

Industrial Product Design based on Convolutional Neural Network Model

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Abstract

Industrial design refers to the practice of applying design principles to produce goods for large-scale manufacturing. Design is the imaginative process that comes before a thing is made to determine and define its shape and characteristics. Thorough industry evaluation is becoming more important to the creation of innovative primary commodities. In this paper, we proposed the use of Convolutional neural networks (CNN) in the design of industrial product design (IPD). Data from China's electronic industrial sector shows that incentives may boost technological advancement in businesses, but an excess of them may limit progress. Subsequently, the manufacturing set of data from china was gathered. Normalization may be used as a preprocessing step for the gathered data. In addition, the CNN method has been suggested. Traditional methods are contrasted with these in terms of several different parameters, including accuracy, precision, recall, implementation cost, and energy utilization. The implementation cost of the proposed model is 70% which seems to be less than the other traditional approaches.

Keywords: Industrial product design (IPD), Convolutional neural networks (CNN), implementation cost, energy utilization

1. INTRODUCTION

An evolution toward smart manufacturing is now taking place in the global industrial sector. The most recent developments addressed by the upcoming industrial revolution have led to the production of increasingly sophisticated, intelligent, and capable goods. With significant modifications to traditional product design procedures, this approach influences the whole product's lifetime. The IPD development process includes the creation of new products, the design of production systems, new products, and the start of the product's manufacturing process. IPD development teams employ technology-supporting tools to improve the effectiveness of product design by minimizing mistakes made very early in the product engineering process [1]. A brand-new approach to product design that is information has recently been developed. The design process has become more digitalized than it has ever been, as shown by the general use of digital production packages. The capacity of the designer to manage data has grown increasingly important in modern IPD. During a product's lifespan, data may be gathered throughout many stages including design, manufacture, distribution, consumption, maintenance, upgrading, and recycling. The state, behavior, and performance of the product are some of the data. In the past, performance analysis, preventative maintenance, and problem detection have been the major uses of digital twins. Several studies have examined the digital twins may be used for IPD; specifically, that communication, synergy, and co-evolution between a real object and its effectiveness can occur [2]. Efficiency and originality in design are being put under increasing pressure due to heightened competition and the quick introduction of new items. A dynamic market, various constraints, and shifting requirements present challenges for the creation of new products. According to this, design frequently involves interactions between the usable, physiological, customer, and procedure domains. Moreover, design should be social and attempt to overcome conventional design via social interaction. Design approaches can be extremely useful during the concept design stage due to offering groups of designing processes a theoretical base and direction. It is consequently vital to build a systematic design strategy rather than only concentrating on the impacts of the IPD process [3]. Figure 1 denotes the process of industrial product design.

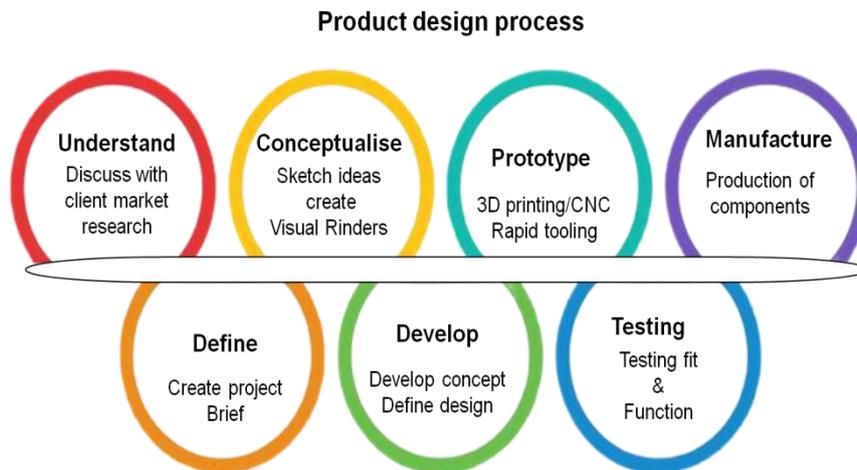


Figure 1: Process of industrial product design

Throughout the last several decades, digital manufacturing has had a significant positive impact across the entire industrial sector. By modeling factories, resources, employees, and their skills digitally, digital manufacturing develops models and models the production of IPD and processes. The capacity of businesses to innovate is more crucial than ever for increasing their profitability and preserving a competitive edge. Research has revealed, however, that just one out of every four newly produced goods is a success, and that 40–50 percent of the total resources used for product development are lost on abandoned projects or products that don't work out well. Lack of adaptability in conventional research and development methods that are frequently based on the waterfall development process is one factor contributing to failure [4]. Several advanced manufacturing models, such as social manufacturing, have been put forward. These models focus on creating sustainability processes and systems to provide more sustainable goods and services. Sustainability is a desirable approach for meeting specific customer expectations, minimizing system risk uncertainty, reducing power consumption, resolving social responsibility, and boosting resource efficiency in the manufacturing industry. The key tendency of the aforementioned ideas for sustainable manufacturing is the novel decentralized connectivity of social production resources and open-architecture products, which entails a fundamental restructuring of cross-enterprise manufacturing [5]. Technology and art, respectively, are IPD. The use of science enables the fulfillment of all performance, reliability, manufacturing ability, creativity, and safety requirements. The trick is to satisfy the customer's wants while making the least amount of concessions to these criteria to maximize cost and profit. The definition of the client's demands is the first step in the design process, followed by the conceptual design stage and finishing with the detailed design. Manufacturing businesses are showing a growing and persistent tendency toward offering a wider range of IPD [6]. A company's ability to develop its product offering is one factor in determining its commercial success. To satisfy shifting consumer, social, and environmental expectations, innovation is necessary. To address the different, frequently apparently incompatible restrictions that must be satisfied, a multidisciplinary approach is necessary. It is acknowledged that a systematic method is tremendously helpful, if not necessary, to accomplish this goal of product design. Regards design must adapt to the changing social and economic circumstances and that education must provide the skills and knowledge to do so. ID with traditional training even if the definition of ID is expanding to include designed services, interaction design, and experience design. New design possibilities are created by developments in work and lifestyle, and learning in design calls for the use of new technology to enhance designs for individuals [8]. New and disruptive technologies used in manufacturing techniques can significantly alter business models in a variety of market areas and raise expectations for a rapid increase in the number of products and services produced and distributed. Product innovations, materials, energy sources, manufacturing techniques, organizational structure, and applicable technologies have continuously evolved through the development of industrialization, enabling abrupt transformations that have been referred to as industrial revolutions [9]. The process of developing products has changed significantly as a result of technological advancements. These modifications may be seen in appearance, quality, individuality, and even innovation. There are several processes involved in conventionally developing a product before it is finished. The extensive use of modern technologies for PD, followed by the evaluation via simulation and production equipment, demonstrates its significance at different stages of product development, from idea to finished product [10].

2. RELATED WORKS

The paper [11] evaluated the state of the art of literature on digital twins in the context of product-service systems. A thoroughly studied initial selection of 59 publications revealed that just 2 researchers seemed to be particularly interested in products and services. The majority of the additional literature is devoted to the use of Digital Twins for certain types of maintenance services. Furthermore, this study will lead to further investigation into the use of Digital Twin technology in the context of IPS2, and it suggests potential uses for the various phases of a closed-loop product life cycle. The study [12] examined a variety of reprocessed PET, PE, and PP samples made from source-separated plastic in Household Waste (HHW) to determine their thermal deterioration, processability, and mechanical qualities. The possibility for closed-loop recycling is assessed in light of that one. The research showed that there are distinct obstacles associated with recycling PET, PE, and PP. Even if the level of heterogeneity in the trash is significant, potential deterioration of the PET polymer may be reversed in a reconditioning process, providing PET trash well enough for shuttered, multiple times recycling. The research [13] investigated the management strategies that businesses use and incorporate into respective business models to control the development of circular products. After a thorough review of the literature in the area, they grouped several pertinent management techniques under the following four Circular Economy (CE) implementation related to the product guiding principles. To implement CE and control the deployment of circular products, the outlined principles establish general goals to be attained. The paper [14] evaluated the digital twin from the standpoint of ideas, technology, and industrial applications by conducting a thorough and in-depth examination of various kinds of literature. The current state of research, the concept's progress, in each lifecycle phase, and different kinds of industrial applications are detailed, along with the important technologies that allow for three components. Based on this, insights and suggestions for future study in the area of digital manufacturing research are provided as several lifespan stages. The study [15] suggested the conventional march toward more integration may be about to reverse. Systems on chips (SoCs) should be disintegrated into several smaller chiplets, according to numerous business and academic organizations. An in-depth discussion of the technological challenges that led to the use of chiplets is provided in this paper, as well as technical solutions developed for their product-expanded chiplet use from single several product lines. The research [16] discussed key elements of industry 4.0 about its background, benefits, and difficulties. Also, for the development of Industry 4.0, researchers spent more than a year drawing out the fundamental principles and an industrial framework, including strategic ideas and procedures. Academics and policymakers now consider Industry 4.0 to be one of the most rapidly developing fields in the world. As technologies enable businesses to concentrate on important choices in their implementation, the benefits and downsides of Industry 4.0 are essential. The paper [17] investigated areas for further research that will broaden and facilitate the framework's deployment. The researchers outline the investigation gaps that need to be explored and examine pertinent literature for the determined research paths. The authors urge academic groups to work together to enable systematic crowd-sourcing projects for engineering design as a way of wrapping up their discussion. The study [18] established a human cyber-physical symbiosis that will facilitate real-time, dynamic interaction between operators, machines, and production systems. Three of the top R&D organizations in the world are researched to develop a robust framework. Real-world pilot experiments have led to the identification of five design factors. The industrial wearable system has enormous potential for the next generation of production, according to future trends and research prospects. The research [19] provided such a review to highlight the advancements and strives to raise awareness of the greatest experiences. It is meant to provide people looking to create a road plan for digitizing the relevant manufacturing suites with a clear sense of what to do. This review's presentation aims to provide academics and industry practitioners alike access to a practical library of Industry 4.0. The study [20] intended to enhance collaboration between energy sales organizations and manufacturing companies by creating and refining an Industrial Product Service System (IPSS) business model. ESC anticipates energy prices and notifies manufacturers of them using a power management tool powered by data-capturing hardware linked to the Cloud [21]. In addition, a flexible production scheduling method that takes into account manufacturers' power use in reaction to fluctuating energy costs is provided.

3. MATERIALS AND METHOD

There is a significant need in the industrial sector for rapid and trustworthy industrial monitoring. Unfortunately, the effectiveness of fault identification relies substantially on characteristics that are established individually. The misunderstanding stems from the fact that industrial design as well as product development shares a lot of common ground. Although product designers focus on high-end items, product designers are responsible for a wider range of products, including those used daily. The CNN model is detailed in great depth here concerning the manufacturing process.

A. Data collection of the samples

Production of electronic devices is under SIC code C40. It's the most technologically advanced and labor-intensive sector in the economy. Electronics manufacturers rely heavily on cutting-edge technology, thus the sector is always buzzing with research and development efforts. By narrowing focus on one particular industry, we can sidestep the variations seen in other sectors. The information for the electronics industrial companies comes from the China Industrial Business Database for the years 2005-2007, which was compiled by the National Bureau of Statistics of China. All businesses, both government and privately held, with yearly revenues of greater exceeding 5 million RMB are counted in the Survey Report of Industrial Production. Companies' patent information is sourced from IncoPat. Using these data, we can collect a representative cross-section of the electronics industries. From 2005 to 2007, we track the success rate of every company in this sector. The number of incentives a firm gets has no bearing on the probability that it would be included in the collection or evaluated for its innovativeness. Efficient statistical analysis outcomes may be obtained when the independent variable and the inherent issue are avoided. Using the data samples for three years in a row, we construct a balanced panel. All companies with yearly revenues over 5 million from 2005-2007 are represented on this diversified platform, and each of their manufacturing and technological data is preserved in full.

B. Preprocessing using normalization

Normalization is the process through which a system's data is organized. Data sources can be altered through a series of operations known as preprocessing. The process of normalizing involves completing several steps, including the inclusion of basic features, a change in object type, and others. The efficiency of processing is boosted because of the elimination of duplicate data and the improvement of data validity. As a result, we normalized the relevant information with both the Min-Max and the Z-Score normalization.

Z-score normalization

With Z-score normalization, the users may better understand where a given rating could fit within a standard normal set of data. Z-Score is carried out to manage outliers in a collection.

$$\bar{z} = \frac{Z - \tau}{\varsigma} \quad (1)$$

Z stands for the quantitative component and \bar{z} is the freshly assumed data point, τ indicates the mean of the data points, and ς indicates the variance of the data points.

Min-Max Normalization

When it comes to normalizing data, min-max normalization is a popular choice. Min Max Normalization is used to impact the change in the data. It takes the least and highest values for every statistical attribute and uses them together to calculate the target value. Normalization in the system may be determined by (2).

$$D_t = \frac{(Y - Y_{min})}{(Y_{max} - Y_{min})} \quad (2)$$

Where Y seems to be the range of predictions for the variables in the data set. Y_{min} and Y_{max} represent the lowest and highest possible values of Y, respectively.

C. Convolutional neural network (CNN)

A Convolutional layer is necessary for a CNN, but additional elements, such as asymmetric, pooling, and fully connected layers, are also possible. CNN may be useful in some contexts. Nonetheless, it does include new training variables. The backpropagation technique is used to train convolution layers in the CNN. The filtering structure's variants are task-specific.

CNNs were multilayered perceptrons that have been normalized. Each cell with one level of a multilayer perceptron is typically coupled to every neuron in the following layer. Due to their high degree of interconnectedness, such systems tend to generalize their inputs. Normalization, or the prevention of overfitting,

often involves punishing variables throughout training or reducing connection. Creating comprehensive statistics also improves the likelihood that CNNs would pick up on the basic assumptions that define a specific sample, as opposed to picking up on the limitations of a sparse one.

A convolutional neural network with deep learning (CNN) is developed in a controlled manner utilizing trained inputs of the type. Equation (3) signifies the collection of all variables collected from every level in a particular CNN model, and let $x^{(t)}$ and $y^{(t)}$ represent the t^{th} inputs and their labeling. Training a system is thus recast as a search for a set of parameters that reduces this goal:

$$\Theta^* = \operatorname{argmax}_{\Theta} \frac{1}{T} \sum_t L(f_{\Theta}(x^{(t)}, y^{(t)}) + \lambda \Omega(\Theta)) \quad (3)$$

Diminishing the expected loss function $L()$ between network outputs $f(x)$ factorized with Θ^* and the accurate identify $y^{(t)}$ yields the sequence Θ^* as the subsequent parameter set for a CNN. Precision may be avoided by using a similarity measure where $\Omega(\Theta)$ is the proportional gain, and excessive neuronal values are punished. When the mistake from the forward phase is sent back to the system to adjust the neuronal weights, this is a way of learning a CNN is a classic backpropagation strategy. Figure 2 depicts the layout of CNN.

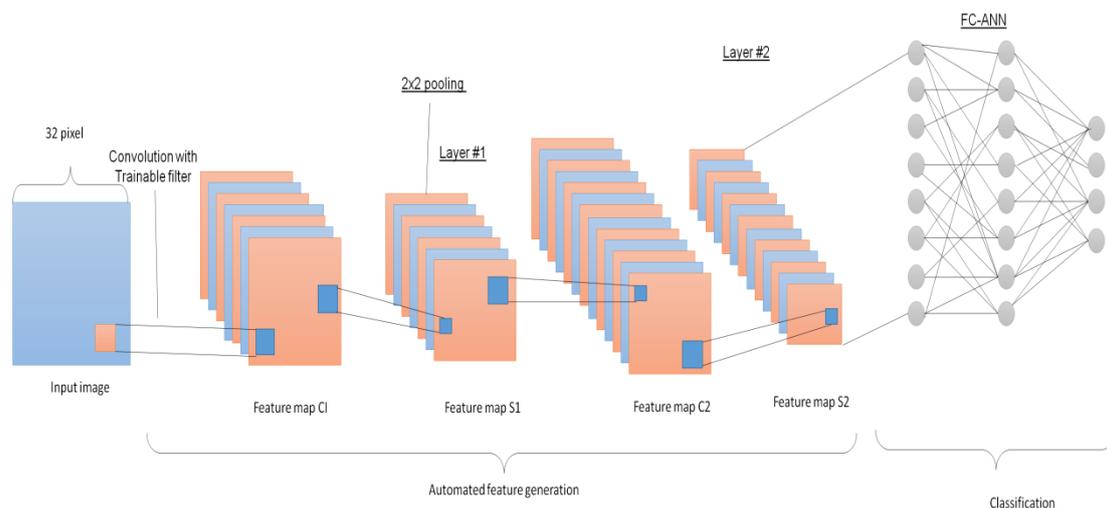


Figure 2: Layout of CNN

Layers of Convolutions:

Several filtering glide across the convolution layers to process the data received. The outcome of such layers is a summed product of the input's filtering and convolution layer multiplications, one component at a time. A component of the subsequent layer contains the weighed summing. The product of this multiplier would be saved in the subsequent layer at the location that represents the focal point. The outcome of the convolution may be adjusted by dragging the focus region and the other components. Each convolutional procedure has its size of filters and zero padding parameters. The moving process is determined by the path, which can be expressed as a positive value. Every filter employed during a single convolutional operation has to be of equal size. To regulate the overall dimensions of the generated convolution layer, zero padding is used to append an extra set of rows as well as columns to the such input vector. The primary goal of zero padding is to preserve the information at the border of the input sequence. The length of the convolutional outcome was reduced concerning the dimensions of the source if zero padding is not used. Hence, restricting the quantity of convolution layer in a system helps to reduce the network size. Yet, our network design benefits from zero padding, which stops networking from diminishing and allows for a limitless number of hidden layers.

Non-linearity layer

The primary goal of implementing nonlinearity will be to regulate or shut off the outputs. CNN may make use of a variety of irregular operations. Yet among the many inhomogeneities used in domains like image analysis, the rectified linear unit (ReLU) stands out.

A mathematical expression for the ReLU is

$$ReLU = \begin{cases} 0, & \text{if } v < 0, \\ v, & \text{if } v \geq 0. \end{cases} \quad (4)$$

Infiltration Layer:

The dimensionality of the sources is approximately reduced by the pooling layer. The result of the most common pooling technique, max pool, is the maximum value within the pooling filters (2×2). Median and summing are two further examples of grouping algorithms. Nonetheless, the pooling layer is a popular and effective approach since it yields substantial gains while reducing the input sample size by just 25% on average.

Layer of Softmax:

The use of a softmax function to represent a categorized dispersion is often regarded as a very effective technique. Often utilized within output nodes, the softmax is a standardized exponential of the sample points. This computable variable may be used to express a likelihood of an outcome. Also, the logarithmic component raises the potential of the highest benefit. This is the form of the softmax formula:

$$p_j = \frac{f^{y_j}}{\sum_{j=1}^N f^{y_j}} \quad (5)$$

where p_j represents the j^{th} terminal in the softmax outcome, y_j represents the j^{th} node in the original output, and N indicates the overall quantity of output modules. Table 1 represents the variables of CNN.

Table 1: Variables of CNN

Layer number	Layers	Variable	Values
1	Convolutional filter	Transmission pathways	8x8x85
		Dimensions	3x3
		Stride	1
		Plate	1
	Max pooling	Dimensions	2x2
		Plate	2
2	Convolutional filter	Transmission pathways	64
		Dimensions	2x2
		Stride	1
		Plate	1
	Max pooling	Dimensions	2x2
		Plate	2
3	Convolutional filter	Transmission pathways	128
		Dimensions	3x3
		Stride	1
		Plate	1
	Max pooling	Dimensions	2x2
		Plate	2

		Transmission pathways	256x2x2
4		Output from Layer	512
5	Softmax	Output units	14

4. RESULT AND DISCUSSION

Convolutional neural networks (CNN) have been suggested for utilization in the design of industrial products (IPD). The effectiveness and reliability of a suggested approach are compared to those of conventional approaches like Artificial intelligence (AI) [22], Big Data (BI) [23] to show that it is effective. These approaches are compared to conventional methods based on a variety of parameters, including accuracy, precision, recall, and implementation cost.

Accuracy

Accuracy is defined as the use of being correctly classified to the total number of instances in the design of industrial products, which is given by

$$Accuracy(\%) = \frac{TP+TN}{TP+FP+FN+TN} (\%) \tag{6}$$

Figure 3 shows the accuracy of the proposed and existing system. The accuracy of the proposed CNN has been suggested for utilization in the IPD. BD has attained 77%, and AI has achieved 85%, whereas the proposed system reaches 95% of accuracy. It shows that the proposed approach has more accuracy than the existing one. Table 2 depicts the values of accuracy.

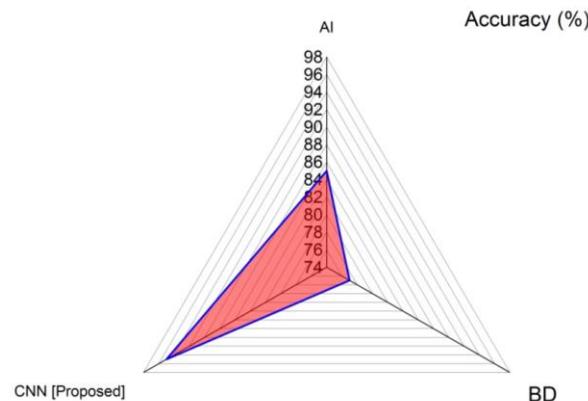


Figure 3: Accuracy

Table 2: Accuracy

Techniques	Accuracy (%)
AI	85
BD	77
CNN [Proposed]	95

Precision

The capacity of a classification model is used to identify just the relevant data points in industrial product design.

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Figure 4 shows the precision of the proposed and existing system. The precision of the proposed CNN has been suggested for utilization in the IPD. BD has attained 88%, and AI has achieved 77%, whereas the proposed system

reaches 95% of precision. It shows that the proposed approach has more precision than the existing one. Table 3 depicts the values of precision.

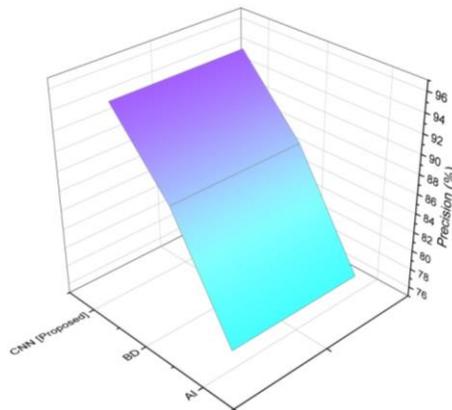


Figure 4: Precision

Table 3: Precision

Techniques	Precision (%)
AI	77
BD	88
CNN [Proposed]	95

Recall

The recall is mathematically defined as the sum of the number of true positives minus the number of false negatives. The capacity of a model can be utilized to locate all relevant instances in a collection of data about industrial products.

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

Figure 5 shows the recall of the proposed and existing system. The recall of the proposed CNN has been suggested for utilization in the IPD. BD has attained 82%, and AI has achieved 73%, whereas the proposed system reaches 97% of recall. It shows that the proposed approach has more recall than the existing one. Table 4 depicts the values of recall.

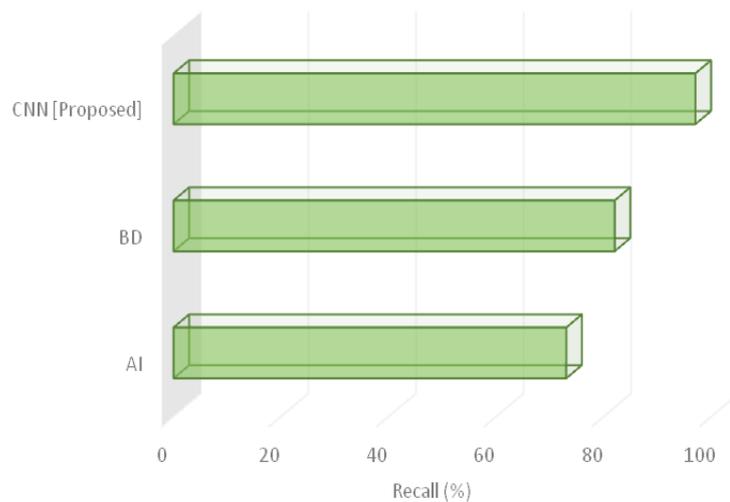


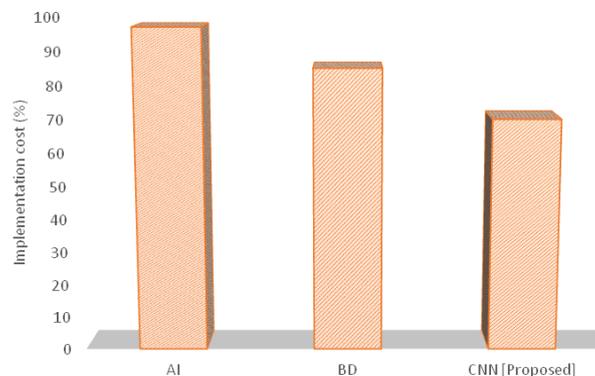
Figure 5: Recall

Table 4: Recall

Techniques	Recall (%)
AI	73
BD	82
CNN [Proposed]	97

Implementation cost

Implementation costs are those associated with planning and carrying out a strategy for implementing one or more particular evidence-based interventions. The prospective intervention will be immediately impacted by the strategy, possibly influencing its efficacy or use in the industrial product design. Figure 6 shows the Implementation costs of the proposed and existing system. The Implementation costs of the proposed CNN have been suggested for utilization in the IPD. BD has attained 85%, and AI has achieved 97%, whereas the proposed system reaches 70% of Implementation costs. It shows that the proposed approach has fewer Implementation costs than the existing one. Table 5 depicts the values of Implementation costs.

**Figure 6: Implementation cost****Table 5: Implementation cost**

Techniques	Implementation cost (%)
AI	97
BD	85
CNN [Proposed]	70

5. CONCLUSION

Rapid advances in industrialization have resulted in design shifting from being top-down to bottom-up, from analog to digital to hybrid. To keep up with consumer demand and boost their companies' competitiveness, manufacturers will need to create innovative approaches to the design of product-service systems. We present a CNN model for industrial product design in this article. The findings indicate that the suggested framework is more dependable than the conventional methods. The suggested technique is effective, with an accuracy of 95% being obtained. The results showed that the proposed approach outperformed the previous work based on the dataset.

REFERENCE

1. Bilal Ahmed, M., Imran Shafiq, S., Sanin, C. and Szczerbicki, E., 2019. Towards experience-based smart product design for industry 4.0. *Cybernetics and Systems*, 50(2), pp.165-175.
2. Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., Guo, Z., Lu, S.C.Y. and Nee, A.Y., 2019. Digital twin-driven product design framework. *International Journal of Production Research*, 57(12), pp.3935-3953.
3. Wu, Y., Zhou, F. and Kong, J., 2020. The innovative design approach for product design is based on TRIZ, AD, fuzzy, and Grey relational analysis. *Computers & Industrial Engineering*, 140, p.106276.

4. Jussila, J., Raitanen, J., Partanen, A., Tuomela, V., Siipola, V. and Kunnari, I., 2020. Rapid product development in university-industry collaboration: A case study of a smart design project. *Technology Innovation Management Review*, 10(3).
5. Leng, J., Ruan, G., Jiang, P., Xu, K., Liu, Q., Zhou, X. and Liu, C., 2020. Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: A survey. *Renewable and sustainable energy reviews*, 132, p.110112.
6. David, J.V., Ana, M.R., Santiago, F.B. and Faustino, A.V., 2021. Aspects of industrial design and their implications for society. Case studies on the influence of packaging design and placement at the point of sale. *Applied Sciences*, 11(2), p.517.
7. ten Kate, A.J., Piccione, P.M., Westbye, P. and Becker, A.F.A., 2022. An industrial and chemical engineering perspective on the formulation of active ingredients in pharmaceuticals and agrochemicals. *Current Opinion in Chemical Engineering*, 36, p.100747.
8. Huang, X., Ball, R. and Wang, W., 2021. Comparative study of industrial design undergraduate education in China and the USA. *International Journal of Technology and Design Education*, 31, pp.565-586.
9. Santos, R.C. and Martinho, J.L., 2020. An Industry 4.0 maturity model proposal. *Journal of Manufacturing Technology Management*.
10. Spahiu, T., Manavis, A., Kazlacheva, Z., Almeida, H. and Kyratsis, P., 2021. Industry 4.0 for fashion products—Case studies using 3D technology. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1031, No. 1, p. 012039). IOP Publishing.
11. Zhang, H., Ma, L., Sun, J., Lin, H. and Thürer, M., 2019. Digital twin in services and industrial product service systems: Review and analysis. *Procedia CIRP*, 83, pp.57-60.
12. Eriksen, M.K., Christiansen, J.D., Daugaard, A.E. and Astrup, T.F., 2019. Closing the loop for PET, PE and PP waste from households: Influence of material properties and product design for plastic recycling. *Waste management*, 96, pp.75-85.
13. Urbinati, A., Chiaroni, D. and Toletti, G., 2019. Managing the introduction of circular products: Evidence from the beverage industry. *Sustainability*, 11(13), p.3650.
14. Liu, M., Fang, S., Dong, H. and Xu, C., 2021. Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems*, 58, pp.346-361.
15. Naffziger, S., Beck, N., Burd, T., Lepak, K., Loh, G.H., Subramony, M. and White, S., 2021, June. Pioneering chiplet technology and design for the amd epyc™ and ryzen™ processor families: Industrial product. In *2021 ACM/IEEE 48th Annual International Symposium on Computer Architecture (ISCA)* (pp. 57-70). IEEE.
16. Sharma, A.K., Bhandari, R., Pinca-Bretotean, C., Sharma, C., Dhakad, S.K. and Mathur, A., 2021. A study of trends and industrial prospects of Industry 4.0. *Materials Today: Proceedings*, 47, pp.2364-2369.
17. Shergadwala, M., Forbes, H., Schaefer, D. and Panchal, J.H., 2020. Challenges and research directions in crowdsourcing for engineering design: An interview study with industry professionals. *IEEE Transactions on Engineering Management*, 69(4), pp.1592-1604.
18. Kong, X.T., Luo, H., Huang, G.Q. and Yang, X., 2019. Industrial wearable system: the human-centric empowering technology in Industry 4.0. *Journal of Intelligent Manufacturing*, 30, pp.2853-2869.
19. Oztemel, E. and Gursev, S., 2020. Literature review of Industry 4.0 and related technologies. *Journal of intelligent manufacturing*, 31, pp.127-182.
20. Mourtzis, D., Boli, N., Xanthakis, E. and Alexopoulos, K., 2021. Energy trade market effect on production scheduling: an Industrial Product-Service System (IPSS) approach. *International Journal of Computer Integrated Manufacturing*, 34(1), pp.76-94.
21. Liu, D., Chen, T., Liu, X. and Yu, Y., 2019. Do more subsidies promote greater innovation? Evidence from the Chinese electronic manufacturing industry. *Economic Modelling*, 80, pp.441-452.
22. Tsang, Y.P. and Lee, C.K.M., 2022. Artificial intelligence in industrial design: A semi-automated literature survey. *Engineering Applications of Artificial Intelligence*, 112, p.104884.
23. Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F., 2018. Digital twin-driven product design, manufacturing, and service with big data. *The International Journal of Advanced Manufacturing Technology*, 94, pp.3563-3576.