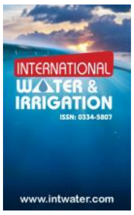

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Application Of Convolutional Neural Network in Industrial Product Design

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Abstract: The term "industrial design" describes the process of creating products using design principles for mass production. Design is the pre-production mental exercise that defines the form and attributes of an object. The development of novel primary commodities is increasingly dependent on comprehensive industry evaluation. We present a proposal for industrial product design (IPD) that makes use of convolutional neural networks (CNN). Incentives may encourage firms to develop new technologies, but too many of them might stifle innovation, according to data from China's electronic manufacturing sector. As a result, we collected the Chinese manufacturing data set. As a preliminary step in processing the collected data, normalization might be employed. Another approach that has been proposed is the CNN method. These are compared to more conventional approaches on a number of metrics, such as precision, accuracy, recall, implementation cost, and energy consumption. Compared to more conventional methods, the suggested methodology appears to have a lower implementation cost of 70%.

Keywords: Industrial Product Design (IPD), Convolutional Neural Networks (CNN), Accuracy, Precision, Recall, 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]. Information-based design of goods has lately undergone a radical change. The widespread usage of electronic manufacturing tools demonstrates how much more digital the creative procedure is nowadays than it has ever been. 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.

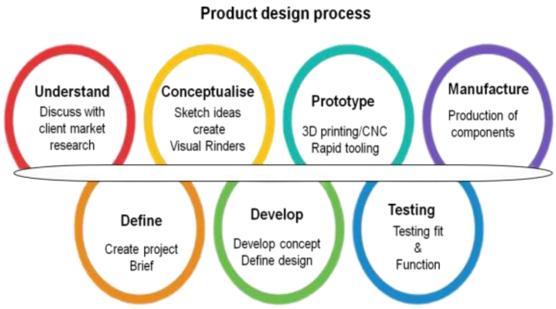


Figure 1: Process Of Industrial Product Design

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].In this work, we suggested applying convolutional neural networks (CNN) to industrial product design (IPD). Data from the electronic industry in China indicates that while incentives may assist companies enhance their technological capabilities, too many of them could restrict development. The Chinese manufacturing set of data was then acquired. One possible preprocessing step for the collected data is normalization.

The rest of this article is divided into the following parts: Part 2, Related Work; Part 3, Materials and method; Part 4, Result and discussion; and Part 5, Conclusion.

2. Related Works

The paper [11] evaluated the most recent research on virtual twins in the setting of systemic product-service interactions. Only 2 scholars appeared to be particularly interested in products and services, according to a carefully examined initial selection of 59 articles. The usage of Digital Twins for specific kinds of maintenance services is the focus of the majority of the supplemental material. They will also prompt greater research into the application of Digital Twin technology in the context of IPS2, and it offers ideas for possible applications for the various stages 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 chaplets, according to numerous business and academic organizations. An in-depth discussion of the technological challenges that led to the use of chip lets is provided in this paper, as well as technical solutions developed for their product-expanded chip let 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 Educational institutions and decision-makers today view Industry 4.0 as one of the global sectors with the fastest rate of development. Understanding the advantages and disadvantages of Industry 4.0 is crucial since technology enables organizations to focus on critical decisions in their deployment. 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

International Water and Irrigation
Volume 44 Issue 2 (2025)
ISSN: 0334-5807
Pages 187 - 199

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.CNN models have the potential to revolutionize the industrial product design process. By examining large design datasets, they can hasten the concept generating process while also inspiring and enlightening designers. These models shorten and lower the cost of iterative design phases by enabling rapid testing and validation of designs. The CNN model is detailed in great depth here concerning the manufacturing process.

3.1 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.

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:

The process of Z-score normalization involves converting manufacturing data into a standard normal distribution, characterized by a mean of 0 and a standard deviation of 1. This facilitates equitable comparison and study of various variables within the dataset.

International Water and Irrigation
Volume 44 Issue 2 (2025)
ISSN: 0334-5807
Pages 187 - 199

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.

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

Zstands 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:

Manufacturing data is scaled to a specific range, usually [0, 1], using min-max normalization. Each data point's minimum value is subtracted, and the result is divided by the range (max-min), guaranteeing consistent data representation and enabling cross-variable comparison.

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}andY_{max}represent the lowest and highest possible values of$Y$, respectively.

3.2 Convolutional Neural Network (CNN)

CNNs are used in industry to improve product design by processing complicated data, including images and 3D models. CNNs streamline design procedures, spot inefficiencies, and promote creativity by extracting significant features. Product creation is streamlined by this technology, which boosts productivity and encourages innovations in industrial design.

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. Compared with traditional design techniques, this strategy has a number of benefits for industrial product design.CNN models are capable of mining huge information for patterns and ideas that human designers could miss and conserves time and materials.

CNNs were multilayered perceptron's 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:

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

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.

CNN is an industry leader in product design thanks to its effective processing and analysis of visual input. They are perfect for jobs like defect detection, design optimization, and quality control since they can recognize shapes, patterns, and characteristics in images. CNNs accelerate the process of developing new products by expediting prototypes and cutting down on mistakes, which saves money and produces better products. They help designers visualize and improve goods through their use in 3D modeling, rendering, and virtual prototyping. Their capacity to manage big datasets and automate processes spurs innovation and guarantees that industrial goods adhere to strict design and functioning guidelines.

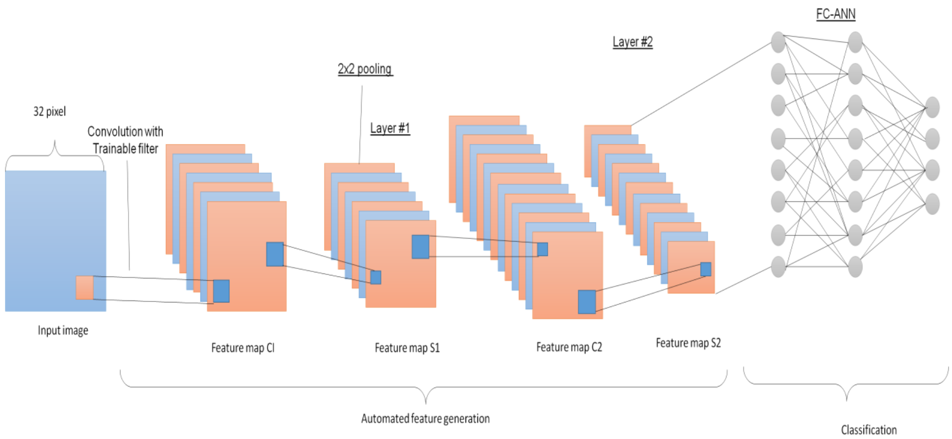


Figure 2: Layout of CNN

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

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

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:

$$p_j = \frac{f^{y_j}}{\sum_{j=1}^{N} f^{y_j}} \tag{5}$$

where$p_j$represents the j^{th} terminal in the softmax outcome, y_j represents the j^{th}node in the original output, and Nindicates 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	Stride	1
		Transmission pathways	8x8x85
		Plate	1
		Dimensions	3x3
	Maximum capacity	Plate	2
		Dimensions	2x2
2	Filtering via exponential	Stride	1
		Dimensions	2x2
		Transmission pathways	64
		Plate	1
	Maximum capacity	Dimensions	2x2
		Plate	2
3	Filtering via exponential	Transmission pathways	128
		Dimensions	3x3
		Stride	1
		Plate	1
	Maximum capacity	Dimensions	2x2
		Plate	2
		Transmission pathways	256x2x2
4		Output from Layer	512
5	Softmax	Output units	14

International Water and Irrigation
Volume 44 Issue 2 (2025)
ISSN: 0334-5807
Pages 187 - 199

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.

4.1 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

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

The accuracy of the suggested and existing systems are shown in Figure 3. It has been recommended to use the planned CNN's accuracy in the IPD. BD has a 77% accuracy rate, AI has an 85% accuracy rate, and the system that was suggested has a 95% accuracy rate. It demonstrates that the suggested method is more accurate than the current one. Table 2 shows the accuracy values.

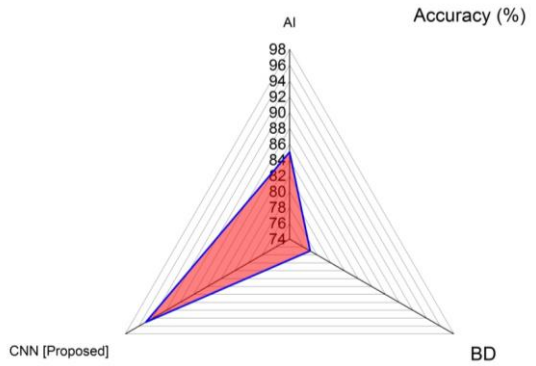


Figure 3: Accuracy

Table 2: Accuracy

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

4.2 Precision

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

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

The precision of the current and proposed systems is shown in Figure 4. It has been recommended to use the planned CNN's precision in the IPD. While BD has an accuracy of 88% and AI has a precision of 77%, the suggested system has a precision of 95%. It demonstrates that the suggested approach is more precise than the current one. The required precision values are shown in Table 3.

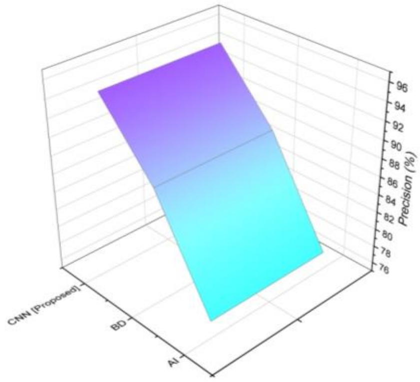


Figure 4: Precision

Table 3: Precision

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

4.3 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 utilizedto locate all relevant instances in a collection of data about industrial products.

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

Figure 5 depicts both the suggested and existing systems' recalls. It has been suggested to use the projected CNN recall in the IPD. The proposed method achieves a 97% recall rate, compared to BD's 82% and AI's 73%. It demonstrates that the suggested method has a higher recall rate than the current one. The recall values are displayed in Table 4.

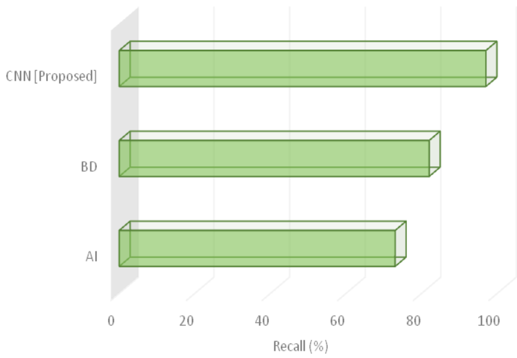


Figure 5: Recall

Table 4: Recall

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

International Water and Irrigation
Volume 44 Issue 2 (2025)
ISSN: 0334-5807
Pages 187 - 199

4.4 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 costsmore than the current one. The figures for each of the execution costs are shown in Table 5.

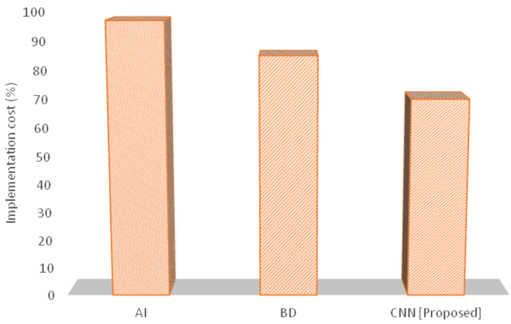


Figure 6: Implementation cost

Table 5: Implementation cost

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

4.5 Risk Assessment

Risk assessment plays a vital role in the field of product design across several industries, as it facilitates the identification, evaluation, and mitigation of possible risks connected with a product during its entire lifecycle. A range of metrics and approaches can be utilized to evaluate risks in the domain of product design. Figure 7 shows the Risk assessment of the proposed and existing system. The Risk assessment of the proposed CNN have been suggested for utilization in the IPD. BD has attained 73%, and AI has achieved 88%, whereas the proposed system reaches 61% of Risk assessment. It shows that the proposed approach has fewer Risk assessment more than the current one. The figures for each of the Risk assessmentare shown in Table 6.

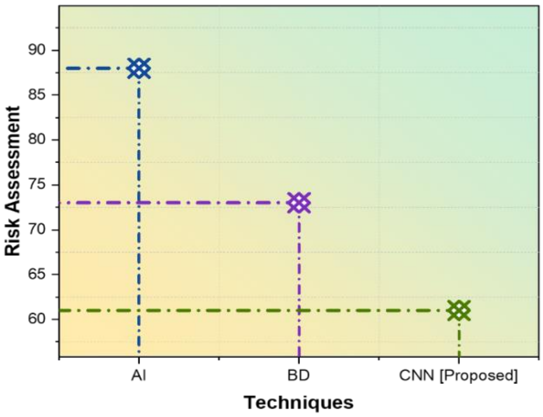
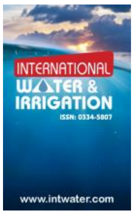


Figure 7: Risk Assessment



International Water and Irrigation
Volume 44 Issue 2 (2025)
ISSN: 0334-5807
Pages 187 - 199

Table 6: Risk Assessment

Techniques	Risk Assessment
AI	88%
BD	73%
CNN [Proposed]	61%

4.6 Design Iteration Time

One of the most important metrics in product design is Design Iteration Time (DIT), which counts the number of iterations it takes to get from a first concept to a finalized design. A shorter DIT is frequently linked to higher productivity, a quicker time to market, and improved adaptability to shifting needs.Figure 8 shows the Design Iteration Time of the proposed and existing system. The Design Iteration Time 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 Design Iteration Time. It shows that the proposed approach has fewer Design Iteration Time more than the current one. The figures for each of the Design Iteration Time are shown in Table 7.

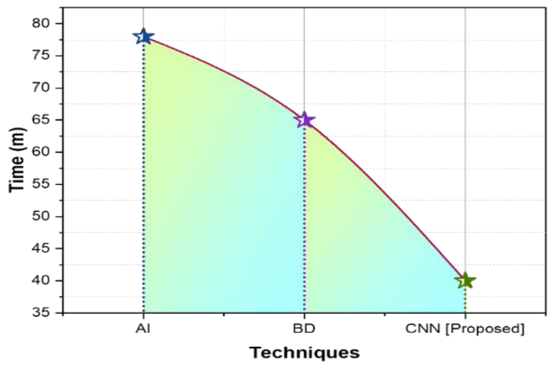


Figure 8: Design Iteration Time

Table 7: Design Iteration Time

Techniques	Time (m)
AI	78
BD	65
CNN [Proposed]	40

4.7 Customer Satisfaction level

An analysis of sensitivity was conducted to assess the impact of changes in the overall customer satisfaction level and the budget. The results are depicted in Figure 9. The data reveals a consistent upward trend in customer satisfaction levels, with an increase from 0.7315 to 0.0.8735 When the budget allocation rises from 1200 to 1800.

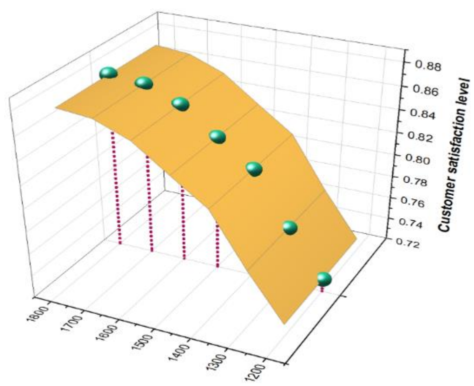
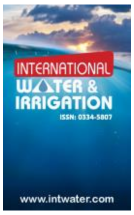


Figure 9: Customer Satisfaction Level



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. The impact of research can be considerably increased by establishing a clear connection between CNN models and product design. By offering data-driven insights into design trends, customer preferences, and functional considerations, CNN models innovate product design. This novel strategy may result in more imaginative, user-centric, and visually beautiful designs, enhancing market competitiveness and client happiness in the process. There are significant practical ramifications. CNN models can be used by designers to speed up the design process and cut down on the time and expense of several iterations. More effective rapid prototyping and design validation enable shorter product development cycles. Additionally, the capacity to examine user input and ergonomic data results in improved user interfaces and more useful designs. However, the challenges exit, among them are the demand for diversified and high-quality datasets, the possibility of subjectively labeling design elements, and the interpretability of CNN-generated design recommendations. To fully utilize CNN models in product design and ensure their seamless integration into conventional design procedures, it is imperative to address these issues. Future research in the realm of industrial design can investigate the application of cutting-edge AI techniques like CNNs to improve the efficiency of product design and manufacturing.

Reference

[1] Bilal Ahmed, M., Imran Shafiq, S., Sanin, C. and Szczerbicki, E., Towards experience-based smart product design for industry 4.0. Cybernetics and Systems, 2019, 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., Digital twin-driven product design framework. International Journal of Production Research, 2019, 57(12), pp.3935-3953.

[3] Wu, Y., Zhou, F. and Kong, J., The innovative design approach for product design is based on TRIZ, AD, fuzzy, and Grey relational analysis. Computers & Industrial Engineering, 2020, 140, p.106276.

[4] Jussila, J., Raitanen, J., Partanen, A., Tuomela, V., Siipola, V. and Kunnari, I., Rapid product development in university-industry collaboration: A case study of a smart design project. Technology Innovation Management Review, 2020, 10(3).

[5] Leng, J., Ruan, G., Jiang, P., Xu, K., Liu, Q., Zhou, X. and Liu, C., Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: A survey. Renewable and sustainable energy reviews, 2020, 132, p.110112.

[6] David, J.V., Ana, M.R., Santiago, F.B. and Faustino, A.V., 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, 2021, 11(2), p.517.

[7] ten Kate, A.J., Piccione, P.M., Westbye, P. and Becker, A.F.A., An industrial and chemical engineering perspective on the formulation of active ingredients in pharmaceuticals and agrochemicals. Current Opinion in Chemical Engineering, 2022, 36, p.100747.

[8] Huang, X., Ball, R. and Wang, W., Comparative study of industrial design undergraduate education in China and the USA. International Journal of Technology and Design Education, 2021, 31, pp.565-586.

[9] Santos, R.C. and Martinho, J.L., An Industry 4.0 maturity model proposal. Journal of Manufacturing Technology Management, 2020.

[10] Spahiu, T., Manavis, A., Kazlacheva, Z., Almeida, H. and Kyratsis, P., 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). 2021, IOP Publishing.

[11] Zhang, H., Ma, L., Sun, J., Lin, H. and Thürer, M., Digital twin in services and industrial product service systems:: Review and analysis. Procedia CIRP, 2019, 83, pp.57-60.

[12] Eriksen, M.K., Christiansen, J.D., Daugaard, A.E. and Astrup, T.F., Closing the loop for PET, PE and PP waste from households: Influence of material properties and product design for plastic recycling. Waste management, 2019, 96, pp.75-85.

[13] Urbinati, A., Chiaroni, D. and Toletti, G., Managing the introduction of circular products: Evidence from the beverage industry. Sustainability, 2019, 11(13), p.3650.

[14] Liu, M., Fang, S., Dong, H. and Xu, C., Review of digital twin about concepts, technologies, and industrial applications. Journal of Manufacturing Systems, 2021, 58, pp.346-361.

[15] Naffziger, S., Beck, N., Burd, T., Lepak, K., Loh, G.H., Subramony, M. and White, S., Pioneering chiplet technology and design for the amdepyc™ and ryzen™ processor families: Industrial product. In 2021 ACM/IEEE 48th Annual International Symposium on Computer Architecture (ISCA) (pp. 57-70). IEEE. 2021, June.

[16] Sharma, A.K., Bhandari, R., Pinca-Bretotean, C., Sharma, C., Dhakad, S.K. and Mathur, A., A study of trends and industrial prospects of Industry 4.0. Materials Today: Proceedings, 2021, 47, pp.2364-2369.

[17] Shergadwala, M., Forbes, H., Schaefer, D. and Panchal, J.H., Challenges and research directions in crowdsourcing for engineering design: An interview study with industry professionals. IEEE Transactions on Engineering Management, 2020, 69(4), pp.1592-1604.

[18] Kong, X.T., Luo, H., Huang, G.Q. and Yang, X., Industrial wearable system: the human-centric empowering technology in Industry 4.0. Journal of Intelligent Manufacturing, 2019, 30, pp.2853-2869.

[19] Oztemel, E. and Gursev, S., Literature review of Industry 4.0 and related technologies. Journal of intelligent manufacturing, 2020, 31, pp.127-182.

[20] Mourtzis, D., Boli, N., Xanthakis, E. and Alexopoulos, K., Energy trade market effect on production scheduling: an Industrial Product-Service System (IPSS) approach. International Journal of Computer Integrated Manufacturing, 2021, 34(1), pp.76-94.

[21] Liu, D., Chen, T., Liu, X. and Yu, Y., Do more subsidies promote greater innovation? Evidence from the Chinese electronic manufacturing industry. Economic Modelling, 2019, 80, pp.441-452.

[22] Tsang, Y.P. and Lee, C.K.M., Artificial intelligence in industrial design: A semi-automated literature survey. Engineering Applications of Artificial Intelligence, 2022, 112, p.104884.

[23] Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F., Digital twin-driven product design, manufacturing, and service with big data. The International Journal of Advanced Manufacturing Technology, 2018, 94, pp.3563-3576.