial structure, promote the development of traditional manufacturing to intelligent manufacturing, green manufacturing, high-end manufacturing, and other directions, and enhance the innovation ability and core competitiveness of the entire industry. Therefore, an in-depth understanding and explanation of the digital transformation of the manufacturing industry is of great significance for guiding the development strategy of enterprises, improving the development level of the industry, and promoting the transformation and upgrading of the economy. In the evaluation of digital transformation in manufacturing, the DEA model can measure the effectiveness of production factors, providing a quantitative analysis of enterprises' resource utilization during the digitization process [23], [24], [25], [26]. Its notable advantage lies in its exemption from necessitating a pre-established functional form for efficiency, endowing it with robust flexibility. Nevertheless, the DEA model faces certain challenges in handling noise and uncertainty, potentially leading to fluctuations in evaluation outcomes [27]. Despite this, DEA, as a comprehensive and flexible efficiency assessment method, forms a robust foundation for this work. It is combined with the BP model to construct a more comprehensive evaluation framework, furnishing nuanced insights into the repercussions of digital transformation in manufacturing.

The BPNN model garners recognition for its formidable prowess in pattern recognition, prediction, and optimization problems, particularly due to its nonlinear and parallel processing structure [28], [29]. Through multi-layered neural connections, the BP model adeptly assimilates intricate nonlinear relationships from data, making it suitable for highly dynamic and nonlinear assessments of the effects of digital transformation [30], [31]. Figure 1 illustrates its structure:

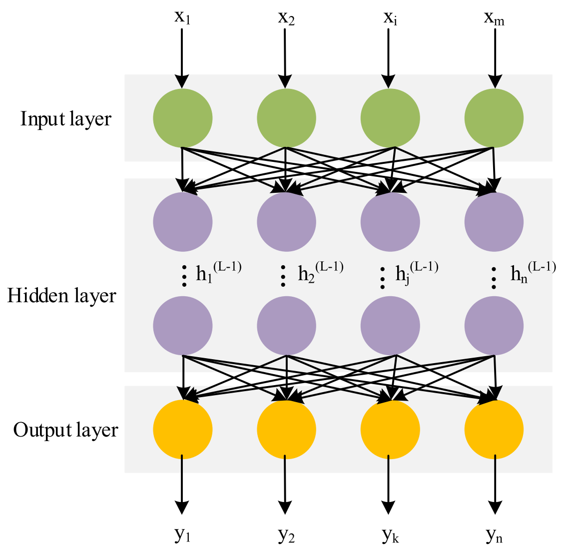

FIGURE 1. Structure of the BPNN.

B. THE CONSTRUCTION OF THE DEA-BP MODEL

To achieve a more comprehensive and accurate evaluation of the effects of digital transformation, this work ingeniously integrates DEA with BP. The fused model aims to synergize the efficiency assessment of DEA with the nonlinear learning capabilities of the BPNN, affording a more comprehensive revelation of digital transformation effects.

First, the construction of the DEA model involves input and output vectors:

Input vector: It can be assumed that there are m input factors for manufacturing enterprises, denoted as X_i $(i = 1,2,\ldots,m)$ [32], [33].

Output vector: Assuming there are n output factors, denoted as Y_j (j = 1,2,...,n).

The mathematical representation of the DEA model is expressed in equation (1) [34], [35]:

$$\max_{\lambda,\theta} \sum\nolimits_{j=1}^{n} \theta_j Y_j - \sum\nolimits_{i=1}^{m} \lambda_i X_i \tag{1}$$

$$s.t. \quad \sum\nolimits_{j=1}^{n} \theta_j Y_{ij} \leq \sum\nolimits_{i=1}^{m} \lambda_i X_{ij} \tag{2}$$

$$\theta_j \geq 0, \quad \lambda_i \geq 0 \tag{3}$$

θ represents the weights, and λ refers to the input coefficients.

Next, the construction of the BP model involves:

Input layer: it comprises m nodes, corresponding to the input vector X_i in the DEA model.

Hidden layer: it is set to h nodes, introducing weight coefficients w_{ij} and an activation function f.

Output layer: it includes n nodes, corresponding to the output vector Y_j in the DEA model.

The mathematical representation of the BP model is expressed in equations (4) and (5) [36], [37], [38]:

$$y_k = f\left(\sum\nolimits_{j=1}^{h} w_{ij} \cdot x_i\right) \tag{4}$$

$$z_l = f\left(\sum\nolimits_{k=1}^{n} w_{jk} \cdot y_k\right) \tag{5}$$

Finally, the fusion of DEA and BP models involves using the efficiency evaluation results of DEA as the target output for the BP model, forming a combined evaluation model. The objective function of the fusion model is as follows [39], [40], [41]:

$$\min_{w_{ij},w_{jk}} \sum\nolimits_{l=1}^{n} (Z_l - \theta_l Y_l)^2 \tag{6}$$

The digital transformation effects' comprehensive evaluation can be achieved by joint training and optimizing DEA weight coefficients (θ) and BP weight coefficients (w). By minimizing this objective function, the model accomplishes the joint optimization of DEA and BP weight coefficients, θ and w, minimizing the error between them [42], [43]. This joint training approach ensures an organic fusion of DEA and BP models in evaluating digital transformation effects.

To more accurately assess the effects of digital transformation in the manufacturing industry, this work carefully selects key input factors, considering the manufacturing environment driven by the IoT. In model construction, the following factors are considered. For example, the information provided by the IoT is introduced, such as real-time monitoring and sensor data, to more comprehensively reflect the impact of digital transformation; The most important production factors that affect the effectiveness of digital transformation have been identified, such as production equipment utilization and personnel skill levels; The investment situation of enterprises in digital transformation is considered, and the contribution of investment to effectiveness is evaluated. The careful selection of these input factors allows the model to focus more on the core influencing factors of digital transformation, making it more practically applicable and useful compared to traditional models [44], [45].

Regarding model output, through joint training, the efficiency evaluation results of DEA and the nonlinear learning results of the BP model form a comprehensive output. The joint output can more intuitively reveal the overall effects of digital transformation. The definition of the comprehensive output is represented by equation (7) [46], [47], [48]:

$$Z_l = \alpha \cdot DEA\_Output + (1 - \alpha) \cdot BP\_Output \tag{7}$$

α is a weighting coefficient used to adjust the relative contributions of the DEA model output and the BP model output in the comprehensive output. The value of this coefficient ranges between 0 and 1.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

To ensure the scientific rigor and credibility of the experiment, this work selects the Semiconductor Manufacturing Process Dataset (SECOM) as a suitable dataset for evaluating the effects of digital transformation in the manufacturing industry. The SECOM dataset includes a large amount of sensor data collected during the semiconductor manufacturing process, covering multiple crucial aspects of the production process.

The SECOM dataset contains 1,558 samples, each consisting of 591 features that represent readings from different sensors and measuring points. The SECOM dataset comprises variables measured by numerous sensors, involving aspects such as the operating status of production equipment, temperature, humidity, and more. This dataset provides a rich source of information for studying the comprehensive impact of digital transformation on the production process. The data in the dataset are presented in a time-series format, enabling dynamic analysis of the effects of digital transformation. This aligns with the progressive and time-dependent characteristics of the digital transformation process.

The rationale for choosing the SECOM manufacturing process dataset lies in its rich manufacturing industry information, covering various key aspects of the digital transformation process. This choice can offer a representative and interpretable experimental basis for this work to delve into the impact of digital transformation on manufacturing efficiency.

To ensure the quality and reliability of the experimental data, this work undergoes rigorous data preprocessing steps. Table 1 outlines the main steps of data preprocessing [49].

In the aspect of anomaly detection and processing, statistical methods and threshold-based methods are used to identify and process anomaly observation points. Specifically, statistical techniques such as boxplot, Z-score, and Tukey methods are utilized to detect outliers on the dataset to find outliers that may affect the experimental results. For the detected outliers, different correction strategies such as replacement, truncation, or elimination are employed to correct the anomaly

TABLE 1. Data preprocessing.

Name	Content
Missing Value Handling	It can analyze the dataset for missing values and identify and address any existing gaps. Appropriate methods such as interpolation or deletion of missing values are utilized to ensure data integrity.
Outlier Detection and Handling	Outlier detection on the dataset is performed to identify potential anomalies that may affect experimental results. Statistical methods or threshold-based approaches are used to eliminate or correct outliers, ensuring data accuracy.
Standardization and Normalization	The data is standardized and normalized to eliminate scale differences between different variables. This aids the model in better understanding the relative relationships between variables, enhancing training effectiveness.
Time Series Processing	Time intervals are normalized for time-series data to ensure temporal consistency. Smoothing techniques or resampling methods are employed to meet the temporal analysis requirements of this work.
Quality Control Variable Selection	Based on the focus of the study, variables related to digital transformation effects and manufacturing quality are selected. This helps reduce model complexity, concentrating on factors more crucial for the experimental objectives.
Dataset Splitting	The dataset is divided into a training set and a testing set (80:20 ratio) to ensure model validation on an independent dataset, assessing its generalization performance.

observation points in the dataset. To ensure the accuracy and reliability of the processing, the operation steps and implementation process of each method are described in detail, and the precautions in practical application and the method of adjusting parameters are explained. Through these detailed contents, readers can gain a deeper understanding of the details and methods of data preprocessing, thus enhancing understanding and trust in the research results.

A combination of oversampling and undersampling strategies is adopted to solve the class imbalance problem in the dataset. Specifically, the Synthetic Minority Over-sampling Technique (SMOTE) algorithm can oversample a minority sample to increase its number. Meanwhile, random undersampling is employed to undersample the majority sample to reduce their number. This strategy aims to make the model learn the dataset features better and improve the classification accuracy of the minority sample by increasing the minority sample and reducing the gap between the majority sample. This combination strategy can effectively deal with the problem of class imbalance in the dataset, and improve the model's classification performance for diverse class samples.

B. EXPERIMENTAL ENVIRONMENT

This work conducts detailed configurations in both hardware and software environments to ensure the smooth progress of the experiment and the accuracy of the results, as shown in Table 2:

TABLE 2. Experimental environment.

Environment Configuration	Name	Content
Hardware	Computer System	Intel Core i7-10700K
	Processor	8 cores
	Memory	32GB (Gigabyte)
	Operating System	Linux
	Programming Language	Python
	Data Processing Tool	Pandas
Software	Deep Learning Framework	TensorFlow
	Data Visualization Tool	Matplotlib
	Database	Deployed database system for storing and managing experimental datasets

In the experimental design, a rigorous strategy of controlling variables is employed to ensure the experimental results' research reliability and the effectiveness. Figure 2 illustrates the main controlled variables during the experimental process:

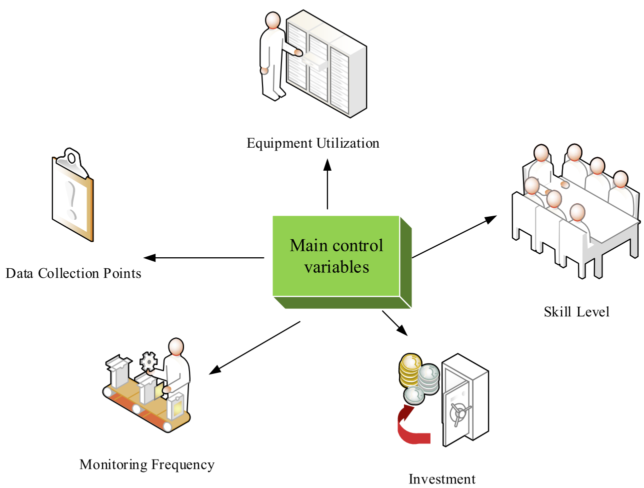

FIGURE 2. Primarily controlled variables.

Figure 2 displays the primary controlled variables: Equipment Utilization, Skill Level of Personnel, Investment, Monitoring Frequency, and Data Collection Points.

C. PARAMETERS SETTING

This work conducts careful parameter selection in the DEA-BP model to ensure the effectiveness of model training and evaluation. Table 3 lists the parameter results obtained through a combination of empirical values and cross-validation:

D. PERFORMANCE EVALUATION OF MODELS

In the model's effect evaluation, the selected evaluation indexes include efficiency evaluation index, predictive

TABLE 3. Experimental parameters.

Parameters	Initial Value	Adjusted Value
The Weight Coefficient of DEA Model (θ)	Random Initialization	0.8
Learning Rate of BP Model	0.01	0.005
Nodes Quantity in the Hidden Layer of the BP Model	50	30
Iteration Count of BP Model	1000	800
DEA-BP Model Trade-off Coefficient (α)	0.5	0.6

performance index, model stability index, classification accuracy index (aiming to comprehensively evaluate the effect of digital transformation in the manufacturing industry by using the information in the SECOM dataset), model explanatory index, and computational efficiency index. The comparison models encompass the traditional DEA model, BPNN, support vector machine (SVM), and decision tree models. Among them, the parameters of the decision tree model include a maximum depth of 10, a minimum sample splitting of 2 for nodes, and a minimum sample analysis of 1 for leaf nodes. The parameter settings of the SVM model include: the penalty parameter C is 1.0, and the kernel function is a radial basis function.

First, regarding the efficiency evaluation of the models, Figure 3 displays the comparative results from three experiments.

The results in Figure 3 demonstrate that the proposed model (DEA-BP) achieves relatively high overall efficiency in all three experiments (up to 93%), significantly outperforming the traditional DEA model (up to 87%) and the standalone BPNN (up to 89%), SVM (up to 90%), and decision tree model (up to 88%). This illustrates that the proposed model, based on the comprehensive utilization of DEA and BP models, more accurately assesses the overall effect of digital transformation in the manufacturing industry.

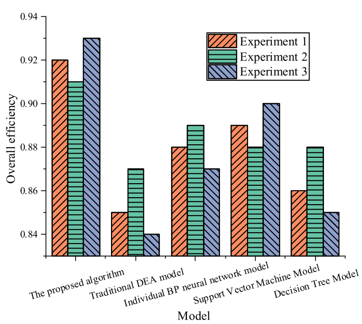

FIGURE 3. Comparison of overall efficiency.

Next, Figure 4 depicts the evaluation results for prediction performance.

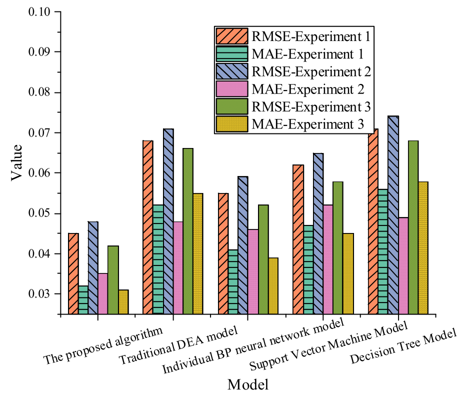

FIGURE 4. Comparison of prediction performance.

Figure 4 suggests that the proposed model achieves relatively low Root Mean Square Error (RMSE) values (averaging 0.042) and Mean Absolute Error (MAE) values (averaging 0.031) in all three experiments. These values significantly exceed those of the traditional DEA model and the standalone BPNN, SVM, and decision tree models in prediction accuracy. This indicates that the proposed model exhibits higher accuracy in predicting the effects of digital transformation.

Figures 5-7 present the model's classification performance evaluation results.

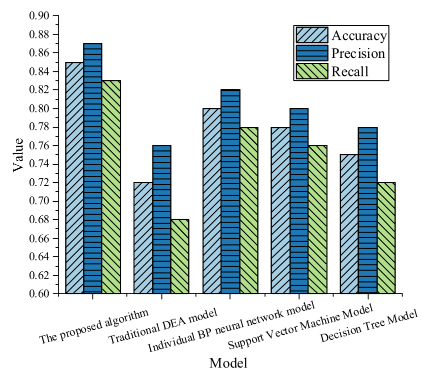

FIGURE 5. Comparison of classification performance (the first experiment).

Figure 7 reveals that in all three experiments, the proposed DEA-BP model demonstrates higher comprehensive performance in the evaluation of digital transformation effects compared to the traditional DEA, standalone BPNN, SVM, and decision tree models. The proposed model shows a stable improvement in average accuracy, precision, and recall, reaching 0.88, 0.89, and 0.87, respectively. In contrast, the traditional DEA model performs relatively lower in these three indicators, especially exhibiting poorer performance in recall. The standalone BPNN, SVM, and decision tree models exhibit similar performance across the indicators, but overall performance is slightly inferior compared to the proposed DEA-BP model.

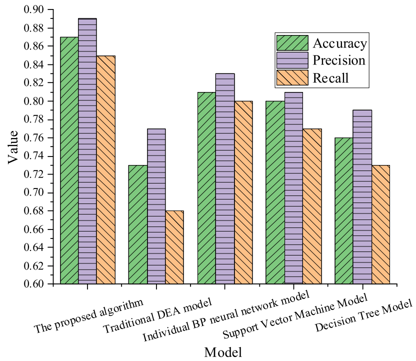

FIGURE 6. **Comparison of classification performance (the second experiment).**

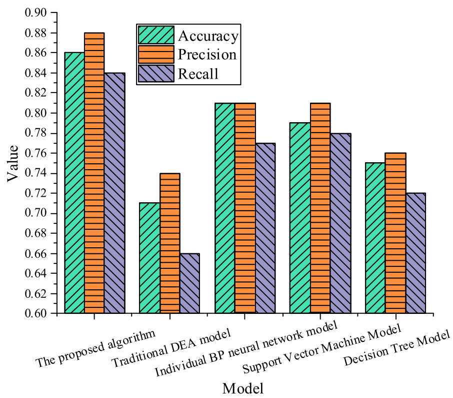

FIGURE 7. **Comparison of classification performance (the third experiment).**

E. DISCUSSION

In the evaluation of effectiveness, this work employs comprehensive indicators, encompassing efficiency evaluation, prediction performance, model stability, classification accuracy, model interpretability, and computational efficiency. Comparative experimental results demonstrate the proposed DEA-BP model's outstanding performance in overall efficiency. This superiority stems from the model's synthesis of the advantages of DEA and BP, enabling a more accurate assessment of the overall impact of digital transformation in the manufacturing industry. Regarding prediction performance, the DEA-BP model consistently achieves low RMSE and MAE values across three experiments, remarkably outperforming other comparative models. This indicates that the proposed model exhibits higher accuracy in predicting the effects of digital transformation. Considering classification performance, the DEA-BP model presents stable improvements in accuracy, precision, and recall. In comparison, the traditional DEA model exhibits relatively lower performance across these three indicators, particularly in recall. Standalone BPNN, SVM, and decision tree models show similar performance but are slightly inferior overall compared to the DEA-BP model. These results suggest that the DEA-BP model excels in multiple aspects, offering a more accurate and reliable tool for the comprehensive evaluation of the effects of digital transformation.

V. CONCLUSION

This work aims to comprehensively assess the effects of digital transformation in the manufacturing industry by integrating DEA with the BPNN to construct the DEA-BP model. Empirical analysis is conducted using SECOM manufacturing process data, and a comparative evaluation is performed against traditional DEA, standalone BPNN, SVM, and decision tree models. The following conclusions are drawn. First, the DEA-BP model exhibits significant superiority in overall efficiency evaluation, leveraging the flexibility of DEA and the nonlinear learning capability of BP. Second, regarding prediction performance, the DEA-BP model demonstrates higher accuracy with low RMSE and MAE values, showcasing its superiority in predicting the effects of digital transformation. Lastly, in classification performance, the DEA-BP model shows substantial accuracy, precision, and recall improvements, making it stabler than other models. Research limitations include the need for further exploration of model interpretability and computational efficiency. Prospects involve expanding the research sample, optimizing model parameter selection, exploring additional evaluation indicators, and enhancing the overall research comprehensiveness and applicability. Additionally, a novel approach is introduced to evaluate the effects of digital transformation in the manufacturing industry and provides practical feasibility and guidance, thus holding significant research and practical value. The research results improve the accuracy and credibility of digital transformation evaluation and provide vital theoretical and methodological support for manufacturing practice. Consequently, it offers powerful guidance for enterprise decision-making and management, thus promoting the upgrading and transformation of the industry.

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